AMERICAN UNIVERSITY OF BEIRUT

QUANTIFYING THE DRIVER STRESS USING A DRIVING SIMULATOR AND PHYSIOLOGICAL MEASUREMENTS

by
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A thesis
submitted in partial fulfillment of the requirements
for the degree of Master of Engineering
to the Department of Civil and Environmental Engineering
of the Maroun Semaan Faculty of Engineering and Architecture
at the American University of Beirut

Beirut, Lebanon
May 2018

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ACKNOWLEDGMENTS

I would like to express my deepest gratitude to my advisor, Professor Maya Abou Zeid, for her wise guidance and unflagging support throughout the stages of this research. I appreciate all the time and effort she generously devoted to follow up on my work and to empower this research. Working with her is a real privilege and a great honor.

I would like to sincerely thank the committee members: Thanks to Professor Isam Kaysi for his invaluable insights, support and advice not only on this research, but also on both academic and professional levels; I am honored to be his student. Special thanks to Professor Ibrahim Alameddine for providing me with the technical tools for the experimental design and the statistical analysis; I am very grateful for his guidance and help. Thanks to Professor Imad Elhajj for sharing his knowledge and feedback on the research instrumentation. Also, thanks to Professor Saif Al-Qaisi for his comments and insights about the thesis work.

I would also like to thank the Chairperson of the *Civil and Environmental Engineering Department* Professor Mounir Mabsout for encouraging me and supporting my research projects at AUB.

Many thanks to the committee members of the *AUB Graduate Student Research Conference (2017)* for providing constructive feedback on this research, and to the Graduate Council for the first place award.

I appreciate the help *of the Civil and Environmental Engineering Department Office and Laboratories* staff, particularly Mr. Helmi El-Khatib, Ms. Dima Al-Hassanieh, Ms. Zakeya Deeb, and Ms. Christiane Chedid for their encouragement and assistance.

I am grateful for the technical help of the *Information Technology Department*: Mr. Saadallah Itani, Mr. Vassili Valerik, Mr. Toufic Karout, and Mr. Saro Koulakezian as well as the *Electrical and Computer Engineering Laboratories* staff: Mr. Mohamad Khaled Joujou, Mr. Salam Abyad, and Mr. Mihran Gurunian.

Thanks a lot for every student who volunteered to participate in this experiment.

Thanks to all the research assistants who helped me at different stages of this research, particularly Ibrahim Itani, Karim Ounsi, Israa Asaad, and Abbas Nassereddine.

I must also acknowledge the previous work of Mazen Danaf in his Master's thesis on quantifying aggressive driving.

I would like to thank my friends and colleagues for their assistance in the recruitment process. Thanks to Georges Sfeir and Najwa Hany for helping and sharing their experience with me.

I owe the most to my wonderful family for the unconditional support and love: Thanks to my amazing brothers Nizar and Naji for their utmost support; thanks to my amazing sister Jana for always being there despite the distance. Thanks to my supportive brother-in-law, Rawad, for introducing me to the Transportation Engineering field and for being a reliable reference in this domain. Thanks to my sweet nephew Rani for cheering up my days with his lovely smile. Finally, the greatest thanks go to my exceptional mother Hoda and father Mounir for their tremendous support, invaluable sacrifice, and endless love…Thank you is never enough!

AN ABSTRACT OF THE THESIS OF

<u>Rana Mounir Tarabay</u> for <u>Master of Engineering</u>
<u>Major</u>: Civil and Environmental Engineering

Title: <u>Quantifying the Driver Stress Using a Driving Simulator and Physiological Measurements</u>

Distraction while driving due to engagement in secondary tasks is considered a leading factor that contributes to car accidents. It affects the driver's reaction towards critical road situations and induces stress. The driver stress in turn affects the driver's performance and physiology. This study utilizes a driving simulation experiment with physiological sensors in order to quantify stress arising from an increase in workload and the resulting impacts on driving performance and physiological measures in the presence of road situations frequently encountered in an urban context: pedestrians, trucks, and traffic lights. A secondary cognitive task with multiple levels of difficulty designed to simulate auditory-vocal distraction is added to the primary driving task. Driving performance (speed, lane position, pedal depression, brake, reaction time) and physiological indices (heart rate, skin conductance) are recorded throughout the experiment. The sample consists of students of the American University of Beirut.

Using non-parametric statistical tests, it is found that the driver adopts a regulatory behavior at the operational level (e.g., reduces the speed) in order to allow the performance of the additional task and driving at the same time. The effect of the regulatory behavior is minor on the longitudinal and lateral control measures (e.g., the speed, the pedal depression, the lane position). However, the impact on the reaction time can have important implications for road safety. An increase in the heart rate and skin conductance level reflects the increase in the cognitive workload when performing the secondary task. No effect is found for the level of difficulty of the secondary task on the driving performance and physiological measures at the three considered road situations. In order to maintain control of driving, particularly at the high levels of difficulty, some subjects are found to pay less attention to the secondary task and shift their focus towards the primary driving task.

Driving behavior is modeled using a dynamic hybrid choice model that incorporates a latent variable quantifying the state stress over time and a discrete choice model of red light violations. Two approaches are used to model dynamics. First, serial correlation is used to capture the effect of time-invariant individual traits on the state stress. Second, Hidden Markov Chains are used to express the state dependence of the driver stress. The driver state stress at a specific time period is found to be affected by the encountered road events, level of difficulty of the secondary task, individual propensity for stress (first approach), and the state stress experienced at the previous time period (second approach). The results also show a pattern of regulatory driving behavior in response to increase in stress. Overall, the study highlights the advantage of quantifying the driver stress and cognitive workload measures in the development, design, and assessment of effective in-vehicle safety systems.

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To my Family

CHAPTER 1

INTRODUCTION

This thesis addresses the topic of driver distraction arising from an auditory-vocal secondary driving task. It particularly assesses the impact of an increase in the driver cognitive workload on driving performance and physiological measures, and models the state of stress generated by the additional workload in the presence of situational roadway characteristics of the urban context.

This chapter presents a motivation for the research and its objectives, questions, and contributions. It is organized as follows. The first section provides an overview of road traffic crashes and associated factors, including driver distraction, based on international and local statistics. The second section presents basic definitions and sources of driver distraction. The third section introduces the notion of driver stress, including its relation with driver distraction and workload; other sources of stress are also discussed. The fourth section discusses the implications of distraction and stress for driving safety. The fifth section describes approaches to measure driver workload and stress. The sixth section motivates why it is important to detect the driver state. The seventh section presents the research objectives, questions, and contributions. The eighth section presents the structure of the thesis.

1.1. Overview

In the “Global Status Report on Road Safety”, data published by the World Health Organization (WHO), posit road traffic crashes in 2012 as a major global cause of death, and as the first cause of death threatening youths and adults aged between 15 and 29 years (WHO, 2015a). The United States Department of Transportation (USDOT) reports that 37,461 lives were victims of road crashes in the U.S. in 2016 (NHTSA, 2017). According to the statistical profile of Lebanon (WHO, 2015b), road injuries are the third cause of death in Lebanon, constituting 4% of the total deaths in 2012. The Internal Security Forces reported that 4,208 accidents occurred in 2012 resulting in 576 fatalities and 5,963 injuries (Mijwez, 2014).

Crash-associated factors include any of these elements: driver, vehicle, roadway (environment) or a combination of them (NHTSA, 2008). The Institute of Transportation Engineers (ITE) reported that the human errors factor is the major contributor to road accidents in the United States: 93% of all crashes involve human errors, while 34% of crashes involve roadway features, and 12% of crashes involve vehicle failure (ITE, 2004). Further, the NHTSA classified errors committed by the driver into recognition errors, decision errors, performance errors, and nonperformance errors. Recognition errors were the most crucial, constituting 41% of all driver-related errors in the U.S. The NHTSA (NHTSA, 2016a, 2008) also identified distraction as an influential factor leading to recognition impairment and considered as a “risky behavior” resulting in 10% of fatal crashes, 18% of injury crashes, and 16% of all police-reported motor vehicle traffic crashes in 2014 in the U.S.

1.2. Driver Distraction

1.2.1. Definition of Driver Distraction

Studying driver distraction has been of interest to road safety researchers and experts from the industry for many years. Several definitions appear in the literature and commonly include terms such as “attention” or “workload”, in addition to a “stimulus”, such as “an object, person, task, activity, event, happening, movement, process, condition, situation, source, or agent” (Foley et al., 2013) that triggers a deviation in the driver’s attention from the primary driving task. In 2012, Toyota’s Collaborative Safety Research Center organized a workshop with the aim of improving both scientific and public policy aspects of driver distraction research, whereby experts thoroughly agreed on a comprehensive and operational definition of driver distraction by Regan et al. (2011): *“Driver distraction is the diversion of attention away from activities critical for safe driving toward a competing activity, which may result in insufficient or no attention to activities critical for safe driving”*. The workshop also defined inherent terms of driver distraction as follows (Foley et al., 2013):

(1) Attention: the set of cerebral functions in charge of “orienting”, “executing”, and “alerting”.

(2) Safe driving: the “reasonable” and “expected” way of operating a motor vehicle.

(3) Competing activity: concurrent activity (or activities) requiring similar resources or demands to those needed for the driving task. Table 1 defines the main involved resources.

Table 1: Definitions of the main resources (demands) (Foley et al., 2013)

Type of Resource	**Definition**
Cognitive	“The alerting, executive, and orienting attentional networks singly or in combination, as well as the memory and representational systems (e.g., working and long-term) from which information may be retrieved and in which it may be held and operated upon”
Auditory	“The sensory organs and associated neurological structures, pathways, and processes by which hearing and perceiving sound occurs”
Vocal/verbal	“The structures, pathways, and processes associated with speaking, verbalizing, or making utterances covertly or overtly”
Visual	“The visual sensory organs and associated neurological structures, pathways, and processes”
Motoric	“The motor/biomechanical system and associated structures of movement within the body”

As such, there are various types of driver distraction depending on the resources involved in the competing activity. For example, an auditory-vocal-cognitive distraction implies that an activity demanding auditory, vocal, and cognitive resources is competing with the safe driving task. In order to simplify, often, these three resources (auditory, vocal, and cognitive) are associated together and referred to as “cognitive workload”, despite their different neurological constructs and potential implications for attention and behavior. Therefore, a broader and simplified classification of distraction is based on three major types of resources that overlap in reality (Reimer, 2012): cognitive, visual, and manipulative (or motoric).

1.2.2. Sources of Driver Distraction

The National Motor Vehicle Crash Causation Survey (NMVCCS), conducted by the NHTSA (2010), addressed several variables associated with distraction from internal sources and cognitive activities. Conversing with a passenger (Figure 1) was the most frequently recorded internal source of distraction, while inattention due to unknown thoughts was the most frequently recorded cognitive activity, followed by inattention due to personal problems (Figure 2).

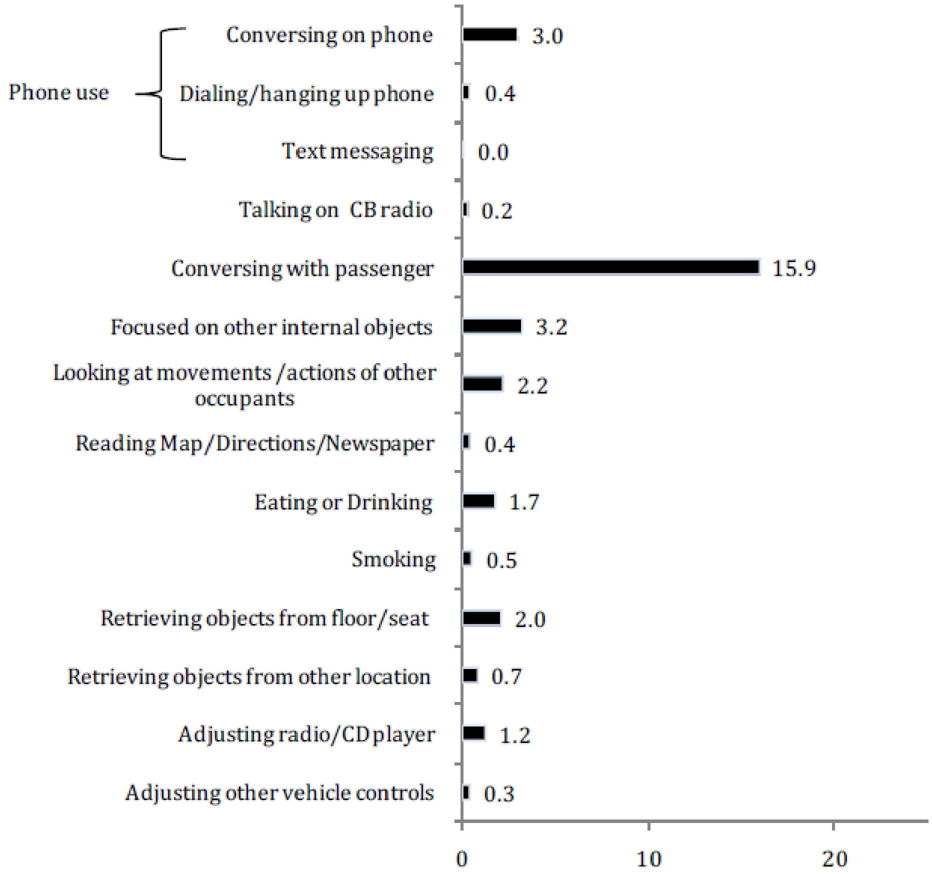

Figure 1: Percentages of crashes with drivers distracted from fourteen internal sources of distraction (one or more distractions may have been present in a crash) (NHTSA, 2010)

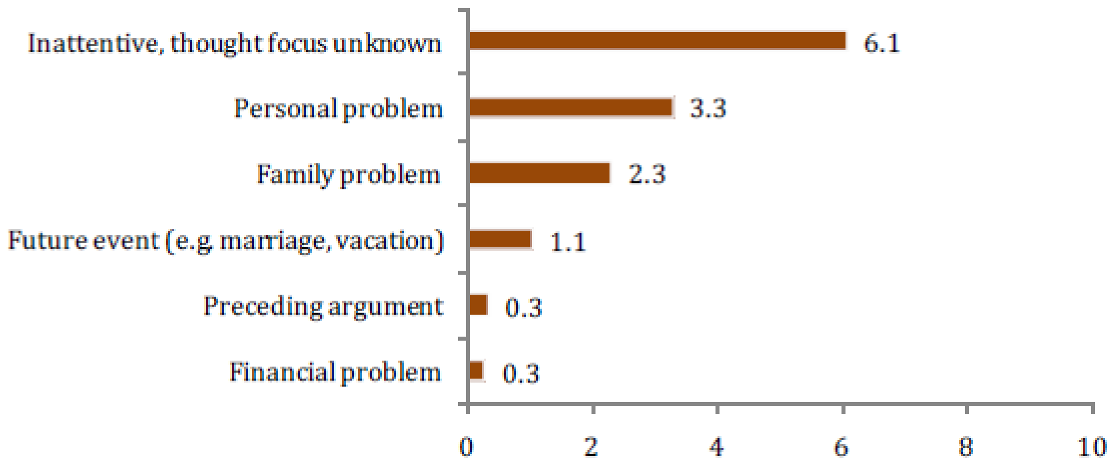

Figure 2: Percentages of crashes with drivers engaged in six cognitive activities (one or more drivers may have been engaged in the same cognitive activity in a crash) (NHTSA, 2010)

More recently, the prevalence of smartphones and in-vehicle devices witnessed in the past ten years has increased the tendency of being distracted while driving. In-vehicle screens, smartphone apps, and social media have increased visual distraction (McGehee, 2014). Figure 3 (NHTSA, 2016b) shows recent statistics from the National Occupant Protection Use Survey (NOPUS) according to probability-based observed data[1] reflecting drivers' use of electronic devices between 2006 and 2015 in the United States. Although the percentage of handheld cell phone use decreased from 5.2% in 2012 to 3.8% in 2015, this percentage remains higher than the percentage of visible headset cell phone use (0.6% in 2015) and the percentage of visible manipulation of handheld devices, which includes behaviors such as text messaging, viewing travel directions, surfing the internet, etc. (2.2% in 2015).

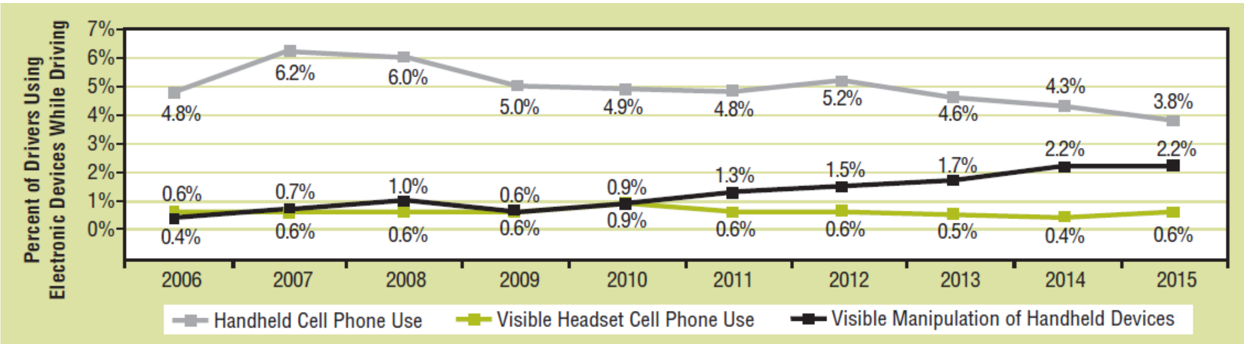

Figure 3: Driver use of electronic devices, 2006-2015 (NHTSA, 2016b)

1.3. Driver Stress

Different factors contribute to the driver state stress. Although stress and workload originate from relatively distinct constructs, they are commonly used to evaluate the effects of internal and external demands on the individual and characterize his/her state, particularly in the driving context (Hancock and Desmond, 2001; Reimer

[1] Data collection process on the usage of electronic device in this survey consists of observing (without conducting any interviews) the behavior of the occupants of passenger vehicles, including the driver, at randomly chosen (i.e., by probabilistic sampling) roadway spots, such as intersections.

et al., 2016). An increase in the driver workload as an outcome of distraction induces high levels of stress (WHO, 2011), referred to as "distress" in Matthews (2002) and as "overarousal" in Coughlin et al. (2011). It is attributed to the actual amount of effort, whether physical or cognitive, required to perform a task. Moreover, the anxiety about not being able to successfully accomplish the task at hand on time and the fear of committing errors generate distress (Reimer et al., 2016). Therefore, distracting activities, such as using mobile phones, conversing with passengers, and manipulating in-vehicle systems as secondary tasks while driving induce stress (Schießl, 2007). The shift in attention from the primary driving task when thinking about life events such as personal, financial, and job problems (Figure 2) also increases the driver stress (Matthews et al., 1996b; Rowden et al., 2011).

Stress can also be induced by driving and contextual factors. The primary task of driving requires attentional demands on the driver such as maintaining longitudinal and lateral control and reacting to hazards (Matthews, 2002; Rowden et al., 2011; Schießl, 2007). The demands of the driving task also depend on the driving environment. For example, driving on highways generates medium level of stress while city driving generates high level of stress (Solovey et al., 2014). Moreover, driving conditions such as low visibility, weather, fog, poor road conditions, and congestion increase the driver stress (Matthews, 2002; Schießl, 2007).

In addition, trait or personality characteristics affect the driver state and they are associated with the driver vulnerability to stress such as aggression, fatigue, dislike of driving, etc. (Matthews, 2002; Matthews et al., 1996a, 1996b; Rowden et al., 2011). Consequently, a particular roadway event or factor might not induce the same level of stress among different individuals (Hill and Boyle, 2007).

1.4. Implications for Driving Safety

Distraction is associated with errors and impairment in the driving performance such as missing stop signs, reduction in lateral and longitudinal control and delayed reaction times when encountering roadway hazards and events (e.g., crossing pedestrians, signalized intersections). Such behavior increases the risk of crashes and threatens driving safety (Young et al., 2013).

Figure 4 illustrates a framework by Hurts et al. (2011) for the sources of demand on the driver and their potential effect on driving performance and crash occurrence. Demands on the driver (box 2) mainly originate from the primary task of driving (box 0) influenced by different factors, e.g., vehicle, road, weather, traffic, etc., and secondary tasks (box 1) including the use of in-vehicle systems (box 1.5). Depending on the driver characteristics, such as age, skills and experience, (box 6), these demands on the driver may interfere with, or deteriorate, the driving performance (box 3). Crashes, or near-crashes may happen (box 5) when such deterioration occurs in the presence of situational factors, such as roadway hazards and events. This framework highlights the impact of the coincidence of the increased demands with the contextual factors on safe driving.

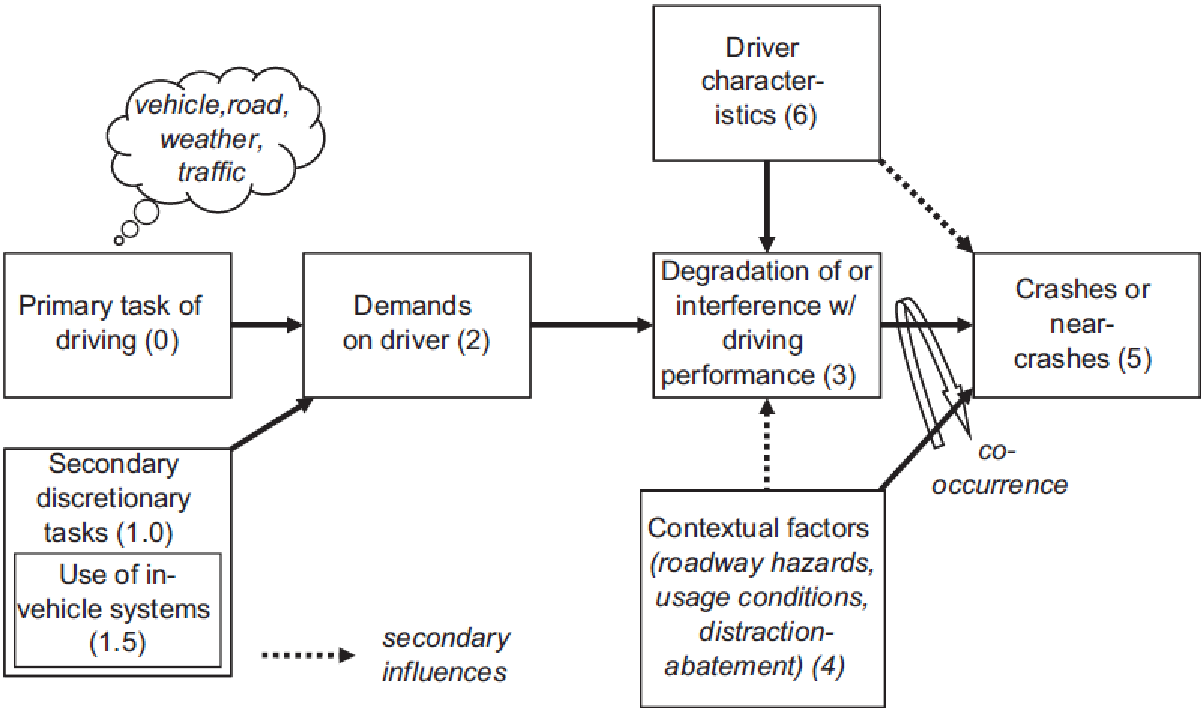

Figure 4: Diagram of sources of demand on the driver and their safety relevance (Hurts et al., 2011)

The impact of workload and stress on driving performance can also be differentiated by accounting for the extent of the workload/stress. Figure 5 depicts this impact as an inverted-U-shaped curve (Coughlin et al., 2011). Critical zones associated with a deterioration in the driving performance are the low end of workload (i.e., underload) that corresponds to fatigue and drowsiness, and the high end of workload (i.e., overload when distraction is excessive) that generates a high level of stress. Both extremities of the driver workload are related to road accidents (Brookhuis and De Waard, 2010) while an optimal driving performance is reached at the middle when an adequate level of arousal and attention is invested for safe driving (Coughlin et al., 2011).

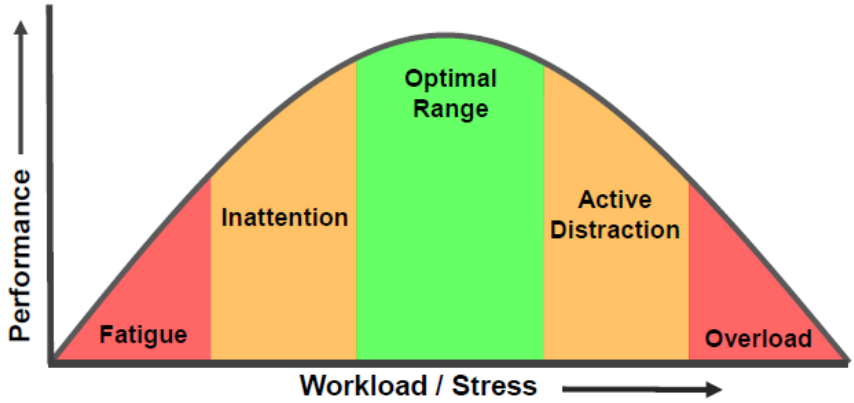

Figure 5: The relationship between driving performance and workload or stress (Reimer, 2011)

1.5. Measuring Driver Workload and Stress

Workload and stress can be measured by objective indicators such as driving performance and physiological measures obtained through sensors, and subjectively by means of self-reports (questionnaires or surveys) (Mehler et al., 2009).

1.5.1. Driving Performance Measures

As discussed above, higher levels of workload and stress can lead to a deterioration in driving performance. Relevant measures of the latter include speed, acceleration, braking, reaction time, steering wheel movements (e.g., wheel reversals), lane position, and following distance (Mehler et al., 2009; Miller, 2001). These measures can be assessed at particular instances in the driving course (e.g. at road events). Their evolution over time is also of interest as an indication of how workload and stress propagate over time.

1.5.2. Physiological Measures

Physiological activity naturally arises when additional workload is exerted leading to variation in physiological measures such as heart rate and skin conductance (Brookhuis and de Waard, 2011; Engström et al., 2005; Hajek et al., 2013). Mehler et al. (2012) observe that physiological disturbances occur when the human body mobilizes resources in order to respond to the task demand and operate. Thus, monitoring physiological indices would give insight into workload and stress magnitude (Mehler et al., 2009). Two main physiological measures of workload and stress are the heart rate and the skin conductance level.

Heart rate refers to the number of heartbeats per minute, and can be measured by the Electrocardiogram (EKG). It is a record of the heart's electrical activity in form of waves labeled PQRS and T. Heart rate is derived from the inter-beat interval (IBI) which corresponds to the interval between the R-waves (or R-spikes). Under conditions of stress, anxiety, or workload increment, heart rate increases, while it decreases with relaxation (Mehler, 2009; Reimer et al., 2006). Skin conductance level (SCL), also referred to as electrodermal activity (EDA), is due to the perspiration phenomenon, i.e., when the dermal cells sweat the skin conductance increases. In response to stress, the sweat gland activity and the skin conductance level increase (Mehler, 2009). Other physiological measures include heart rate variability, blood pressure, respiration rate, eye activity (e.g., eye blink rate and interval of closure), speech measures (e.g., pitch, rate), and brain activity (e.g., electroencephalogram, electrooculogram) (Miller, 2001).

1.5.3. Subjective Measures

Subjective measures of driver workload and stress are based on surveys or questionnaires consisting of subjective evaluation and rating of workload, such as NASA Task Load Index Scale or NASA-TLX (Miller, 2001). Surveys that capture the driver trait stress reflect individual differences in the perception of stress and coping styles, such as the Driver Stress Inventory (DSI) and the Driving Coping Questionnaire (DCQ) (Matthews et al., 1996a).

1.6. Importance of Detecting the Driver State

The driver state represents the physical and the functional conditions of the operator such as the level of stress, cognitive workload, distraction, and fatigue (Coughlin et al., 2011). Detecting the driver state could be based on objective and subjective measures such as those described earlier in the previous section. Integrating the driver state detection within in-vehicle systems can have important implications for the driver safety.

Several systems may be incorporated within the car to enhance safety according to different types of interventions classified as follows (Reimer, 2013): (1) injury mitigation/reduction or passive safety (e.g., airbags), (2) accident avoidance provided by an automatic response implemented by the system (e.g., braking, lane correction) or by warning the driver to implement the response (e.g., collision warning, lane departure warning), and (3) driver performance enhancement and incident prevention by detecting the driver state and managing the driver workload and wellbeing. Coughlin et al. (2011) discussed the importance of detecting the driver state (stress, fatigue, inattention) in order to enhance the driver safety and well-being. They highlighted the importance of considering the driver an “active participant” who controls, operates the vehicle, and interacts with the overall environmental changes. They also proposed a framework for an integrated vehicle safety/wellness system, illustrated in Figure 6. Once the driver state is detected and monitored, the resulting information is displayed and provided to the driver, the vehicle systems, and the

Intelligent Transportation System (ITS) infrastructure to promote and support safety features (e.g., alert or calm the driver) in response to the driving situation (refresh).

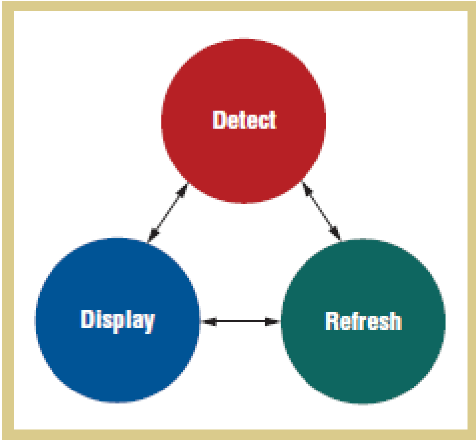

Figure 6: Framework for an integrated vehicle safety/wellness system (Coughlin et al., 2011)

Moreover, integrating the state detection in the design of safety systems of the second category mentioned earlier in this section can help increase the predictability of the crash occurrence. For instance, Figure 7 illustrates the current architecture of Vehicle Collision Avoidance Systems (VCAS) in the upper panel (a), and the state-integrated system in the lower panel (b). The crash prediction in the current system (a) is only based on data provided by sensors from the surrounding traffic environment, and interventions are generated according to risk-estimation algorithms. In the more advanced system (b), the human state is detected/quantified based on behavioral and physiological data and serves as input for crash prediction (Ba et al., 2017).

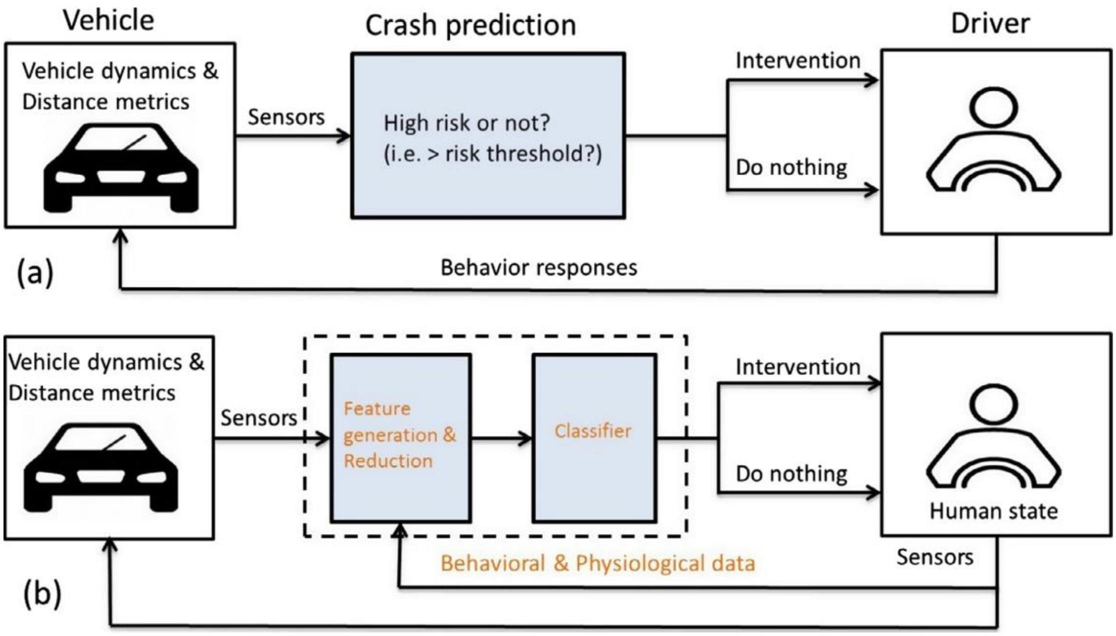

Figure 7: Architecture of Vehicle Collision Avoidance Systems (VCAS) without/with state detection (Ba et al., 2017)

Other applications of the driver state detection fall within the artificial intelligence technology whereby the car "perceives" the environment and the driver conditions and takes actions to maximize the driver safety and well-being. This is the case of the "emotion engine" applied within the automated electric car Honda NeuV (Lacey, 2017). This car detects the driver's emotions using physiological sensors and cameras. If the driver is found to be stressed and driving aggressively for example, the "network assistant" in the car would encourage him or her to calm down by recommending relaxing music and adjusting the lighting scheme. Furthermore, to ensure the driver safety, the vehicle's power might be temporarily reduced and the driving mode might be switched to the autonomous mode until the driver restores the well-being state. As such, the car "learns" from the driver state and takes over the control accordingly.

Detecting the driver state will remain important despite the direction of the automation technology towards driverless cars. Nunes et al. (2018) emphasize that even high levels of automation need a kind of human interventions and *“Driverless does not, and should not, mean without a human operator”*. Current fully autonomous vehicles require the presence of a safety driver whose intervention could save lives in case of failure of the autonomous system. Recently, an accident involving a self-driving car killed a pedestrian in Arizona; the distracted safety driver inside the vehicle could not prevent the crash (Griggs and Wakabayashi, 2018). If a state detection system was present to detect the driver state and warn him to restore attention to the road, such incident might be prevented.

In this context, we aim to develop a dynamic behavioral model capable of detecting the driver state and that could still be of value even in the presence of future autonomous technology.

1.7. Research Objectives, Questions, and Contributions

Based on the above motivation, auditory-vocal-cognitive distraction remains an important concern and a crucial area to further investigate as evidenced by the high percentage of crashes involving conversations with passengers as internal source of distraction, and by the high percentage of cell phone use for auditory conversations specifically. Therefore, this research focuses on studying auditory-vocal distraction and utilizes an auditory-vocal secondary task to simulate this particular type of cognitive distraction in a driving simulation experiment with physiological measures. Moreover, since the presence of roadway hazards or events amplifies the risk of crash occurrence when the driver is distracted, this research studies auditory-vocal distraction particularly at three road events. In the first event, pedestrians cross the road suddenly in front of the driver. In the second event, a truck initially moving ahead of the driver suddenly stops. In the third event, the subject encounters a signalized intersection; initially set to the green indication, the traffic light turns yellow, then red just before the subject reaches the intersection. Those events are frequently encountered in an urban driving context whereby the driving task demands a high workload. In response to the increase in workload level added by the secondary task and the road events, the driver is expected to experience a higher level of stress. Toward this end, this research has two main objectives:

1. To quantify the effect of an increase in workload arising from a secondary auditory-vocal distracting task, on driving performance and physiological measures, particularly at road situations often encountered in cities
2. To quantify the impact of different factors that affect the driver state stress and model its evolution over time

Measurements of workload/stress consist of (1) driving performance measures (speed, accelerator pedal depression, brake, lane position, reaction time) extracted from the driving simulator, and (2) physiological measures (heart rate and skin conductance) derived from the physiological sensors. The study targets the student population of the American University of Beirut (AUB) as an age segment mostly exposed to distraction and road accidents in general.

To achieve the first objective, driving performance and physiological measures are compared between a control phase whereby the driver is not subjected to the secondary cognitive task and a treatment phase whereby the driver is subjected to the secondary task. This analysis is conducted at each road event separately. Since the task used is designed with multiple levels of workload, differences between groups are also assessed in terms of driving performance and physiological measures across the workload levels of the task. Therefore, we address the following questions:

- *How does the secondary task affect driving performance and physiological measures?*
- *To what extent may there be self-regulation in driving to allow the performance of the secondary task?*
- *Do the levels of the secondary task have different effects on driving performance and physiological measures?*
- *Do the drivers ignore the secondary task when its level of difficulty increases?*

To achieve the second objective, a dynamic hybrid choice model is developed, whereby all scenario variables are accounted for as predictors of the driver state stress. Individual traits derived from the responses on the survey questions are also assessed whether they influence the state stress or not. Two approaches are used to model the evolution of stress over time. The first approach uses serial correlation and tests the effect of individual traits that persist over time on the driver state. The second approach uses Hidden Markov Chains and tests whether the state stress at a specific time period is affected by the state stress at the previous time period. Therefore, we address two questions:

- *Do the individual traits affect the actual state stress of the driver?*
- *Does stress carry over from one time period to another while driving?*

The findings of this study contribute to a better understanding of the impacts of auditory-vocal distraction at frequently encountered road situations in urban settings. The theoretical contribution of this study consists of implementing the concept of driver stress in a dynamic model that accounts for contextual and individual factors affecting the driver behavior and physiology. From a practical standpoint, the study highlights the advantage of implementing the driver stress and cognitive workload measures in the development, design, and assessment of effective in-vehicle safety systems. The model could be potentially integrated within in-vehicle systems to detect the driver state and help the driver improve his/her driving performance.

1.8. Thesis Organization

The remainder of this thesis is structured as follows.

- Chapter 2 reviews the literature of driver stress and workload.
- Chapter 3 presents the research methods including the apparatus and tasks, experimental design and procedure, dependent variables, and data collection and analysis techniques.
- Chapter 4 presents the results of the statistical descriptive analysis that evaluates the impacts of the auditory-vocal distracting task on the driving performance and the physiological measures without accounting for the dynamics in driving performance (objective 1 of the study).
- Chapter 5 models dynamically the driver stress (objective 2 of the study).
- Chapter 6 concludes the thesis and presents its contributions and potential application. It also presents limitations and possible extensions for future research.

CHAPTER 2

LITERATURE REVIEW

Several research studies have addressed the topic of driver stress and/or examined physiological monitoring as a measure of variation in the driver's cognitive workload and stress. The first section of this chapter reviews the most relevant studies of stress and workload. The second section discusses the use of physiological measures in the driving context. The third section discusses the gaps in the literature and how this research intends to fill these gaps.

2.1. Stress and Workload

Matthews (2002) reviewed and outlined a transactional model for driver stress and fatigue based on the approach developed by Lazarus (1999). In this model, the dynamic interaction between the individual and the driving environment, promoted by the perception of external commands, produces stress. The model differentiates between situational stressors controlling the "state stress" and personality characteristics defining the "trait stress". As shown in Figure 8, a high level of workload is perceived as an environmental stress factor, whereas aggressiveness, tendency to experience fatigue, and dislike of driving are seen as individual characteristics affecting the vulnerability to stress. In response to these factors, the driving behavior is influenced by the "appraisal process" that consists of the personal assessment and tolerance of the stress impact, and the "coping process" that determines strategies and actions to manage the perceived stress. As such, the consequences of these two cognitive processes are classified into “subjective outcomes” reflected in anger, worry, tension, etc., and “performance outcomes” reflected in deterioration of control and speed variations.

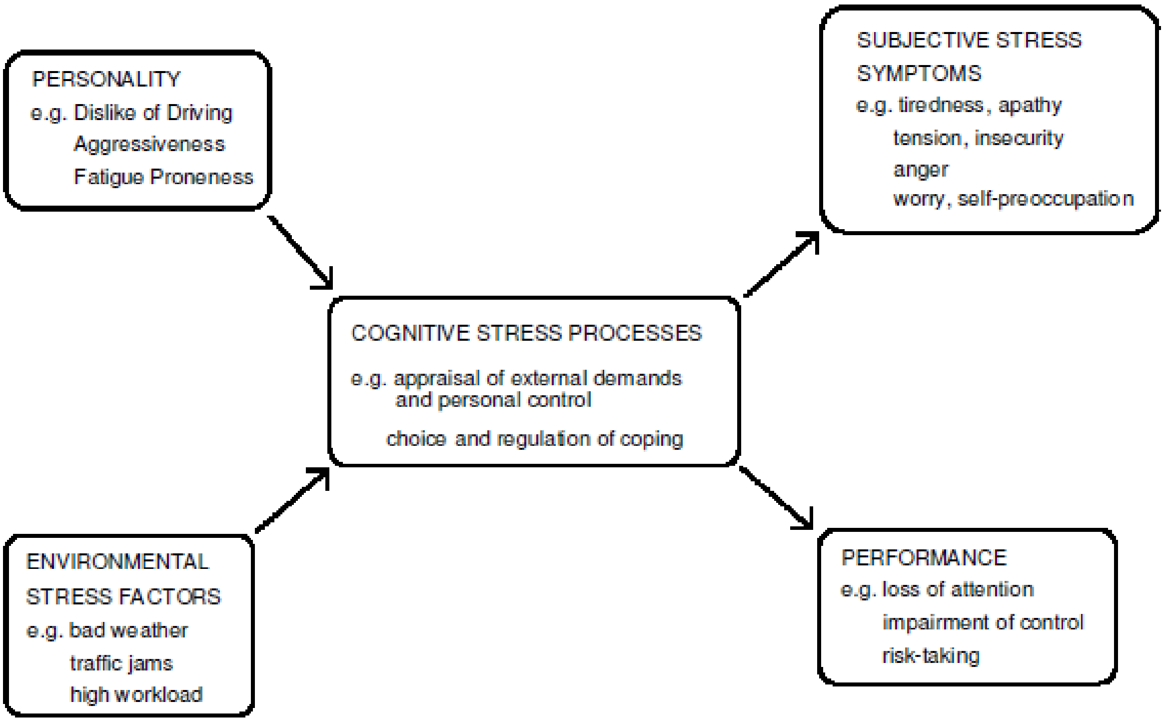

Figure 8: An outline of the transactional framework for driver stress (Matthews, 2002)

Brookhuis and De Waard (2010) defined the driver’s cognitive workload as arising from the driving task’s demand, besides other factors. They distinguished between two types of workload: (1) underload that contributes to impairment in both attention and alertness, and (2) overload that leads to distraction and lack in time and capacity required to process the information.

Recent research work (Zhou et al., 2016) studied the effect of compensatory beliefs in changing the behavior to self-regulate the increased demand from additional tasks at different levels. For instance, (a) at the strategic level, the driver decides not to perform a secondary task (e.g., using a mobile phone), (b) at the tactical level the driver regulates and adjusts the engagement time with the secondary task, and (c) at the operational level, the driver reduces the speed when performing the secondary task.

Mehler et al. (2012) distinguished between the demand and the workload. They related the demand to the objective requirements of a certain task, and the workload to the effect on a subject due to task enrollment. And, to transition from the objective demand to the experienced workload, multiple person-specific characteristics are involved, such as individual capabilities and training, motivational factors, mood, etc.

2.2. Physiological Measures in the Driving Context

Different physiological measures, such as heart rate, skin conductance, respiration rate, and muscle activity appeared in the literature as indices of increment in stress and workload. This section discusses their particular use in the driving context.

Healey and Picard (2005) detected the stress induced by real-world driving by means of physiological metrics. Electrocardiogram, electromyogram (record of the muscle electrical activity), skin conductance, and respiration rate were continuously collected during real trips made by subjects in the Greater Boston Area. Stressors experienced throughout the drives were extracted from the recorded and scored video for each participant by developing a continuous stress metric based on the number of stress indicators at each second and accounting for the expectation effect and the past events. Physiological time series were also derived from the output of physiological sensors. It was found that heart rate metrics and skin conductance were the most correlated measures with the stress level while driving.

Reimer et al. (2006) stated that physiological arousal, as an indicator of the body’s response to physical and cognitive workload, is frequently measured by means of heart rate; particularly, both heart rate and blood pressure have been found to increase with intensifying cognitive demand. For example, a simulation experiment conducted on two age groups (younger and older drivers), in four distinct driving environments along with different cognitive tasks (including a cellular phone conversation), showed that younger drivers exhibited a significant increase in heart rate between the single task condition and the dual task condition: their average heart rate increased from 69.26 BPM (beats per minute) to 72.98 BPM, respectively. Heart rate was also higher under the suburban and city driving conditions compared to rural and highway driving conditions.

Mehler et al. (2009) inspected the sensitivity of physiological signals as measurements of cognitive workload in conjunction with a driving simulation experiment. They assessed the impact of the incremental increases in cognitive workload on physiological arousal and driving performance by introducing a secondary cognitive “n-back” task (a delayed digit recall task) that was assigned to the participants in addition to the primary simulated driving task. Physiological data on heart rate, skin conductance, and respiration rate, in addition to driving performance measures (forward velocity and lateral position), were collected. Results showed that the three collected physiological measures can provide indications of differences in the relative workload assigned to subjects prior to, or in absence of, significant performance level decrements. In the same research context, data on the forearm muscle tension have been collected in the pilot study; results showed that variations due to additional workload were hidden by the dominant steering activity when driving.

Eye tracking can also be used to measure distraction due to additional cognitive workload. For instance, Niezgoda et al. (2015) showed that changes in workload level can be detected by variation in the pupil size in reaction to a secondary cognitive auditory prompt and verbal response task while driving in simulated conditions of a highway scenario. Another driving simulator study inspected the effect of time pressure on driving performance and physiological state. Measures of interest were eye movement and pupil diameter, cardiovascular and respiratory activity, driving performance, vehicle control, etc. Under time pressure conditions, heart and respiration rates increased, pupil diameter increased, and the blink rate decreased (Rendon-Velez et al., 2016).

2.3. Conclusion

Based on the above literature, driver stress arises from different sources. The driving task contributes to the state of stress, particularly in complex environments (e.g., city driving). When the driver is distracted by additional secondary tasks, cognitive workload and stress increase. Individual characteristics or traits influence the state of stress as well. Such variations translate into variations in the driver behavior and physiology. Therefore, driving performance and physiological measures, in addition to personality traits, can be useful indicators of cognitive workload and stress.

Though the transactional model of driver stress (Gulian et al., 1989; Lazarus, 1999; Matthews, 2002) is widely referred to in the literature (see as examples Abdu et al. (2012); Funke et al. (2007); Saxby et al. (2013); Staal (2004); Stephens and Groeger (2009)), to our knowledge, this conceptual model has not been implemented in a mathematical model that accounts for the different factors affecting the driver stress. This research intends to fill this gap by operationalizing the transactional approach (including environmental/situational factors and individual traits) in a mathematical dynamic model that quantifies the state stress over time.

As will be described in the following chapter, a driving simulation experiment will be used to generate road events frequently encountered in an urban context. The delayed digit recall task (n-back) will be used as a secondary task to simulate an increase in the cognitive workload. By analyzing the effects of the n-back task on the driver behavior and physiology at three particular road events, this study differs from previous research work (e.g., Mehler et al. (2012, 2009); Niezgoda et al. (2015)) that has investigated the effect of an increase in workload in the absence of particular road events. Therefore, this study contributes to a better understanding of the effects of auditory-vocal tasks, including potential self-regulatory strategies that have been investigated to a limited extent in the literature.

CHAPTER 3

RESEARCH METHODS

This research utilizes a driving simulation experiment and physiological sensors to test the effect of an increase in the cognitive workload on driving performance and physiological measures. A secondary auditory-vocal task, with multiple levels of difficulty, designed to simulate auditory-vocal distraction in specific is added to the primary task of driving. The impact of this task is investigated at three particular road events often encountered in an urban context. In addition to a baseline, two main phases are designed: the control phase in which the subject encounters the road events without being subjected to the secondary task, and the treatment phase in which the subject encounters the road events while being subjected to the secondary task.

This chapter describes the research methods as follows. The first section introduces the research tools, including the apparatus (the driving simulator and the physiological instrumentation and sensors) and the experimental tasks. The second section presents the experimental design and the third section presents the experimental procedure. The fourth section describes the data collection methods, the fifth section presents the dependent variables, and the sixth section presents an overview of the data analysis methods used.

3.1. Research Tools

3.1.1. Apparatus

3.1.1.1. The Driving Simulator

Driving simulation data are collected using the driving simulator DriveSafety DS-600c (Figure 9), a full-width Ford automobile cab, available at the Transportation and Infrastructure Research Laboratory of the American University of Beirut (AUB). This driving simulator has been used in previous research at AUB to study driving aggressiveness (Danaf et al., 2015) and pedestrian-vehicular interaction (Obeid et al., 2017). It is a fully integrated simulator characterized by its high performance and fidelity and is used to assess the driving behavior under controlled and customizable conditions. This simulator is classified as a band D simulator on a scale from A (band of simulators that are not used for research/training, e.g., computer and video games) to E (band of complex or high-level simulators). The relative validity of the DS-600c simulator is assumed to hold.

Driving scenarios are designed using the HyperDrive Authoring Suite that allows the user to create driving scenes from a wide library of cultures, roadways, intersections, and entities. Events are generated by means of scripted triggers (location or time based). Data are collected at the frequency of 10 Hz and are recorded in the output file of each session (can be opened in Microsoft Office Excel). The output file includes setting data (e.g., time, frame, terrain type, number of lanes), subject data (e.g., position, speed, pedal depression, lateral position), entities data (e.g., position, speed, distance from subject, time to subject), scenario tools data (e.g., active triggers, intersection signal state). The user can also specify other variables to be output in the file using HyperDrive syntax.

Figure 9: DriveSafety DS-600c driving simulator (DriveSafety, 2016)

3.1.1.2. The Physiological Instrumentation and Sensors

Physiological data are collected using MEDAC System/3 instrumentation unit (Figure 10) and sensors from NeuroDyne Medical, Corp.[2] as follows. Heart rate data are collected using the Electrocardiogram (EKG) sensor (Figure 11) which consists of three leads that are attached to the subject near the collarbones (left and right) and on the left side near the bottom rib. Skin conductance data are collected using the electrodermal sensor (Figure 12) which consists of two electrodes that are attached on the adjacent fingers of the non-dominant hand (Mehler, 2009). NeuGraph software is used to collect data and display physiological signals in real-time (NeuroDyne Medical, 2004). A sampling rate of 250 Hz is adopted to allow the detection of EKG R-spikes (Mehler et al., 2009). EKG data stored in NeuGraph software are then edited using EKG Wave Editor in order to remove movement artifacts and detect heart beats. For more information about the EKG editing process, the reader is referred to Appendix A. To ensure the consistency and the synchronization with the driving simulation data, edited

[2] The company is currently managed by Tenacity Medical, Inc.

physiological data are saved with a reduced sampling rate of 10 Hz (NeuroDyne Medical, 2009).

Figure 10: MEDAC System/3 instrumentation

Figure 11: EKG sensor (Mehler, 2009)

Figure 12: Skin conductance sensors (Mehler, 2009)

3.1.2. Tasks

3.1.2.1. Driving Task

The driving simulation occurs in an urban context in which the subject is required to drive straight and curved roadways with one lane in each direction and parked cars on both sides. The total length of the driving course is approximately 7.5

km. Road directions are provided by means of billboards indicating the direction to be followed (e.g., “Turn Right”, “Turn Left”, and “Continue Straight”). A visual display of road directions is adopted in order to prevent interference with the auditory secondary task. If the subject does not abide by the posted directions, a dead end is reached and the experiment is terminated.

Three different road situations or events, illustrated in Figure 13, are encountered during the driving course. In the first situation, pedestrians cross the road suddenly in front of the driver. The start point of the segment of interest for analysis is defined as the time at which the subject reaches the location-based trigger (located 80 m before the crosswalk) which is scripted to provoke the walking movement of the pedestrians. The event ends when the subject reaches the crosswalk, which constitutes the end of the segment of interest. In the second situation, a truck initially moving ahead of the subject suddenly stops. The start point of the segment of interest is defined as the time at which the truck starts decelerating, while the end point is defined as the time at which the subject stops. In the third situation, the subject encounters a signalized intersection. Initially set to the green indication, the traffic light turns yellow, then red just before the subject reaches the intersection. The start point of the segment of interest is the time at which the traffic light turns to the yellow indication (100 m before the intersection), while the end point is defined as the time at which the traffic light turns to the red indication (30 m before the intersection).

The traffic flow in the opposite direction is light except for the truck situation, where it increases to prevent the subject from overpassing the truck. Other environmental factors such as weather conditions and time of day were not varied throughout the experiment in order to prevent any interference with the scenario variables of interest.

Figure 13: The encountered road situations

3.1.2.2. Secondary Task

Description

The delayed digit-recall (n-back) task developed by the MIT AgeLab is adopted in this study as a secondary task assigned to the subjects in addition to the primary task of driving. This task entails three different levels of cognitive demand. In the first level (0-back), the subject is required to hold in memory one single digit number presented to him/her randomly (between 0 and 9), and to repeat it immediately after it was presented. In the second level (1-back), the subject has to recall from memory and repeat out loud the number that was presented one back prior to the current number. In the third level (2-back), the subject is required to recall from memory and to respond with the number that was presented two numbers prior to the current number (Reimer et al., 2014). The n-back task has been adopted in several research studies such as Hajek et al. (2013), Mehler et al. (2012, 2009), Niezgoda et al. (2015), Reimer et al. (2012), and Reimer and Mehler (2011), and has been demonstrated to be relevant for driving research on workload and distraction as follows.

Relevance in Driving Research

Due to the cognitive resources involved in the n-back task which are the auditory attention (i.e., the driver needs to pay attention in order to hear the number) and the memory component (i.e., the driver needs to store the information in the short term memory before delivering the response), this task simulates several activities that the driver may be subjected to while driving. These include using navigation systems with auditory instructions, conversing with passengers, responding to incoming cell phone calls, etc. (Mehler et al., 2011). Since these tasks are based on speech interaction, they demand auditory memory as does the n-back task. PDST (2014) identifies the auditory memory as a main component of an effective oral language that "*involves the ability to assimilate information presented orally, to process that information, store it and recall what has been heard. Essentially, it involves the task of attending, listening, processing, storing, and recalling*" (PDST, 2014). As such, the memory component is associated with the aforementioned tasks as well as the n-back task.

Moreover, being audio-based makes the n-back task convenient for driving research studies addressing workload, whereby executing the secondary task does not conflict with the visual demand of the primary task of driving. The n-back task also has the advantage of varying the workload in systematic patterns according to the intensity of the cognitive demand. That is, the 0-back level is considered as a low level of demand, the 1-back level is considered as an intermediate stage of the task, and the 2-back level is considered as a high challenging workload. Finally, the task needs minimal time for learning, i.e., the subject can be easily trained to fulfill the requirements of this task. The experimental setup is not complex in terms of the used equipment, and the performance on this task can be easily and objectively assessed due to its uncomplicated scoring.

3.2. Experimental Design

The experiment includes a baseline phase, a control phase, and a treatment phase. The subject first drives a baseline phase that takes about two minutes to be completed. The baseline does not include any particular driving scenario/road situation; only traffic flow in the opposite direction is encountered. This phase will be used to quantify the initial state stress of the subject before encountering the road events and the secondary task, as will be later explained in Chapter 5 of the thesis.

In the control phase, the subject encounters the three aforementioned road situations (pedestrians, truck, and traffic light scenarios) without being assigned the auditory n-back task. This phase lasts for five minutes. In the treatment phase, the subject encounters the three road situations while performing the n-back task at the same time. The order of presentation of the levels of the n-back task (0, 1, and 2) is randomized among subjects; however, the same sequence of numbers is presented to all subjects at each level. Each combination of the n-back levels is scripted within one audio message.

The treatment phase is initiated when the driver reaches the location-based trigger which prompts the audio message. The duration of the n-back task is five minutes in the driving course, and is independent of the driver's speed to ensure that all subjects are assigned the same workload regardless of their speed. The treatment phase is designed so that the driver encounters each of the three driving situations occurring at one particular level of the n-back task, i.e., each road event (pedestrians, truck, and traffic light) is associated with one level of the n-back task (0,1, and 2).

The order of presentation of the control/treatment phases is counterbalanced among subjects. The order of presentation of the three driving scenarios is also randomized among subjects in both phases (control/treatment). No breaks occur between the two phases; once the control phase ends, the treatment phase starts and vice versa. To summarize, a subject encounters (after driving the baseline phase) three situations twice in the overall drive: once at the control phase and another at the treatment phase. An example of the driving course design is shown in Figure 14.

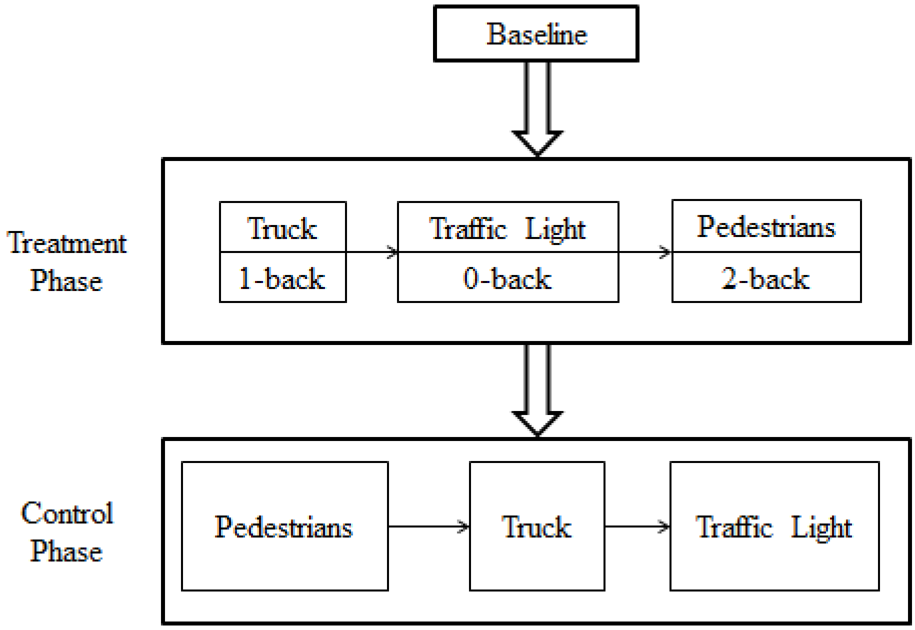

Figure 14: Example of one possible driving course

3.3. Experimental Procedure

The experimental procedure consists of a number of steps that were approved by the Institutional Review Board at AUB. A screening interview (presented in Appendix B) is conducted first to assess the subject’s eligibility to participate in the experiment based on age, possession of driving license, and absence of medical conditions that may interfere with the ability to drive. Then, the subject is informed about the steps of the experiment, without being told its actual objective of assessing workload in order not to influence his/her driving behavior. After the subject signs the consent form (presented in Appendix C), the research associate explains the n-back task and conducts a training session with the subject as per the training material provided in Mehler et al. (2011) and presented in Appendix D. After schematically showing the road to be driven in the experiment, the research associate attaches the EKG and the skin conductance sensors as per the equipment set-up documented in Mehler (2009).

A practice session on the simulator then takes place to familiarize the subject with driving the simulator while the sensors are attached. The driving context in this session is similar to that of the actual experiment with no exceptional driving situations. Subjects are instructed to drive as they do in their real life and told that they are expected to abide by the traffic regulations. In order to ensure that the subject is still comfortable with performing the n-back task, he/she is reminded of the n-back task by performing one additional trial (presented in Appendix E) with randomized levels (conducted inside the vehicle by the research associate), while the driving simulation is turned off. After a break of one minute, the actual driving experiment (around 12 minutes depending on the subject's speed) takes place in which driving performance and physiological measures are collected. The subject's answers to the n-back task are also recorded. Once completed, the subject is asked to fill out a post driving survey (presented in Appendix F). The post driving survey asks the subject about his/her driving behavior (derived from the Driver Stress Inventory (DSI) and the Driving Coping Questionnaire (DCQ)). It also asks the subject to evaluate the workload level at each of the control and treatment phases (derived from the Driving Activity Load Index presented in Appendix G). The experiment sheet specific to each subject is filled out by the research associate (presented in Appendix H).

3.4. Data Collection

Recruitment was based on convenience sampling of AUB students during class announcements or by randomly approaching students and inviting them to participate. A pilot test was done on three subjects before the actual start of data collection, and the experimental design was adjusted accordingly. Data collection extended from March 2017 till October 2017.

3.5. Dependent Variables

Dependent variables of this study can be classified into driving performance and physiological measures calculated along each segment of interest at each situation in the control and treatment phases. Driving performance measures are speed-related measures (average, standard deviation, and maximum), standard deviation of the lane position, accelerator pedal depression related measures (standard deviation and maximum), brake related measures (standard deviation and maximum), and the reaction time. The lane position corresponds to the lane position offset for the vehicle from the centerline of the current lane (in meters); it is positive when the offset is to the right and negative when it is to the left. The accelerator pedal depression and the brake measures are dimensionless values ranging between 0 (pedal is not being depressed) and 1 (pedal is at the maximum depression) (HyperDrive, 2006).

The definition of the reaction time depends on the encountered situation. For the pedestrians situation, the reaction time is defined as the time since the subject sees the pedestrians until he/she implements the first reaction. For the truck situation, the reaction time is defined as the time since the truck starts decelerating until the subject implements the first reaction. For the traffic light situation, the reaction time is defined as the time since the signal indication turns yellow until the subject implements the first reaction. For all situations, the first reaction is considered as braking or releasing the gas pedal. The reaction time for a red light violator is not calculated since he/she did not implement any reaction in the segment of interest.

Physiological measures are heart rate and skin conductance measures (average, standard deviation, minimum, and maximum calculated along each segment of interest at each situation in the control and treatment phases).

The segment of interest of the baseline phase consists of 400 meters of a straight roadway. Dependent measures of interest at the baseline phase are calculated within this segment of interest, and they are the same as those described above except that they do not include reaction time since there are no road events in the baseline phase. As mentioned earlier, the baseline data are only used at the modeling stage.

3.6. Data Analysis Methods

The statistical descriptive analysis presented in Chapter 4 consists of a static analysis. First, it compares the driving performance and physiological measures within each subject at each road situation between the control and treatment phases using Wilcoxon Signed-Ranks test. Second, it compares the driving performance and physiological measures between subjects at each road situation across the three levels of the secondary task (0-back, 1-back, and 2-back) using Kruskal-Wallis H test. Mann-

Whitney U-Test is also used to compare the driving performance measures between subjects who perfectly performed the n-back task and those who committed errors at each level. The analysis presented in Chapter 5 is dynamic. It consists of developing a hybrid choice model that integrates latent (or unobserved) variables with their manifestations and discrete choice. Dynamics are modeled using two approaches. The first approach is based on serial correlation and reflects the effect of individual traits (agent effect). The second approach is based on Hidden Markov Chains and reflects the state dependence across time periods.

CHAPTER 4

STATISTICAL ANALYSIS

This chapter presents a descriptive statistical analysis of the data collected from the driving simulator and the physiological sensors. The objective of this chapter is to assess the effect of the auditory-vocal distraction (n-back task) on driving performance and physiological measures, particularly at three road events (pedestrians, truck, and traffic light). In this chapter, each road situation is considered separately; therefore, the cognitive workload level arising from the secondary task is the only variable (the road event variable is fixed at each road situation). The analysis is static, i.e., observations are not classified with respect to their occurrence in time; they are classified according to the encountered road event. Each road event is encountered twice in the driving course, once given the n-back task (treatment), and another without the n-back task (control). A paired within-subject comparison is conducted to capture differences between the two phases. The order of presentation of the treatment phase in the drive (whether it comes after the control phase or before it) is further investigated. In addition, the effect of the n-back levels is evaluated between subjects. Non-parametric tests are used for analysis as several data vectors were not normal[3].

This chapter is organized as follows. The first section consists of the sample description, the second section assesses the effect of the n-back task, the third section investigates the effect of the order of presentation of the treatment phase in the drive,

[3] Shapiro test was used to test the normality of data. Several data vectors were not normal at the 95% level of confidence ($p<0.05$), such as the average speed ($p=0.006$) and the standard deviation of the heart rate ($p=0.003$) at the 0-back level for the pedestrians situation.

the fourth section compares between the levels of the n-back task across subjects, and the fifth section concludes the chapter.

4.1. Sample Description

A total of 103 AUB students volunteered for enrollment in the study, but several of them were dropped from the analysis for a variety of reasons including: dizziness, driving in different (from instructed) directions and reaching a dead end, technical failure in the simulation or EKG sensor, overspeeding during the treatment phase and encountering more than one level of the n-back task at one particular road event, or subjects' request for withdrawal. The remaining sample consists of 80 students: 53 males and 27 females. Thirty-five students were considered inexperienced drivers who have been driving for less than two years, and forty-five students were considered experienced drivers who have been driving for more than two years. Thirty-seven subjects encountered the control phase before the treatment phase and forty-three subjects encountered the treatment phase before the control phase.

4.2. Effect of the n-back Task

In this section the effect of the n-back task on driving performance and physiological measures is investigated using paired comparison within each subject. Wilcoxon Signed-Ranks test[4] is used to test for differences between the control and treatment phases. Descriptive statistics of each dependent variable of interest (median

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[4] Wilcoxon Signed-Ranks test is a non-parametric test used when observations are paired and have not met the normality assumption. It is analog to the paired two-sample t-test and tests the median difference between the pairs of each dependent variable of interest.

and interquartile range or IQR[5]) along with the resulting p-values are presented in Table 2 for the driving performance measures and Table 3 for the physiological measures.

[5] IQR of each data vector is presented as 1st quartile-3rd quartile.

Table 2: Driving performance measures (comparing control/treatment phases)

Situation	**Phase**	**Descriptive Statistics**	**Speed (km/hr)**			**Lane Position (m)**	**Acc. Pedal Depression (Dimensionless)**		**Brake (Dimensionless)**		**Reaction Time (s)**
			Av.	**S.D.**	**Max.**	**S.D.**	**S.D.**	**Max.**	**S.D.**	**Max.**	
Pedestrians	Control	Median	32.85	15.47	51.39	0.08	0.16	0.45	0.13	0.38	0.50
		IQR	30.56-35.87	11.33-18.00	50.01-53.81	0.05-0.11	0.12-0.21	0.36-0.53	0.09-0.17	0.27-0.53	0.20-0.80
	Treatment	Median	32.54	14.02	50.55	0.08	0.15	0.41	0.12	0.37	0.50
		IQR	30.18-35.12	10.39-18.21	46.15-53.46	0.06-0.11	0.12-0.19	0.33-0.50	0.07-0.18	0.20-0.52	0.30-0.83
	p-value		0.891	0.170	0.022**	0.808	0.008**	0.004**	0.090*	0.117	0.330
Truck	Control	Median	21.31	17.49	47.89	0.06	0.11	0.33	0.06	0.21	3.20
		IQR	18.42-24.39	15.07-19.75	43.57-52.37	0.04-0.09	0.07-0.15	0.25-0.43	0.04-0.09	0.13-0.31	1.93-4.68
	Treatment	Median	21.29	17.47	46.80	0.05	0.10	0.31	0.06	0.19	3.50
		IQR	17.99-23.02	15.12-19.34	42.12-50.65	0.03-0.07	0.08-0.13	0.26-0.39	0.03-0.10	0.12-0.29	2.73-4.58
	p-value		0.340	0.521	0.068*	0.001**	0.121	0.128	0.478	0.692	0.178
Traffic Light	Control	Median	46.22	1.85	49.31	0.06	0.09	0.39	0.00	0.00	5.80
		IQR	42.66-49.20	1.29-2.86	45.40-52.26	0.05-0.10	0.04-0.16	0.29-0.50	0.00-0.00	0.00-0.02	4.50-6.60
	Treatment	Median	44.90	1.70	47.53	0.05	0.09	0.39	0.00	0.00	6.10
		IQR	41.38-47.85	1.09-2.17	43.43-50.84	0.04-0.08	0.03-0.15	0.27-0.45	0.00-0.00	0.00-0.00	5.20-6.60
	p-value		0.007**	0.187	0.006**	0.109	0.094*	0.005**	0.012**	0.012**	0.164

* Significance at the 90% level of confidence.
** Significance at the 95% level of confidence.

As shown in Table 2, there are statistically significant differences at the 95% level of confidence in the maximum speed (p=0.022), the standard deviation of pedal depression, and the maximum pedal depression (p=0.008 and p=0.004, respectively) between the control and treatment phases at the pedestrians situation with higher median values in the control phase. A statistically significant difference in the standard deviation of the lane position (p=0.001) is found at the truck situation with higher median value in the control phase. Statistically significant differences in the average and maximum speed (p=0.007 and p=0.006, respectively), maximum pedal depression (p=0.005), standard deviation of brake, and maximum brake (p=0.012) are found at the traffic light situation, with higher median values in the control phase. Additional statistically significant differences are observed at the 90% level of confidence between the control and treatment phases in terms of the standard deviation of brake (pedestrians situation), maximum speed (truck situation), and standard deviation of the pedal depression (traffic light situation).

While an anticipated effect of the n-back task would be to increase variability as indication of driving performance decrement, results have shown a decrease in the standard deviation of the lane position, pedal depression, and brake at the treatment phase. Results also showed a decreasing trend in the average and maximum speed, maximum pedal depression, and maximum brake in the treatment phase. This occurs because additional cognitive resources (i.e., auditory attention and memory) are utilized in response to the increase in workload while driving and performing the secondary task at the same time (treatment phase). Figure 15 represents a boxplot[6] of the average speed at the traffic light event (calculated within the segment of interest). The median average

[6] The boxplot is a standardized display of the data distribution. The line in the box represents the median value, the lower line of the box represents the first quartile, and the upper line of the box represents the third quartile.

speed decreases at the treatment phase by approximately 1.3 km/hr. Such modest decrease in the average speed should not be seen as improvement in the driving performance; it could be explained by the compensatory effort of the driver who adopts a regulatory behavior that rectifies the effect of the distracted task by an additional control over the driving task as discussed in Mehler et al. (2009) where a decrease in the variability of the lateral control is found when cognitive workload increases.

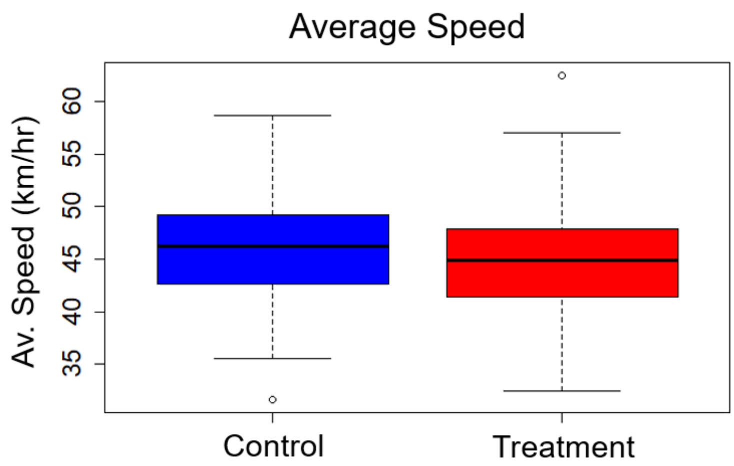

Figure 15: Boxplot of the average speed at the traffic light event

Zhou et al. (2016) stated the contribution of compensatory beliefs with respect to the usage of the mobile phone while driving, manifested by statements such as “I can use a mobile phone now because I will slow down”. They showed that drivers with higher propensity to compensatory beliefs were more involved in road accidents as a result of the usage of mobile phone while driving at the same time. Clarkson et al. (2010) reported that resources will deplete after excessive self-regulatory efforts on successive tasks, and subsequently, any attempt of self-regulation will fail.

To summarize, the regulatory behavior caused minor variations in the longitudinal and lateral control measures (e.g., speed, lane position) between the treatment and the control phases and had a more significant impact on the reaction time as shown by this experiment. Additionally, resources available to keep control of the driving task might deplete over time causing an impairment in the driving performance as evidenced by the literature. Therefore, the self-regulatory behavior adopted by the driver in response to distracting tasks is a risky behavior that endangers driving safety.

Table 3: Physiological measures (comparing control/treatment phases)

Situation	**Phase**	**Descriptive Statistics**	**Heart Rate (Beats/min)**				**Skin Conductance Level (micromhos)**			
			Av.	**S.D.**	**Min.**	**Max.**	**Av.**	**S.D.**	**Min.**	**Max.**
Pedestrians	Control	Median	77.25	4.04	71.09	85.23	15.70	0.21	15.44	16.52
		IQR	69.47-88.01	2.67-5.83	64.66-78.95	79.37-96.77	11.24-21.89	0.10-0.47	10.84-21.68	11.59-22.86
	Treatment	Median	84.10	3.98	78.13	92.59	16.26	0.21	15.99	17.16
		IQR	73.48-90.45	2.56-5.14	67.26-85.71	83.33-100.00	13.02-22.47	0.11-0.41	12.24-21.98	13.4-22.94
	p-value		0.000**	0.289	0.000**	0.000**	0.000**	0.611	0.000**	0.009**
Truck	Control	Median	75.83	3.60	68.50	84.99	16.00	0.12	15.83	16.43
		IQR	69.79-84.55	2.63-5.19	62.57-79.37	76.44-93.17	11.36-21.81	0.07-0.31	11.21-21.22	11.75-22.15
	Treatment	Median	81.85	4.01	73.00	91.74	16.93	0.16	16.54	17.31
		IQR	73.68-90.85	2.89-5.87	66.37-83.68	84.04-100.67	12.16-22.09	0.10-0.37	11.78-21.68	12.73-22.80
	p-value		0.000**	0.101	0.000**	0.000**	0.000**	0.245	0.000**	0.000**
Traffic Light	Control	Median	78.59	2.81	73.53	85.23	16.11	0.09	15.91	16.24
		IQR	70.04-90.13	2.05-4.01	65.08-84.99	75.19-95.24	11.64-21.81	0.05-0.19	11.42-21.48	11.75-22.00
	Treatment	Median	89.61	2.71	81.97	94.34	16.74	0.10	16.65	17.10
		IQR	79.53-98.50	1.83-4.09	73.71-93.46	85.13-102.04	12.87-23.00	0.07-0.18	12.70-22.68	13.00-23.29
	p-value		0.000**	0.734	0.000**	0.000**	0.000**	0.646	0.000**	0.000**

** Significance at the 95% level of confidence.

As shown in Table 3, statistically significant differences are observed, at the 95% level of confidence, between the control and treatment phases in the average, minimum and maximum heart rate and skin conductance level values at the three situations ($p<0.05$), with higher median values observed in the treatment phase, demonstrating a higher workload, and a higher level of stress, due to the n-back task. Figure 16 represents a boxplot of the average heart rate at the pedestrians situation. As shown in this figure, the average heart rate at the treatment phase increased by approximately 7 beats/min. These results are in accordance with the findings of Mehler et al. (2012, 2009) that state that the driver exhibits an increase in the heart rate and skin conductance as a result of the body's activation of resources to perform additional cognitive tasks.

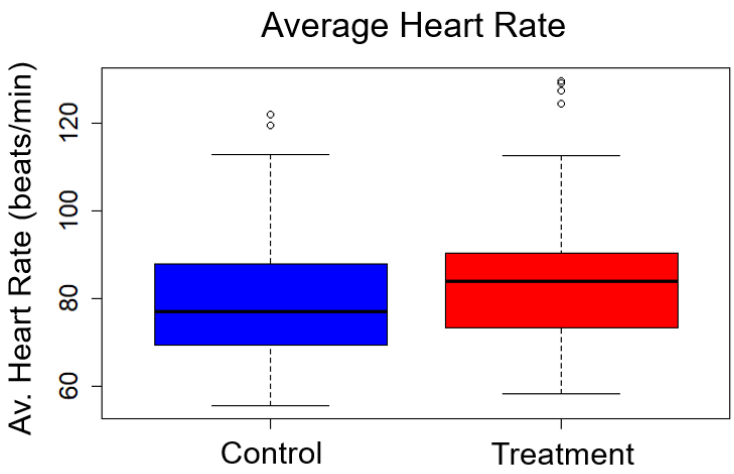

Figure 16: Boxplot of the average heart rate at the pedestrians event

4.3. Effect of the Order of Presentation of the Treatment Phase

We further investigate the effect of the order of presentation of the treatment phase (i.e. whether it occurred before or after the control phase) on the variables of interest. A mixed design analysis was done including the effect of the encountered phase as a within-subject variable with two levels (control or treatment), the effect of the order of presentation of the treatment phase in the driving course as a between-subjects variable with two levels (before or after the control phase), and the interaction between the two variables. The analysis showed that there is only an effect of the encountered phase variable on the variation of the physiological measures between the treatment and the control phases. However, the interaction between the two factors (the encountered phase and the order of presentation of the treatment phase) is found to affect the reaction time, i.e., the effect of the encountered phase (whether it is a control or treatment) on the reaction time depends on the order of presentation of the treatment phase in the driving course (whether it is encountered before or after the control phase).

To further investigate the effect of the order of presentation of the treatment phase in the driving course, subjects were classified into two groups according to the order of presentation of the treatment phase. Paired within-subject comparisons were then conducted on each group separately with respect to driving performance measures.

For the case where subjects encountered the treatment phase before the control phase, there was a statistically significant difference between the control and treatment phases, at the 95% level of confidence, in the reaction time at the pedestrians and the traffic light situations ($p=0.001$ and $p=0.037$, respectively) with a higher reaction time occurring in the treatment phase, an expected distraction outcome of the n-back task. Similar results were reported in Reimer et al. (2016a) where engaging in cell phone conversations while driving increased the reaction time. For the case where subjects encountered the control phase before the treatment phase, a statistically significant difference (95% level of confidence) at the pedestrians situation was found in the reaction time ($p=0.026$) with higher median value in the control phase. The difference in the direction of variation observed in the reaction time between the two cases could be attributed to the effect of learning and expectation that might have influenced the driver's reaction time when the same road situation is encountered twice.

Figure 17 represents a boxplot of the reaction time at the traffic light event for the case whereby the treatment phase is encountered before the control phase. As shown in this figure, the reaction time increased at the treatment phase by approximately 1 second due to the secondary task. Such increase in the reaction time is reported in Lee et al. (2001) to have important implications for the driver safety and thus demonstrates that being engaged in cognitive tasks is a risky behavior.

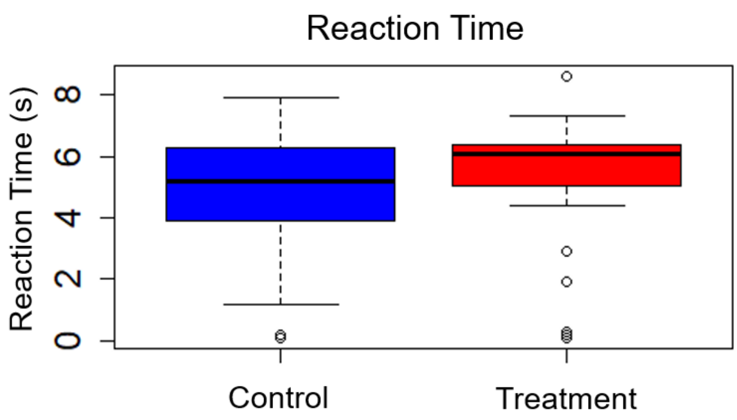

Figure 17: Boxplot of the reaction time at the traffic light event

4.4. Differences Between Levels of the n-back Task

A comparison between the levels of the n-back task (0, 1, and 2) is conducted for each road situation using Kruskal-Wallis H test[7]. For example, data extracted from subjects who encountered the truck situation at the 0-back level are compared to data extracted from subjects who encountered the truck situation at the 1-back level, and to data extracted from subjects who encountered the truck situation at the 2-back level.

[7] The Kruskal-Wallis H test is a non-parametric test that is analog to the one-way ANOVA. It is used to determine whether three or more independent samples were selected from populations having the same distribution.

Results for all situations with respect to driving performance measures are presented in Table 4, and with respect to physiological measures in Table 5.[8]

As shown in Table 4, there are no statistically significant differences in the driving performance measures at the 95% confidence level between the three levels of the n-back task at all situations. These results are in line with the findings of Niezgoda et al. (2015) where driving performance measures such as the lateral and longitudinal control of the vehicle and the mean and standard deviation of the speed were not affected by the difficulty level of the n-back task. They are also in line with the findings of Mehler et al. (2009) where the effect of the n-back task level on the driving performance measures was reported as "modest". Moreover, since the effect of the levels of the n-back task is assessed in this study at three particular road situations, the non-existence of statistically significant differences in the driving performance measures can also imply that the encountered situation dominates the secondary task, and the driving behavior is dictated by the situation itself regardless of the level of the secondary task; thus, drivers respond to the driving task needs and react relatively in a similar manner in order to fulfill the safety requirements of the driving task (e.g., reducing the speed, braking, etc.).

[8] Difference-in-differences measures (to net out any differences arising due to different driving behavior or physiological measures in the control phase) were also computed across the three samples and have led to similar conclusions.

Table 4: Driving performance measures (comparing the n-back levels)

Situation	**n-back Level**	**Descriptive Statistics**	**Speed (km/hr)**			**Lane Position (m)**	**Acc. Pedal Depression (Dimensionless)**		**Brake Dimensionless**		**Reaction Time (s)**
			Av.	**S.D.**	**Max.**	**S.D.**	**S.D.**	**Max.**	**S.D.**	**Max.**	
Pedestrians	0	Median	33.13	15.22	51.19	0.08	0.15	0.42	0.12	0.37	0.30
		IQR	31.49-35.12	10.39-17.36	47.99-53.70	0.06-0.10	0.12-0.19	0.34-0.51	0.06-0.16	0.19-0.50	0.20-0.80
	1	Median	33.35	12.23	52.72	0.08	0.16	0.44	0.13	0.36	0.50
		IQR	30.38-38.83	7.3-18.52	46.77-53.55	0.06-0.09	0.13-0.21	0.36-0.50	0.07-0.16	0.22-0.47	0.23-0.68
	2	Median	32.07	15.52	50.55	0.08	0.14	0.36	0.14	0.40	0.50
		IQR	29.41-33.72	12.07-18.92	46.04-52.99	0.06-0.11	0.12-0.16	0.32-0.46	0.09-0.19	0.26-0.55	0.28-0.90
	p-value		0.468	0.348	0.920	0.977	0.306	0.337	0.632	0.798	0.618
Truck	0	Median	20.71	17.77	47.20	0.05	0.09	0.31	0.07	0.22	3.10
		IQR	17.83-22.93	16.34-19.25	44.10-51.30	0.04-0.07	0.08-0.11	0.27-0.35	0.04-0.11	0.12-0.38	2.40-4.10
	1	Median	21.59	17.50	47.99	0.06	0.10	0.30	0.06	0.18	3.85
		IQR	18.28-23.20	15.81-19.37	41.94-50.69	0.03-0.08	0.08-0.13	0.26-0.41	0.04-0.09	0.13-0.27	2.40-4.75
	2	Median	21.05	17.43	45.42	0.05	0.10	0.35	0.05	0.17	3.55
		IQR	18.36-23.67	14.44-19.81	42.52-49.86	0.03-0.06	0.08-0.14	0.25-0.42	0.03-0.08	0.10-0.26	2.93-4.18
	p-value		0.852	0.817	0.760	0.867	0.374	0.726	0.285	0.448	0.518
Traffic Light	0	Median	45.20	1.81	48.19	0.06	0.11	0.39	0.00	0.00	6.20
		IQR	41.57-48.68	1.27-2.19	43.58-51.31	0.03-0.08	0.03-0.15	0.29-0.43	0.00-0.00	0.00-0.00	5.43-6.73
	1	Median	44.49	1.30	47.05	0.05	0.09	0.37	0.00	0.00	5.65
		IQR	41.39-47.36	1.02-1.89	43.16-49.45	0.03-0.08	0.03-0.14	0.27-0.46	0.00-0.00	0.00-0.00	5.20-6.05
	2	Median	44.90	1.78	49.48	0.05	0.10	0.39	0.00	0.00	6.35
		IQR	41.57-48.60	1.13-3.11	45.56-51.12	0.04-0.07	0.05-0.14	0.29-0.49	0.00-0.00	0.00-0.01	4.50-7.25
	p-value		0.732	0.156	0.308	0.730	0.689	0.743	0.449	0.615	0.197

As shown in Table 5, there are no statistically significant differences, at the 95% level of confidence, in the physiological measures across the three levels of the n-back task at the traffic light situation. Statistically significant differences at the 95% level of confidence in the average (p=0.023), minimum (p=0.009), and maximum (p=0.035) heart rate are found at the truck situation. Multiple comparisons (with Bonferroni adjustment) showed statistically significant differences at the 95% level of confidence between the 0-back and 2-back levels in the average (p=0.022), minimum (p=0.006), and maximum (p=0.040) heart rate with higher median values at the 2-back level. Statistically significant differences at the 90% level of confidence are observed at the pedestrians situation in terms of the average heart rate (p=0.065), minimum heart rate (p=0.054), and the standard deviation of the skin conductance level (p=0.097). Multiple comparisons (with Bonferroni adjustment) only showed statistically significant differences at the 90% level of confidence between the 0-back and 2-back levels in the average (p=0.088) and minimum (p=0.070) heart rate with higher median values observed at the 2-back level. Although variation in physiological indices is expected to reflect variation in the workload level, particularly in the n-back task, the results of this study did not show a prevailing effect of the task difficulty levels on the physiological measures, unlike the findings of previous studies. This may be because previous studies such as Mehler et al. (2009) used a period of analysis of two minutes for each level of the n-back task with no variation in the driving environment (a 2-minute period of analysis is justified in Mehler et al. (2011) as a sufficiently wide duration to reveal variations in physiological metrics), while this research studied the effect of the secondary task at a particular instantaneous event, with a shorter duration of time (less than 10 seconds), which may not necessarily lead to significant variations in the physiological measures with respect to the levels of the secondary task.

Table 5: Physiological measures (comparing the n-back levels)

Situation	**n-back Level**	**Descriptive Statistics**	**Heart Rate (Beats/min)**				**Skin Conductance Level (micromhos)**			
			Av.	**S.D.**	**Min.**	**Max.**	**Av.**	**S.D.**	**Min.**	**Max.**
Pedestrians	0	Median	78.34	3.99	71.09	84.75	16.10	0.21	15.79	16.94
		IQR	69.17-89.44	2.67-4.57	65.79-82.42	76.14-100.00	13.02-21.28	0.15-0.40	12.82-20.14	13.42-22.34
	1	Median	83.49	3.83	77.93	90.10	16.26	0.16	16.10	16.88
		IQR	76.31-89.95	2.70-5.39	69.61-83.45	85.12-97.72	10.36-21.95	0.06-0.36	10.19-21.45	10.43-23.75
	2	Median	89.21	3.85	81.97	98.68	18.08	0.35	17.11	19.23
		IQR	83.55-99.04	2.38-4.74	77.93-91.75	88.76-107.14	14.12-22.74	0.14-0.68	13.27-22.03	14.89-23.46
	p-value		0.065*	0.874	0.054*	0.162	0.543	0.097*	0.645	0.534
Truck	0	Median	79.22	4.28	70.09	86.71	16.55	0.16	16.42	16.83
		IQR	73.49-84.63	3.26-6.04	60.98-79.37	81.97-93.17	12.15-21.50	0.11-0.37	11.74-21.08	13.20-21.90
	1	Median	81.65	4.20	72.12	93.46	16.55	0.14	16.02	16.79
		IQR	75.01-92.76	2.82-5.78	66.46-85.71	81.60-102.06	12.08-22.23	0.09-0.25	11.86-21.89	12.35-22.57
	2	Median	89.57	3.50	81.54	96.46	17.43	0.21	17.02	18.86
		IQR	76.54-98.66	2.71-5.67	71.35-93.40	85.24-104.94	12.57-23.56	0.11-0.41	12.19-23.04	13.20-23.87
	p-value		0.023**	0.350	0.009**	0.035**	0.848	0.553	0.849	0.801
Traffic Light	0	Median	91.80	3.32	86.72	97.41	17.34	0.10	17.11	17.71
		IQR	82.90-96.99	2.14-4.21	77.72-93.61	88.76-101.35	12.10-23.66	0.05-0.18	12.01-23.47	12.18-23.83
	1	Median	87.98	2.50	81.09	92.59	16.86	0.14	16.73	17.11
		IQR	75.25-101.08	2.03-4.04	70.36-95.88	77.52-106.40	14.53-20.89	0.09-0.18	14.15-20.52	14.69-21.06
	2	Median	84.57	2.16	78.95	92.02	16.71	0.09	16.65	16.84
		IQR	80.61-93.58	1.58-4.09	75.00-89.56	85.96-97.47	12.12-21.59	0.08-0.18	12.01-21.36	12.24-21.85
	p-value		0.455	0.585	0.525	0.367	0.637	0.381	0.637	0.677

* Significance at the 90% level of confidence.
** Significance at the 95% level of confidence.

As for the performance on the secondary task, Kruskal-Wallis H test showed a statistically significant difference between the levels of the n-back task in terms of the number of errors occurring at each level ($p=0.000$). Nineteen percent of the total errors occurred at the 0-back level, 20% at the 1-back level, and 61% at the 2-back level, implying a decrement in the overall performance on the n-back task as the cognitive workload increases.

Further investigation is conducted to compare the driving performance of the subjects who perfectly performed the n-back task with its three levels of difficulty (i.e., they did not commit errors when performing the n-back task) and the subjects who at least committed one error when performing the n-back task. This analysis is motivated by the fact that drivers in real life might completely pay attention to the secondary task (those are represented in the experiment by the group of subjects who perfectly performed the n-back task) or ignore/pay less attention to it at some level of difficulty (those are represented by the group of subjects who at least committed one error in the n-back level). Table 6 shows a breakdown of the subjects according to their performance on the secondary task at each level.

Table 6: Breakdown of the subjects according to their performance on the secondary task at each level

Secondary Task Performance	**0-back**	**1-back**	**2-back**
Subjects who perfectly performed the n-back level of the secondary task (0 errors)	72	52	39
Subjects who at least committed one error in the n-back level	8	28	41

For this comparison, the Mann-Whitney U-Test[9] is used. Results showed that driving performance measures at the three road situations did not statistically significantly differ at the 95% level of confidence between subjects who perfectly performed the n-back task and those who at least committed one error when performing the secondary task. This implies that subjects had relatively similar driving performance (i.e., average speed, standard deviation of lane position, maximum accelerator pedal depression, reaction time) regardless whether they performed the n-back task completely correctly or not. Thus, we conclude that drivers were behaving in such a way that they remain attentive to the primary driving task as if they were prioritizing it. Nevertheless, some subjects had to pay less attention to the secondary task (they responded incorrectly to the n-back task as a result), particularly at the high levels of difficulty, in order to retain control of driving when performing the secondary task at the same time. On the other hand, others were able to maintain their driving performance and perfectly perform the n-back task. Subjects seemed to distribute the resources so that the main driving task does not suffer differently as a result of performing additional tasks. For some subjects, executing more effort to keep control of the primary driving task and investing less resources on the secondary task lead to an impairment of the latter.

4.5. Conclusion

The analysis in this chapter presents a static evaluation of the impact of an increase in the cognitive workload level originating from a secondary task simulating auditory-vocal distraction at three road events often encountered in an urban context.

[9] The Mann-Whitney U-Test is a non-parametric statistical test analog to the two-sample t-test. It is also known as the Wilcoxon Rank Sum test.

Results highlight the effect of the regulatory behavior adopted by the driver to allow the performance of the secondary task while driving. Exerting additional effort to keep control of the main driving task when performing the secondary task caused the shift in attention from the latter to the former; for some subjects paying less attention to the secondary task was reflected in deterioration in its performance. In the following chapter, a dynamic analysis is conducted to represent the evolution of the driver behavior and physiological measures over time.

CHAPTER 5

BEHAVIORAL MODELING

This chapter aims at quantifying the driver stress arising from cognitive workload in a dynamic model that controls for all scenario variables of the driving simulation experiment (road events and levels of the secondary task). Hybrid choice modeling that integrates discrete choice and latent (or unobserved) variables with their manifestations is used to model the driver behavior. The dynamic model captures the evolution of the behavior (e.g., speed, accelerator pedal depression) and physiology (e.g., heart rate) over time throughout the driving course based on the evolution of the driver stress. Two approaches are used in this chapter to model dynamics. The first approach is based on the serial correlation of the choices/actions made by the same individual throughout the whole experiment at the different phases. The second approach is based on the dependence of the current choice/action on the previous behavior (called state dependence). The modeling results are discussed and the estimated parameters are used to do an in-sample prediction of the driver performance and physiology.

This chapter is organized as follows. The first section provides theoretical background on hybrid choice models, serial correlation, and state dependence. The second section presents the behavior model formulation of the dynamic hybrid choice model applied to the driving simulator experiment including the notation, the modeling approaches, the dynamic model with serial correlation, and the dynamic model with state dependence. The third section, concludes the chapter by comparing the two approaches.

5.1. Theoretical Background

5.1.1. Hybrid Choice Models

Behavioral models represent how people act or make decisions under different conditions or factors. Given behavioral data extracted from any tracking platform, modeling methods can provide behavioral representation in different fields including economics, transportation, systems management and planning, operational research, etc. Understanding the behavioral process consists of finding a causal relationship between the behavior as an outcome and the factors that influence it (Train, 2009).

Discrete choice analysis is a common method used to model decision processes and behavior in the presence of discrete outcomes based on random utility maximization: a decision maker selects the alternative that maximizes his or her utility from a set of alternatives (Ben-Akiva and Lerman, 1985; Train, 2009). The classic theory assumes that the utility of an alternative is a function of observed variables (e.g., attributes of the alternative) and a random disturbance. The latter captures unobserved variables reflecting the limitations in the analyst's knowledge and capability to identify all factors affecting the choice, e.g., missing data, measurement errors, taste heterogeneity, etc. (Ben-Akiva and Bierlaire, 1999).

Hybrid choice models (HCM) or integrated choice and latent variable models introduce latent or unobserved variables such as attitudes and perceptions within the choice model (Ben-Akiva et al., 2002; Walker and Ben-Akiva, 2002). By explicitly modeling individual differences, these models offer better prediction capabilities and are more behaviorally realistic, rich, and efficient than a traditional discrete choice model. Further, increasing the accuracy of predictions by modeling latent variables and assessing their impact on the choice can lead to better design of effective policies and can be particularly of advantage when latent variables evolve through time (Abou-Zeid and Ben-Akiva, 2014). The framework of the HCM is presented in Figure 18 (Ben-Akiva et al., 2002). In this figure (as well as in all other figures of this chapter), rectangles represent observed variables and ellipses represent latent or unobserved variables. Structural relationships (cause-and-effect) are represented using solid arrows, and measurement relationships (between the observed indicators and the underlying latent variables) are represented using dashed arrows. As shown in Figure 18, the integrated choice and latent variable model is made up of two components: the latent variable model and the choice model.

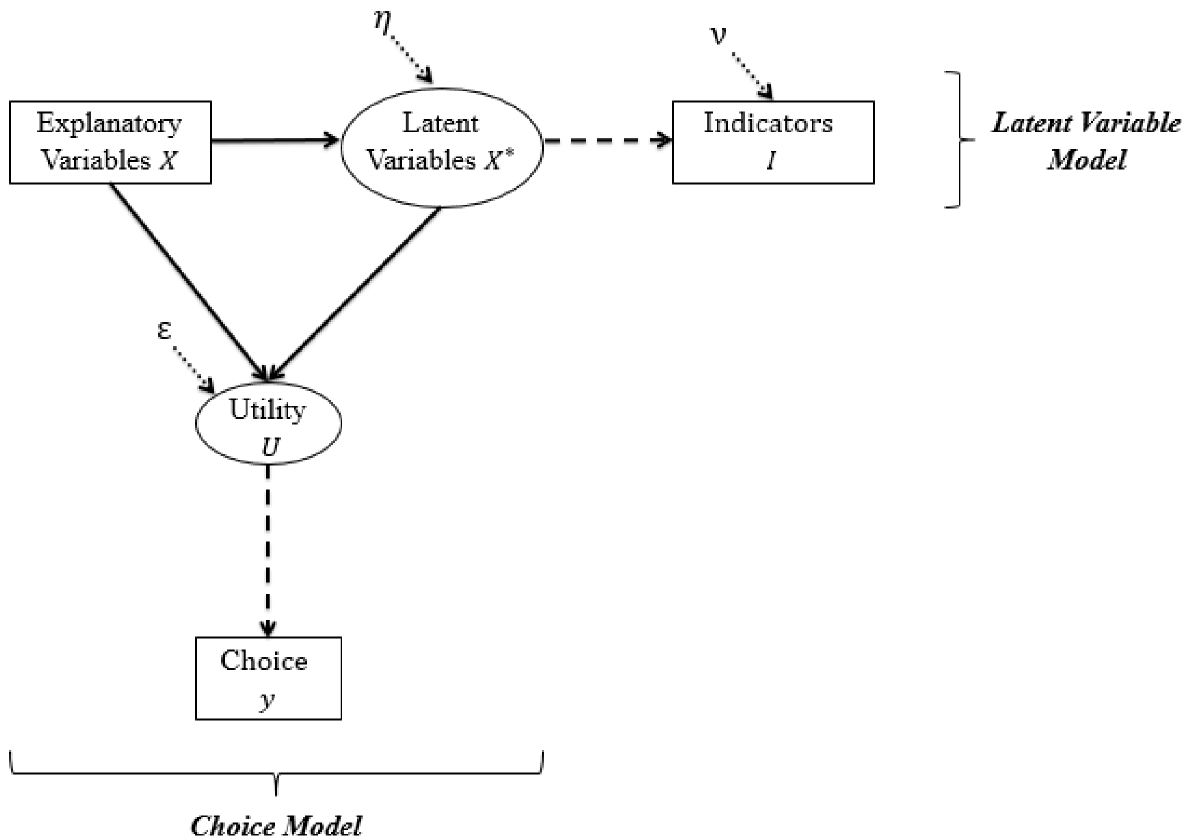

Figure 18: Framework of integrated choice and latent variable model

The latent variable model intends to model explicitly unobserved variables. A structural equation (equation 1) defines the causal relationship between observed explanatory variables X and the latent variable X^*. For simplicity, the presentation below assumes one latent variable X^* with multiple indicators. The index n designates an individual or a decision maker, and D denotes a generic distribution.

$$\mathrm{X}_\mathrm{n}^* = \mathrm{h}(\mathrm{X}_\mathrm{n}; \gamma) + \eta_\mathrm{n} \qquad \eta_\mathrm{n} \sim \mathrm{D}(0, \sigma_\eta^2) \tag{1}$$

$h(.)$ is a function, γ are parameters to be estimated, and η is a random disturbance term with zero mean and a variance σ_η^2. Though the latent variable is unobserved, it is manifested by observed indicators (e.g., responses to survey questions) that help identify the latent variable. Therefore, a measurement relationship, links the observed indicators to the underlying latent variable. For example, equation (2) relates an indicator I_r to the latent variable X^*, where $r = 1, \dots, R$, and R is the total number of indicators of the latent variable.

$$\mathrm{I}_{\mathrm{r,n}} = \mathrm{q}(\mathrm{X}_\mathrm{n}, \mathrm{X}_\mathrm{n}^*\,; \alpha_\mathrm{r}) + \nu_{\mathrm{r,n}} \qquad \nu_{\mathrm{r,n}} \sim \mathrm{D}\left(0, \sigma_{\nu_\mathrm{r}}^2\right) \tag{2}$$

$q(.)$ is a function, α_r is a parameter to be estimated, and ν_r is a random measurement error term with zero mean and variance $\sigma_{\nu_r}^2$.

The other component of the HCM is the choice model. The utility function associated with an alternative is influenced by the observed explanatory variables X and the latent variable X^* as shown in equation (3).

$$\mathrm{U}_\mathrm{n} = \mathrm{V}(\mathrm{X}_\mathrm{n}, \mathrm{X}_\mathrm{n}^*; \beta) + \varepsilon_\mathrm{n} \qquad \varepsilon_\mathrm{n} \sim \mathrm{D}(0, \sigma_\varepsilon^2) \tag{3}$$

$V(\,.\,)$ is the systematic or deterministic utility function, β are parameters to be estimated and ε is a random disturbance term with zero mean and variance σ_ε^2 which is usually normalized to an arbitrary value to set the scale of the utility.

If a decision maker n selects the alternative i that maximizes utility (among other alternatives $j;\ j \in J_n$, where J_n is the choice set of an individual n), the choice can be expressed as in equation (4).

$$y_{n,i} = \begin{cases} 1, & if\ U_{n,i} = \max_{j \in J_n}\{U_j\} \\ 0, & otherwise \end{cases} \quad (4)$$

The integrated model is estimated simultaneously using the maximum likelihood technique. In the following we explain how the likelihood function to be maximized is derived. Because of the unobserved correlation between the choice and the indicators (they both depend on the latent variable), the joint probability of the observed choice and indicators of the latent variable cannot be written as the product of the unconditional probabilities of the choice and the indicators. However, conditioning on the latent variable X_n^*, the probability P of the choice and the density function g of the indicators are independent. Therefore, the conditional likelihood, designated as K_n^* for an individual n, is the joint conditional probability of the observed choice and indicators, as given by equation (5), where y_n is a vector of choices made by individual n, and I_n is a vector of all indicators used to quantify the latent variable X_n^*.

$$\mathrm{K}_\mathrm{n}^*(\mathrm{y}_\mathrm{n}, \mathrm{I}_\mathrm{n}|\mathrm{X}_\mathrm{n}, \mathrm{X}_\mathrm{n}^*; \beta, \alpha, \sigma_\varepsilon, \sigma_\nu) = \mathrm{P}(\mathrm{y}_\mathrm{n}|\mathrm{X}_\mathrm{n}, \mathrm{X}_\mathrm{n}^*; \beta, \sigma_\varepsilon).\, \mathrm{g}(\mathrm{I}_\mathrm{n}|\mathrm{X}_\mathrm{n}, \mathrm{X}_\mathrm{n}^*; \alpha, \sigma_\nu) \quad (5)$$

$P(y_n|X_n, X_n^*; \beta, \sigma_\varepsilon)$ is the choice probability and it is determined based on the assumption about the distribution of the disturbance ε (the unobserved component of the utility). For example, if ε for each alternative is independently and identically distributed Extreme Value Type I (0,1), the choice probability is logit and is given by equation (6).

$$\mathrm{P}_{\mathrm{n,i}} = \frac{\mathrm{e}^{\mathrm{V}_{\mathrm{n,i}}}}{\sum_\mathrm{j} \mathrm{e}^{\mathrm{V}_{\mathrm{n,j}}}} \quad (6)$$

$g(I_n|X_n, X_n^*; \alpha, \sigma_\nu)$ is the joint density function of the indicators of the latent variable. To obtain the unconditional likelihood, designated as K_n, the conditional likelihood K_n^* is then integrated over the density of the latent variable X_n^* as shown by equation (7):

$$K_n(y_n, I_n | X_n; \gamma, \alpha, \beta, \sigma_\eta, \sigma_\nu, \sigma_\varepsilon) \tag{7}$$

$$= \int_{X_n^*} P(y_n | X_n, X_n^*; \beta, \sigma_\varepsilon).\, g(I_n | X_n, X_n^*; \alpha, \sigma_\nu).\, f\left(X_n^* \middle| X_n; \gamma, \sigma_\eta\right) dX_n^*$$

where $f\left(X_n^* \middle| X_n; \gamma, \sigma_\eta\right)$ denotes the density function of the latent variable X_n^*.

The functional forms in the likelihood function $f(.)$ and $g(.)$ are determined based on the forms of the variables (discrete/continuous) and assumptions about the disturbance terms η in the structural equations and the error terms ν in the measurement equations. For example, if η is assumed to have a normal distribution, f can be expressed as in equation (8):

$$f\left(X_n^* \middle| X_n; \gamma, \sigma_\eta\right) = \frac{1}{\sigma_\eta} \emptyset\left(\frac{X_n^* - h(X_n; \gamma)}{\sigma_\eta}\right) \tag{8}$$

where the function $h(.)$ represents the causal relationship between the observed variables X_n and the latent variable X_n^* as presented earlier in equation (1), and $\emptyset(.)$ represents the standard normal density function. If multiple latent variables are considered, the integration of the conditional likelihood has to be done over the joint density function of all latent variables.

If ν is assumed to have a normal distribution, g can be expressed as in equation (9):

$$g(I_n | X_n, X_n^*; \alpha, \sigma_\nu) = \prod_{r=1}^{R} \frac{1}{\sigma_{\nu_r}} \emptyset\left(\frac{I_{r,n} - q(X_n, X_n^*; \alpha_r)}{\sigma_{\nu_r}}\right) \tag{9}$$

where the function $q(.)$ represents the measurement relationship between the indicators I_n and the latent variable X_n^* as presented earlier in equation (2).

Assuming that the behavior of an individual is independent of that of other individuals in the sample, the unconditional likelihood function for the sample is the product of the unconditional likelihood over all individuals as shown in equation (10).

$$K = \prod_{n=1}^{N} K_n(y_n, I_n | X_n; \gamma, \alpha, \beta, \sigma_\eta, \sigma_\nu, \sigma_\varepsilon) \tag{10}$$

where N represents the total number of individuals in the sample.

The log-likelihood of an individual in the sample is given by equation (11.a) and the log-likelihood for the entire sample is given by equation (11.b).

$$LK_n = \ln[\, K_n(y_n, I_n | X_n; \gamma, \alpha, \beta, \sigma_\eta, \sigma_\nu, \sigma_\varepsilon)] \tag{11.a}$$

$$LK = \ln[K] = \sum_{n=1}^{N} LK_n = \sum_{n=1}^{N} \ln[K_n(y_n, I_n | X_n; \gamma, \alpha, \beta, \sigma_\eta, \sigma_\nu, \sigma_\varepsilon)] \tag{11.b}$$

The maximum likelihood technique consists of maximizing LK.

5.1.2. Serial Correlation

When multiple observations are collected from the same individual over time, the resulting data are called panel data. Serial correlation, also known as agent effect, arises when individual related unobserved factors persist over time and affect the decision outcomes of an individual over time (Ben-Akiva, 2013). In this case, the disturbance terms will be dependent across time t, as in equation (12):

$$\mathrm{\varepsilon_{i,n,t}} = \mathrm{\alpha_n} + \mathrm{\varepsilon'_{i,n,t}} \tag{12}$$

where α_n is the agent effect of individual n (which may also be specific to alternative i), and $\varepsilon'_{i,n,t}$ is a random term that is independently and identically distributed over time and over alternatives. The framework of a simple choice model with serial correlation is presented in Figure 19. The serial correlation is represented by the bidirectional arrow which represents a correlation between the disturbance terms in two successive time periods.

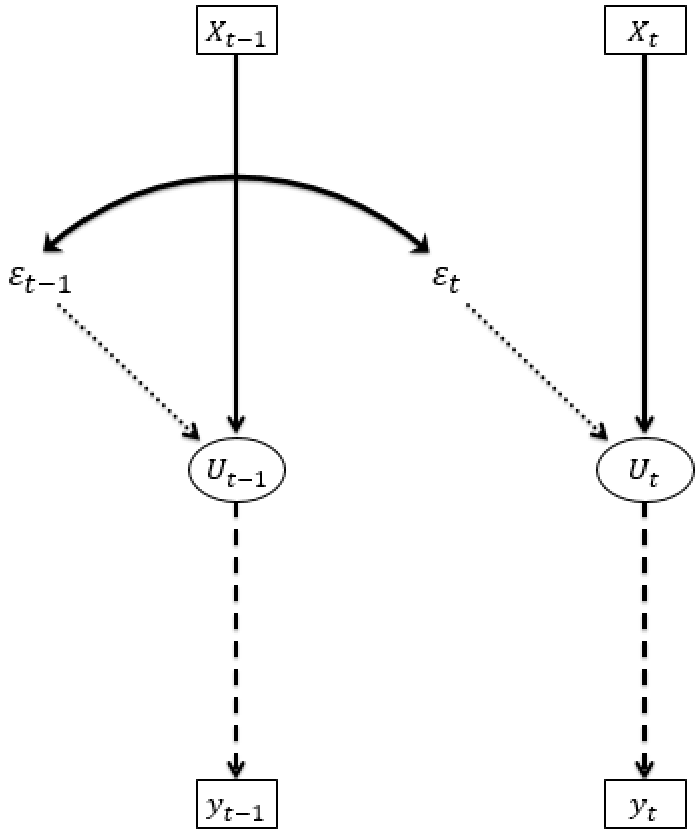

Figure 19: Simple choice model with serial correlation (adapted from Ben-Akiva, 2013)

In this case, the utility function of alternative i for an individual n at time t is given by equation (13):

$$\mathrm{U_{i,n,t} = V_{i,n,t} + \alpha_n + \varepsilon'_{i,n,t}} \tag{13}$$

where $V_{i,n,t}$ is the systematic component of the utility (function of observed variables). Conditional on α_n, the choices of an individual are independent over time. For a random agent effect α_n distributed with density $h(\alpha)$, the unconditional probability of the series of choices made by individual n through time $t = 1, 2, \ldots, T$ is given by equation (14).

$$P(y_{n,1}, y_{n,2}, \dots, y_{n,T}) = \int_{\alpha} \prod_{t=1}^{T} P(y_{n,t}|\alpha).\, h(\alpha)\, d\alpha \tag{14}$$

5.1.3. State Dependence

Modeling dynamics using the state dependence approach is based on the assumption that the action of an individual at one time period depends on his/her action in the past. Such behavior is associated with learning effect and habits that arise when the choice/action process evolves through time (Ben-Akiva, 2013).

State dependence is often modeled using a Markov model whereby the utility function at time t, in a simple choice model, depends on the choice made by individual n at time $t-1$ (equation 15).

$$U_{i,n,t} = V_{i,n,t} + \delta y_{i,n,t-1} + \varepsilon_{i,n,t} \tag{15}$$

where $y_{i,n,t-1}$ is the choice made by individual n at time period $t-1$ and it is given by equation (16). δ is a coefficient representing the effect of the previous choice on the utility function of alternative i for individual n at time period t. $\varepsilon_{i,n,t}$ is a random term that is independently and identically distributed over time and over alternatives

$$y_{i,n,t-1} = \begin{cases} 1, & \mathit{if\ alternative\ i\ was\ chosen\ by\ n\ at\ time\ t-1} \\ 0, & \mathit{otherwise} \end{cases} \tag{16}$$

The framework of a dynamic Markov simple choice model is presented in Figure 20.

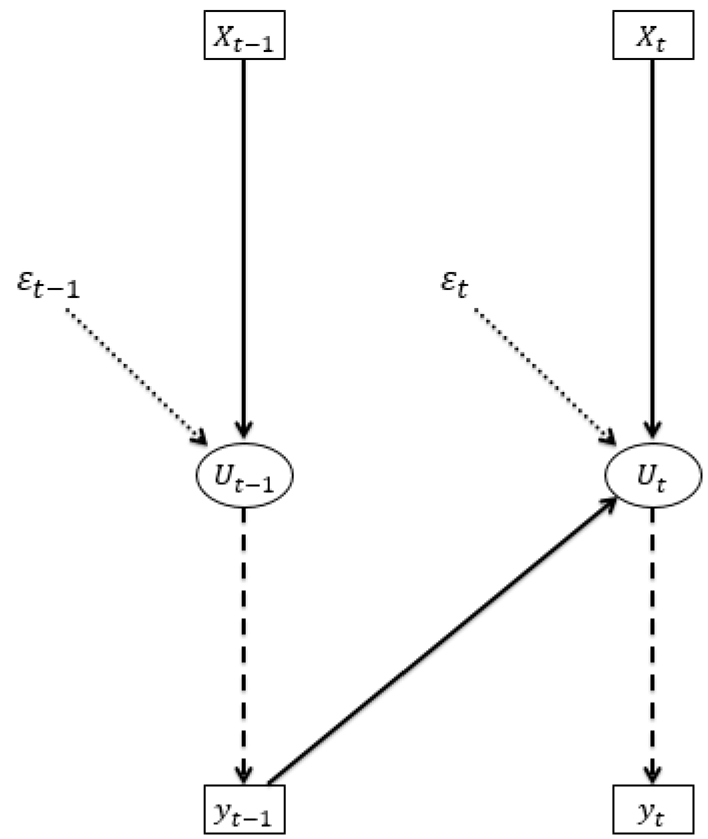

Figure 20: Simple choice model with state dependence (Markov model) (adapted from Ben-Akiva, 2013)

Dynamics represented by the state dependence may also be integrated within hybrid choice models where there is a latent variable that evolves over time (Ben-Akiva, 2010; Choudhury et al., 2010). Assume for example that the latent variable in this case is an unobserved plan, decision strategy, or emotional state of the individual that controls his/her subsequent action/choice. State dependence arises when a sequence of plans (or generally unobserved variables) and actions is modeled with an assumption that plans are affected by the previous plans and the past actions. Such dynamic behavior is illustrated in Figure 21. In the following, y_t designates the action (the choice) at time t, l_t designates the plan at time t, and $1{:}\,t$ denotes the sequence of time periods $1, 2, \dots, t$. The available alternatives if plan l is selected are $1, 2, \dots, j, J_l$, where J_l

is the number of possible alternatives under plan l. This framework shows that the dynamics of the actions arises from the dynamics of the underlying latent plans.

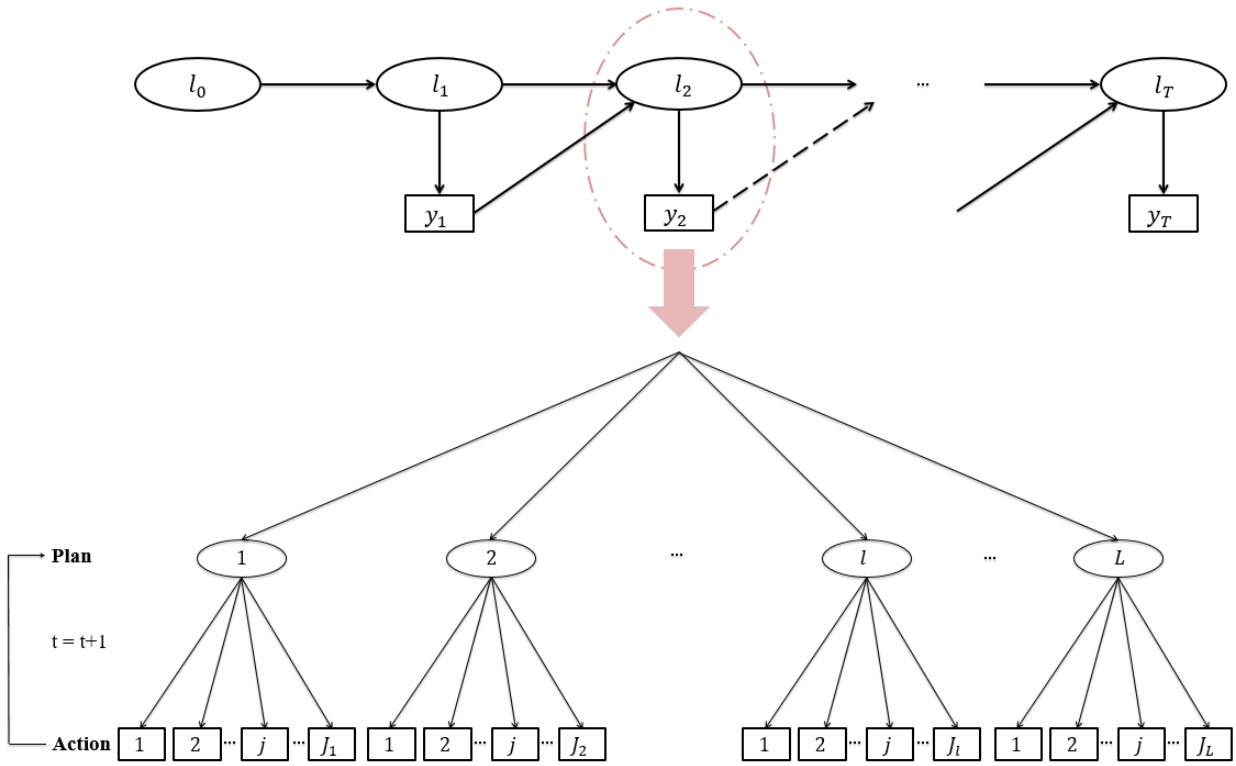

Figure 21: Modeling plans and actions with state dependence (adapted from Choudhury et al., 2010)

Conditioning on the past plans and actions, the probability of selecting the plan l at time t is $P(l_t|l_{1:t-1}, X, y_{1:t-1})$. Conditioning on the current plan and the past plans and actions, the probability of executing action y at time t is $P(y_t|l_{1:t}, X, y_{1:t-1})$. The resulting joint probability of the sequence of plans and actions may be too complex (see equation 21). In order to simplify the computation of the joint probability, Hidden Markov Model (HMM) is used with the following assumptions:

1. The current plan only depends on the previous plan as expressed in equation (17):

$$P(l_t|l_{1:t-1}, X, y_{1:t-1}) = P(l_t|l_{t-1}, X, y_{1:t-1}) \tag{17}$$

2. The current action only depends on the current plan as expressed in equation (18):

$$P(y_t|l_{1:t}, X, y_{1:t-1}) = P(y_t|l_t, X) \tag{18}$$

Therefore, conditioning on the past actions, the joint probability of the plan and action at time t is

$$P(y_t|l_t, X). P(l_t|l_{t-1}, X, y_{1:t-1}). \tag{19}$$

The joint probability of a sequence of plans and actions is

$$\prod_{t=1}^{T} P(y_t|l_t, X). P(l_t|l_{t-1}, X, y_{1:t-1}). \tag{20}$$

Finally, the probability of a sequence of actions, given initial conditions, is

$$P(y_1, \dots, y_T|l_0, X) \quad = \sum_{(l_1,\dots,l_T)} \prod_{t=1}^{T} P(y_t|l_t, X). P(l_t|l_{t-1}, X, y_{1:t-1}) \tag{21}$$

$$= \sum_{l_T} P(y_T|l_T, X) \sum_{l_{T-1}} P(l_T|l_{T-1}, X, y_{1:T-1})\, P(y_{T-1}|l_{T-1}, X) \dots \tag{22}$$

$$\sum_{l_1} P(l_2|l_1, X, y_1)\, P(y_1|l_1, X)\, P(l_1|l_0, X)$$

where l_0 is the initial plan at time $t = 0$.

By using the HMM assumptions, the number of summations in equation (22) is reduced from $|L|^T$ to $|L|T$, where $|L|$ is the number of possible plans in the case where the unobserved variable is a discrete plan. Where the unobserved variable is a continuous latent variable such as the emotional state of the driver, the summations above are replaced by integrals over the states.

5.2. Behavior Model Formulation

In this section, we apply the theoretical formulations presented above on the driving simulation experiment to model the driver stress dynamically. We present the adopted notation, the modeling approaches, the dynamic model with serial correlation, and the dynamic model with state dependence.

5.2.1. Notation

The notation used in the modeling throughout this chapter is as follows. Vectors and matrices are shown in bold font.

- N : Total number of individuals (*n* is an index for an individual)
- T : Number of time periods (*t* is an index for a time period)
- $\mathbf{S}_{\mathbf{events}}$: Independent variables representing the road events encountered during the driving simulation experiment at both control and treatment phases (dummy, i.e. binary variables):

  Truck = Truck event

  Ped = Pedestrians event

  TL = Traffic light event
- $\mathbf{S}_{\mathbf{n\text{-}back}}$: Independent variables representing the workload levels of the secondary cognitive n-back task activated at the treatment phase of the driving simulation experiment (dummy variables):

  Zero = 0-back

  One = 1-back

  Two = 2-back

- **S** : Independent variables designating all scenario variables ($\mathbf{S}_{\mathbf{events}}$ and $\mathbf{S}_{\mathbf{n\text{-}back}}$), used compactly in the likelihood function for simplicity ($\boldsymbol{S_n}$ is a matrix of all scenario variables encountered by individual n, $\boldsymbol{S_{n,t}}$ is a vector of all scenario variables encountered by individual *n* at time period *t*)
- **SS** : State Stress (latent or unobserved variable) ($SS_{n,t}$ is the state stress of individual *n* at time *t*)
- **O** : Observed dependent variables measured by the driving simulator (maximum speed, maximum accelerator pedal depression, and reaction time) and the EKG sensor (maximum heart rate), and used as indicators of the state stress ($\boldsymbol{O_n}$ is a matrix of all indicators of the state stress of individual *n*, and $\boldsymbol{O_{n,t}}$ is a vector of all indicators of the state stress of individual *n* at time period *t*)
- R : Number of indicators of state stress (r is an index for an indicator)
- **y** : Binary choice indicator associated with the traffic light event ($\boldsymbol{y_n}$ is a vector of choices made by individual n, $y_{n,t}$ is the choice made by individual *n* at time period *t* and it is equal to 1 if the subject violates the red light, and 0 otherwise)
- **U** : Matrix of utilities of the choice alternatives ($\boldsymbol{U_{n,t}}$ is a vector of the utilities of the alternatives available to individual *n* at time period *t*)
- AE : Agent Effect (latent or unobserved variable) representing an individual-specific time-invariant factor (AE_n is the agent effect of individual *n*)

5.2.2. Modeling Approaches

The dynamic model aims at quantifying the driver stress as it evolves through time in the three phases of the driving simulation experiment (baseline, control, and treatment). A latent variable labeled “state stress” is introduced. Though it is unobserved, it is manifested by the driver behavior and physiology. The analysis conducted in this section considers the sequence of observations over time for every subject as follows.

Since the subject drives first the baseline in the absence of road events and while not being involved in the secondary task, the baseline phase is assumed to represent initial conditions and is associated with time period $t=0$. As such, the baseline phase captures the initial level of stress before encountering the control/treatment phases that comprise the independent variables of interest ($\mathbf{S}_{\mathbf{n\text{-}back}}$, $\mathbf{S}_{\mathbf{events}}$). The following treatment and control phases characterized by the occurrence of six successive road events are associated with six time periods $t = 1, 2, \dots, 6$, whereby each time period includes the occurrence of one particular road event. Moreover, three among these time periods (either *1, 2, 3* or *4, 5, 6*) are coupled with the three levels of the secondary cognitive n-back task, corresponding to the treatment phase. Accordingly, the subject’s behavior is analyzed at seven different spots in the driving simulation experiment based on the data collected over each time period. In order to model dynamics, two approaches are used: (1) serial correlation, presented in subsection (5.2.3), and (2) state dependence, presented in subsection (5.2.4).

The dynamic model, presented in each subsection, consists of a hybrid choice model that integrates the latent variable (state stress) with the choice model. The choice whether to violate the red light or not is associated with the traffic light event. Explanatory variables include the scenario variables (the encountered road events and the levels of the n-back task) and they structure the equation of the latent variable state stress (causal relationship). Driving performance and physiological measures are used as indicators of the state stress at each time period. The state stress is included in the utility function of the choice as will be discussed in the first model presented.

5.2.3. Serial Correlation

In this first model, we represent the correlation between dependent variables of a given subject over time through serial correlation. Since each subject passes through the seven time periods in the driving course, the resulting data are panel data. An agent effect consisting of an individual-specific random component is added in the structural equation of the state stress at each time period to capture unobserved heterogeneity arising from individual related unobserved factors that persist over time across the seven time periods of interest. For example, such differences among individuals might be a personality trait such as an individual propensity to experience stress. The agent effect is assumed to be normally distributed: $\mathrm{AE} \sim \mathrm{N}\ (0, \sigma_{\mathrm{AE}}^2)$, and can be expressed as in equation (23):

$$AE = \sigma_{AE} * \Omega_{AE} \tag{23}$$

where σ_{AE} is the standard deviation of the agent effect AE, and Ω_{AE} is the standardized normal form of AE, i.e., $\Omega_{AE} \sim N\ (0,1)$. Statements (manifest variables) of the post-driving survey were used to quantify an individual trait stress based on an exploratory factor analysis; however, the impact of this latent variable was not statistically significant on the state stress. Therefore, heterogeneity among individuals in the sample was only captured by the agent effect without indicators from the survey.

The framework of this model is presented in Figure 22, and the formulation is presented in the following subsection.

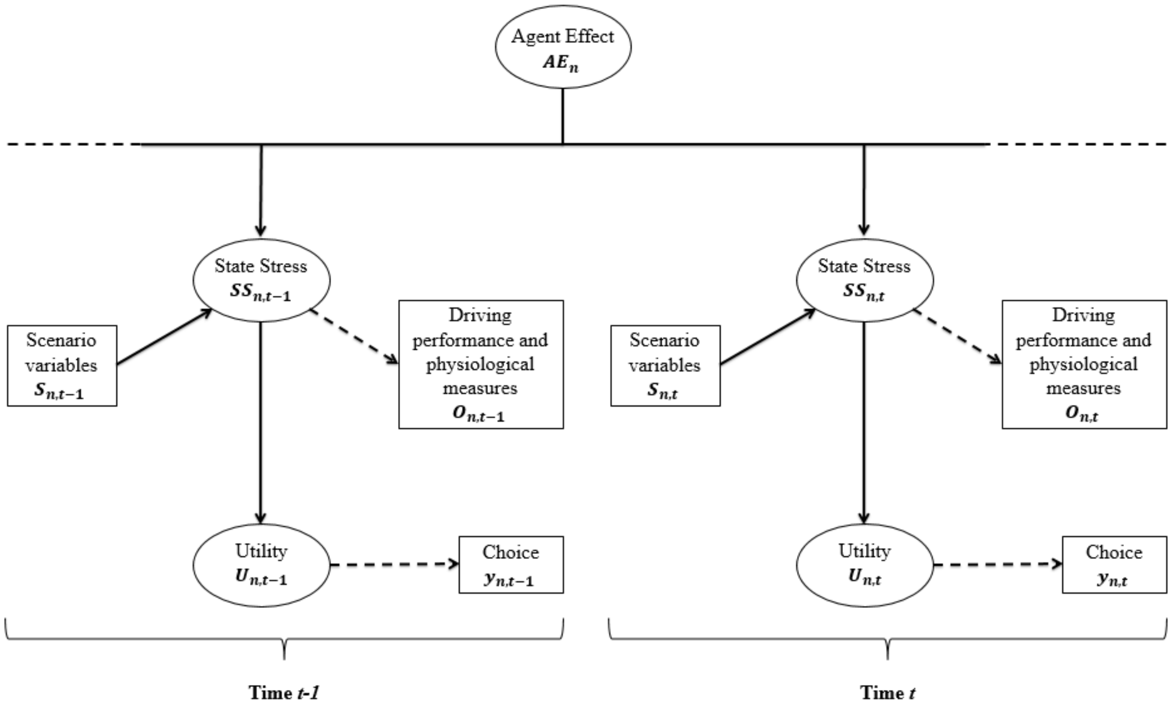

Figure 22: Framework of the HCM with serial correlation

5.2.3.1. Model Formulation

Structural Equations of State Stress

As mentioned earlier, initial conditions, at *t=0*, correspond to the baseline phase. The initial state of stress is a function of a constant (Cte_{SS_0}), the agent effect AE, and a random disturbance $\epsilon_{n,0}$, as given by equation (24):

$$SS_{n,0} = Cte_{SS_0} + AE_n + \epsilon_{n,0} \tag{24}$$

where $\epsilon_{n,0}$ is independently and identically normally distributed as in equation (25) with standard deviation $\sigma_{\epsilon_0}$to be estimated.

$$\epsilon_{n,0} \sim N\ (0, \sigma_{\epsilon_0}^2) \tag{25}$$

The state stress at time periods $t = 1, 2, \dots, 6$ is a function of the road events and the cognitive workload level of the secondary task at the treatment phase. The state stress equation at each of these time periods is normalized with respect to the truck event and the control phase. The effects of the Ped and TL road events are analyzed with respect to the Truck event (which is not included in the SS equations), and the effects of the n-back levels ($Zero$, One, Two) are analyzed with respect to having no n-back task. The state stress is also a function of the agent effect that persists over time and a random disturbance. Equations (26.a) to (26.f) express the state stress experienced at the six time periods from $t = 1$ to $t = 6$, respectively.

t = 1

$$SS_{n,1} = Cte_{SS_1} + \beta_{Ped}\, Ped_{n,1} + \beta_{TL}\, TL_{n,1} + \beta_{Zero}\, Zero_{n,1} + \beta_{One}\, One_{n,1} + \beta_{Two}\, Two_{n,1} + AE_n + \epsilon_{n,1} \quad (26.a)$$

t = 2

$$SS_{n,2} = Cte_{SS_2} + \beta_{Ped}\, Ped_{n,2} + \beta_{TL}\, TL_{n,2} + \beta_{Zero}\, Zero_{n,2} + \beta_{One}\, One_{n,2} + \beta_{Two}\, Two_{n,2} + AE_n + \epsilon_{n,2} \quad (26.b)$$

t = 3

$$SS_{n,3} = Cte_{SS_3} + \beta_{Ped}\, Ped_{n,3} + \beta_{TL}\, TL_{n,3} + \beta_{Zero}\, Zero_{n,3} + \beta_{One}\, One_{n,3} + \beta_{Two}\, Two_{n,3} + AE_n + \epsilon_{n,3} \quad (26.c)$$

t = 4

$$SS_{n,4} = Cte_{SS_4} + \beta_{Ped}\, Ped_{n,4} + \beta_{TL}\, TL_{n,4} + \beta_{Zero}\, Zero_{n,4} + \beta_{One}\, One_{n,4} + \beta_{Two}\, Two_{n,4} + AE_n + \epsilon_{n,4} \quad (26.d)$$

t = 5

$$SS_{n,5} = Cte_{SS_5} + \beta_{Ped}\, Ped_{n,5} + \beta_{TL}\, TL_{n,5} + \beta_{Zero}\, Zero_{n,5} + \beta_{One}\, One_{n,5} + \beta_{Two}\, Two_{n,5} + AE_n + \epsilon_{n,5} \quad (26.e)$$

$t = 6$

$$SS_{n,6} = Cte_{SS_6} + \beta_{Ped}\, Ped_{n,6} + \beta_{TL}\, TL_{n,6} + \beta_{Zero}\, Zero_{n,6} + \beta_{One}\, One_{n,6} + \beta_{Two}\, Two_{n,6} + AE_n + \epsilon_{n,6} \quad (26.f)$$

In each of the equations above, Cte_{SS_t} $(t = 1, 2, \ldots, 6)$ is a constant term specific for time period t, and β's are parameters (to be estimated) representing the effect of the variable on the state stress. $\epsilon_{n,t}$ is an independently and identically normally distributed disturbance (equations 27.a – 27.f) with variance σ_ϵ^2 assumed to be identical across time periods $t = 1, 2, \ldots, 6$ as it will be discussed later in the Model Estimation section.

$$\epsilon_{n,1} \sim N\,(0, \sigma_\epsilon^2) \quad (27.a)$$

$$\epsilon_{n,2} \sim N\,(0, \sigma_\epsilon^2) \quad (27.b)$$

$$\epsilon_{n,3} \sim N\,(0, \sigma_\epsilon^2) \quad (27.c)$$

$$\epsilon_{n,4} \sim N\,(0, \sigma_\epsilon^2) \quad (27.d)$$

$$\epsilon_{n,5} \sim N\,(0, \sigma_\epsilon^2) \quad (27.e)$$

$$\epsilon_{n,6} \sim N\,(0, \sigma_\epsilon^2) \quad (27.f)$$

Measurement Equations of State Stress

In order to quantify the latent variable "state stress", four dependent variables are used as indicators. These include three driving performance measures (extracted from the driving simulator) and one physiological measure (extracted from the EKG sensor), as below.

1. The maximum speed $(r = 1)$
2. The maximum accelerator pedal depression $(r = 2)$

3. The reaction time ($r = 3$)

4. The maximum heart rate ($r = 4$)

As discussed in Chapter 3, these measures were calculated along each segment of interest, which is defined by the time the event starts (e.g., when pedestrians start to cross the road, the truck starts decelerating, and the traffic light turns to the yellow indication) until the event ends (e.g., when the subject reaches the crosswalk, the subject stops behind the truck, and the traffic light turns to the red indication). As for the baseline phase, the segment of interest consists of 400 meters of a straight roadway. The above measures used as indicators were selected based on the statistical analysis presented in Chapter 4 where they were found to be statistically significantly affected by the additional cognitive workload of the n-back task. It should be noted that other measures were also tested (e.g., the maximum skin conductance level and the standard deviation of the lane position); however, the impact of state stress on these variables was low in magnitude, and therefore, they were not used as indicators of the state stress.

Moreover, the selected indicators take non-negative values, so they should have a distribution with non-negative support. Each of them was found to have a lognormal distribution and thus can be written in exponential form. The measurement equation associated with each indicator is given below (equation 28).

$$O_{r,n,t} = \exp(\alpha_{SS,r} + \lambda_{SS,r} SS_{n,t} + \omega_{r,n,t}) \tag{28}$$

$\alpha_{SS,r}$ (Constant) and $\lambda_{SS,r}$ (factor loading) are parameters to be estimated. $\omega_{r,n,t}$ (equation 29) is a measurement error term specific for each indicator and is independently and identically normally distributed with standard deviation σ_{ω_r} to be estimated.

$$\omega_{r,n,t} \sim N(0, \sigma_{\omega_r}^2) \tag{29}$$

$\lambda_{SS,r}$ captures the effect of the underlying state stress on the indicator r. We assume here that $\lambda_{SS,r}$ is fixed over time, i.e., a variation in the state stress (measured at two time periods) will be manifested in the same way across individuals by a variation in the values of an indicator (measured at the same two time periods). Since heterogeneity among individuals, e.g., differences in heart rate values, differences in reactions, etc., might lead to an error in the measurement relationship between the indicator and the underlying latent variable, such differences are captured by the error term of the measurement equation of the latent variable. Alternatively, one might assume that the effect of the latent variable on the indicator (i.e., $\lambda_{SS,r}$) is randomly distributed over individuals rather than fixed.

Choice Model

The traffic light event consists of a choice situation where the subject has to decide whether to cross the intersection on the red light (i.e. violate) or not. Every subject faces this event twice in the experiment, so there are two choices made by every subject. The choice is modeled using a random utility framework with utility maximization as decision protocol. An alternative specific constant ASC_1 is included in the utility equation of violating at the first phase (for the first choice situation that occurs at one of the time periods 1, 2, or 3), and another alternative specific constant ASC_2 is included in the utility equation of violating at the second phase (for the second choice situation that occurs at one of the time periods 4, 5, or 6). Since stress level has been reported in literature to influence the process of decision making (see as examples Porcelli and Delgado (2017); Starcke and Brand (2012)), the state stress is included in the utility function as a predictor of the choice whether to violate the red light or not.

Moreover, the effect of stress on performance has been found to depend on the situation whether it is perceived as “threat” or “challenge”: detriments in performance are observed in the former while improvements are observed in the latter (Starcke and Brand, 2012).

The utility equations for individual n of violating the red light at the first intersection and the second intersection are given respectively by equations (30.a) and (30.b), while the utility equation of not violating the red light is given by equation (31) which applies for all time periods t where there is a traffic light event.

$$t = 1, 2, 3 \qquad U_{violate\ (n,t)} = ASC_1 + \beta_{SS}\, SS_{n,t} + \varepsilon_{violate\ (n,t)} \tag{30.a}$$

$$t = 4, 5, 6 \qquad U_{violate\ (n,t)} = ASC_2 + \beta_{SS}\, SS_{n,t} + \varepsilon_{violate\ (n,t)} \tag{30.b}$$

$$t = 1, 2, \ldots, 6 \qquad U_{don't-violate\ (n,t)} = 0 + \varepsilon_{don't-violate\ (n,t)} \tag{31}$$

Where $\varepsilon_{violate\ (n,t)}$ and $\varepsilon_{don't-violate\ (n,t)}$ are random disturbances of the violate and don’t-violate alternatives for individual n at time period t, respectively. These terms are independently and identically distributed as Extreme Value Type I (0,1). β_{SS} is a parameter to be estimated and it represents the effect of the state stress on the choice.

Likelihood Function

To estimate the model, we use the method of maximum likelihood. The likelihood is the joint probability of the sequence (over time) of observed dependent variables. The resulting joint probability of choices (violations or non-violations at the two intersections) and the measures of driving performance and physiology (maximum speed, maximum accelerator pedal depression, reaction time, and maximum heart rate) for individual n is given by equation (32). Conditional on the agent effect, the density functions of the state stress over the seven time periods are independent of each other.

And conditional on the state stress at a given time period, the probabilities/density functions of the indicators of state stress are independent of each other. So the conditional probabilities are multiplied, and the resulting joint probability is then integrated over the state stress variables and the agent effect to obtain the unconditional probability.

$$
\begin{aligned}
&K_n(y_n, O_n|S_n) \\
&= \\
&\int_{AE=-\infty}^{+\infty} \int_{SS_0=-\infty}^{+\infty} g\left(O_{n,0}\middle|SS_{n,0}\right) * \ f\left(SS_{n,0}\middle|\ AE_n\right) \\
&\quad * \int_{SS_1=-\infty}^{+\infty} P\left(y_{n,1}\middle|SS_{n,1}\right) * \ g\left(O_{n,1}\middle|SS_{n,1}\right) * \ f\left(SS_{n,1}\middle|S_{n,1}, AE_n\right) \\
&\quad * \int_{SS_2=-\infty}^{+\infty} P\left(y_{n,2}\middle|SS_{n,2}\right) * \ g\left(O_{n,2}\middle|SS_{n,2}\right) * \ f\left(SS_{n,2}\middle|S_{n,2}, AE_n\right) \\
&\quad * \int_{SS_3=-\infty}^{+\infty} P\left(y_{n,3}\middle|SS_{n,3}\right) * \ g\left(O_{n,3}\middle|SS_{n,3}\right) * \ f\left(SS_{n,3}\middle|S_{n,3}, AE_n\right) \\
&\quad * \int_{SS_4=-\infty}^{+\infty} P\left(y_{n,4}\middle|SS_{n,4}\right) * \ g\left(O_{n,4}\middle|SS_{n,4}\right) * \ f\left(SS_{n,4}\middle|S_{n,4}, AE_n\right) \\
&\quad * \int_{SS_5=-\infty}^{+\infty} P\left(y_{n,5}\middle|SS_{n,5}\right) * \ g\left(O_{n,5}\middle|SS_{n,5}\right) * \ f\left(SS_{n,5}\middle|S_{n,5}, AE_n\right) \\
&\quad * \int_{SS_6=-\infty}^{+\infty} P\left(y_{n,6}\middle|SS_{n,6}\right) * \ g\left(O_{n,6}\middle|SS_{n,6}\right) * \ f\left(SS_{n,6}\middle|S_{n,6}, AE_n\right) \\
&\quad * h(AE_n) * dSS_0 . dSS_1 . dSS_2 . dSS_3 . dSS_4 . dSS_5 . dSS_6 . dAE
\end{aligned} \tag{32}
$$

The functional forms of the different probability components are given by the following equations (33 – 36). Conditional on $SS_{n,t}$, the choice model is a binary logit model at time $t = 1, 2,..., 6$ such that there is an intersection event at t, as shown in equations (33.a) and (33.b).

$$P(y_{n,t} = 1|SS_{n,t}) = \frac{e^{(ASC + \beta_{SS}\, SS_{n,t})}}{1 + e^{(ASC + \beta_{SS}\, SS_{n,t})}} \tag{33.a}$$

$$P(y_{n,t} = 0|SS_{n,t}) = \frac{1}{1 + e^{(ASC + \beta_{SS}\, SS_{n,t})}} \tag{33.b}$$

Conditional on $SS_{n,t}$, the probabilities of the maximum speed, maximum accelerator pedal depression, reaction time, and maximum heart rate are independent. Therefore, their joint conditional density function is the product of the conditional density functions of lognormal variables for $t = 0, \ldots, 6$ as shown in equation (34).

$$g\left(O_{n,t} \mid SS_{n,t}\right) = \prod_{r=1}^{R} \frac{1}{O_{r,n,t} * \sigma_{\omega_r}} \, \emptyset \left[\frac{\ln\left(O_{r,n,t}\right) - \alpha_{SS,r} - \lambda_{SS,r}\, SS_{n,t}}{\sigma_{\omega_r}} \right] \tag{34}$$

where $\emptyset(\,)$ is the standard normal density function.

As discussed at the beginning of this chapter, the time period $t=0$ corresponds to the baseline phase which does not include any road event; therefore, the reaction time is excluded from the vector of indicators of the state stress of individual n at time period $t=0$, i.e., $O_{n,0}$ consists of the maximum speed, the maximum accelerator pedal depression, and the maximum heart rate measured within the defined segment of interest at time period $t=0$. Also, it should be noted that the reaction time indicator is excluded from the vector of indicators of the state stress of a red light violator at the time period t at which the violation occurs since the reaction time is not defined for violators (as discussed in Chapter 3).

The density function of $SS_{n,t}$ is that of a normal variable as shown in equations (35.a) and (35.b).

$$t = 0 \qquad f(SS_{n,0}|\ AE_n) = \frac{1}{\sigma_{\epsilon_0}} \emptyset\ [\frac{SS_{n,0} -\ Cte_{SS_0} -\ AE_n}{\sigma_{\epsilon_0}}] \tag{35.a}$$

$$t = 1, 2, \dots, 6 \qquad f(SS_{n,t}|S_{n,t}, AE_n) = \frac{1}{\sigma_{\epsilon}} \emptyset\ [\frac{SS_{n,t} -\ Cte_{SS_t} - \beta_S\, S_{n,t} -\ AE_n}{\sigma_{\epsilon}}] \tag{35.b}$$

Finally, the density function of the agent effect is also that of a normal variable as shown in equation (36).

$$h(AE_n) = \frac{1}{\sigma_{AE}} \emptyset\ [\frac{AE_n}{\sigma_{AE}}] \tag{36}$$

Since each individual in the sample is assumed to act (e.g., violate/not violate the red light, decrease/increase the speed, etc.) independently of other individuals, the likelihood function over all individuals in the sample acting the way they were observed actually to do is

$$K = \prod_{n=1}^{N} K_n(y_n, O_n|S_n) \tag{37}$$

The log-likelihood of an individual in the sample is given by equation (38.a) and the log-likelihood for the entire sample is given by equation (38.b).

$$LK_n = \ln[K_n(y_n, O_n|S_n)] \tag{38.a}$$

$$LK = \ln[K] = \sum_{n=1}^{N} LK_n = \sum_{n=1}^{N} \ln[K_n(y_n, O_n|S_n)] \tag{38.b}$$

5.2.3.2 Model Estimation

The sample used to estimate the model consists of 74 subjects who completed the entire driving course. Subjects who did not encounter the last event assigned in the drive for example were excluded from the estimation sample at the modeling stage.

In order to estimate the model, two parameters were fixed. In the measurement equation corresponding to the maximum heart rate ($r = 4$), the constant parameter ($\alpha_{SS,4}$) is fixed to 0 for identification purposes, and the factor loading of the state stress latent variable ($\lambda_{SS,4}$) is fixed to 1 to set the scale of this latent variable. Setting the factor loading to 1 in one of the measurement equations of a latent variable is a standard way to set its scale. The following restrictions are also assumed:

1. The state stress structural equations at time periods *t = 1,2, …, 6* have the same constant term, i.e., $Cte_{SS_1} = Cte_{SS_2} = Cte_{SS_3} = Cte_{SS_4} = Cte_{SS_5} = Cte_{SS_6}$. This restriction was imposed after several model runs which showed that these constants were almost identical.
2. The coefficients of the scenario variables are assumed to be generic across all time periods *t = 1,2, …, 6* in the structural equations of the state stress.
3. The variances of the disturbances in the structural equations of the state stress are assumed to be the same across time periods *t = 1,2, …, 6* as mentioned earlier, i.e., $\sigma^2_{\epsilon_1} = \sigma^2_{\epsilon_2} = \sigma^2_{\epsilon_3} = \sigma^2_{\epsilon_4} = \sigma^2_{\epsilon_5} = \sigma^2_{\epsilon_6} = \sigma^2_{\epsilon}$
4. The error term of each indicator of the state stress latent variable is assumed to have the same variance across all time periods, i.e., $\sigma^2_{\omega_{r,0}} = \sigma^2_{\omega_{r,1}} = \cdots = \sigma^2_{\omega_{r,6}}$

Restrictions 2, 3, and 4 are imposed to obtain a more parsimonious model and to ease model estimation.

For numerical reasons, it is good practice to scale the data (Bierlaire, 2016). Since the observed values of the maximum heart rate (order of 90 beats/min), maximum speed (order of 50 km/hr), and reaction time (order of 4 seconds) have higher ranges than the maximum accelerator pedal depression (order of 0.4), the maximum heart rate and maximum speed values were divided by 10 and the maximum accelerator pedal depression was multiplied by 10. These scaling factors were adopted after several trials and lead to reasonable and significant magnitude of the major estimated parameters (particularly the constant terms).

The model is estimated in PythonBiogeme (Bierlaire, 2016; Bierlaire and Fetiarison, 2009) using the simulated maximum likelihood. Because of the dimensionality of the integrals in the likelihood function, it was not possible to estimate the model via numerical integration. Monte-Carlo integration is performed using "Halton" draws implemented in PythonBiogeme and reported to perform well for discrete choice models (Bierlaire, 2015). Estimation results are presented in Table 7.

It should be noted that several model specifications with serial correlation such as including demographics (e.g., gender, driving experience) were also tested and analyzed; however, the presented model was found to perform better than other trials in terms of the statistical significance of the variables and goodness-of-fit.

Table 7: Estimation results of the dynamic HCM with serial correlation (parameter estimates and standard errors are reported with 3 significant figures while t-tests and p-values are reported with 2 digits after the decimal point)

State Stress – Structural Equations				
Variable/Parameter	**Parameter Estimate**	**Robust Standard Error**	**Robust t-test**	**p-value**
Constant (*t=0*)	2.23	0.0137	162.22	0.00
Constant (*t=1, … ,6*)	2.14	0.0153	140.39	0.00
Ped	0.0157	0.00740	2.12	0.03
TL	0.0164	0.00894	1.84	0.07
Zero	0.0543	0.00978	5.55	0.00
One	0.0722	0.0118	6.11	0.00
Two	0.0902	0.0104	8.67	0.00
State Stress – Measurement Equations				
Variable/Parameter	**Parameter Estimate**	**Robust Standard Error**	**Robust t-test**	**p-value**
$\alpha_{SS,1}$ (Constant – Max. Speed)	1.69	0.177	9.57	0.00
$\alpha_{SS,2}$ (Constant – Max. Acc. Pedal Depression	2.81	0.633	4.44	0.00
$\alpha_{SS,3}$ (Constant – Reaction Time)	0.0637	0.854	0.07	0.90
$\alpha_{SS,4}$ (Constant – Max. Heart Rate)	0.00	-	-	-
$\lambda_{SS,1}$ (Factor loading – Max. Speed)	-0.0424	0.0807	-0.53	0.60
$\lambda_{SS,2}$ (Factor loading – Max. Acc. Pedal Depression)	-0.700	0.294	-2.38	0.02
$\lambda_{SS,3}$ (Factor loading – Reaction Time)	0.517	0.387	1.33	0.18
$\lambda_{SS,4}$ (Factor loading – Max. Heart Rate)	1.00	-	-	-
Choice Model				
Variable/Parameter	**Parameter Estimate**	**Robust Standard Error**	**Robust t-test**	**p-value**
ASC_1 (Violate Constant at *t=1, 2, 3*)	8.88	5.43	1.64	0.10
ASC_2 (Violate Constant at *t=4, 5, 6*)	7.29	5.52	1.32	0.19
State Stress	-4.92	2.55	-1.93	0.05

Table 7 (cont.): Estimation results of the dynamic HCM with serial correlation

Standard Deviations of Error Terms				
Variable/Parameter	**Parameter Estimate**	**Robust Standard Error**	**Robust t-test**	**p-value**
σ_{ϵ_0} (SS – Structural) at *t=0*	0.0114	0.00918	-1.24	0.22
σ_{ϵ} (SS – Structural)	0.0362	0.00594	-6.10	0.00
σ_{AE} (Agent effect)	0.151	0.0104	14.50	0.00
σ_{ω_1} (S.D. Max. Speed)	0.134	0.00701	19.13	0.00
σ_{ω_2} (S.D. Max. Acc. Pedal Depression)	0.565	0.0684	8.26	0.00
σ_{ω_3} (S.D. Reaction Time)	1.07	0.125	8.51	0.00
σ_{ω_4} (S.D. Max. Heart Rate)	0.0681	0.00507	13.42	0.00
Model Statistics				
Final Log-Likelihood	-3463.637			
Final Gradient Norm	+4.677e-03			

Analysis of Results

Based on the estimation results we can draw the following conclusions.

State Stress – Structural Equations

The constant in the structural equation of the state stress at time $t = 0$ is positive and statistically significant at the 95% level of confidence. It represents the mean of the unobserved factors (other than the agent effect) contributing to the initial level of stress of the subject including the stress induced by the mere driving task (i.e., maintaining the lateral/longitudinal control of the vehicle). Moreover, since it is measured at the baseline phase, this constant also reflects the stress induced by the experimental environment and could be attributed to the novelty factor at the beginning of the driving simulation experiment, in addition to a potential residual stress that had previously influenced the state stress before the start of the experiment. The constant at time periods $t = 1, 2, \dots, 6$ is positive and statistically significant at the 95% level of confidence. Since the structural equations of the state stress do not include the truck event and the control phase, the constant at time periods $t = 1, 2, \ldots, 6$ represents the state stress of the subject if the truck event is encountered at the control phase. The constant additionally captures the mean of other variables not included in the state stress equation, including the stress induced by the mere driving task. The standard deviation of the agent effect σ_{AE} is statistically significant at the 95% level of confidence, implying that the serial correlation has a significant effect on the state stress.

The positive coefficients of the pedestrians and the traffic lights events imply that these events generate a higher level of stress compared to the truck event. The coefficient of Ped is significant at the 95% level of confidence, while the coefficient of TL is significant at the 90% level of confidence. However, the difference between the coefficients of Ped (0.0157) and TL (0.0164) is not statistically significant at the 95% level of confidence (t-statistic of the difference = 0.078 < 1.96), implying that the effects of the Ped and TL events are relatively similar on the state stress.

The positive coefficients of the n-back task show that the state stress is statistically significantly higher at the treatment phase than at the control phase. The highest level of stress is experienced when performing the 2-back task, and the lowest level of stress is induced by the 0-back task. This observation confirms that an increment in the workload level of the secondary task contributes to a higher level of stress experienced by the individual. While the statistical analysis (presented in Chapter 4) did not show statistically significant differences between subjects in terms of driving performance and physiological measures across the levels of the secondary task, the results of the latent variable model (particularly the coefficients of the levels of the n-back task) capture the hidden effect of the increase in the cognitive workload level arising from the secondary task on the state stress.

State Stress – Measurement Equations

The negative signs of the factor loadings of the maximum speed and maximum accelerator pedal depression imply that the subject tends to reduce his/her maximum speed and maximum accelerator pedal depression when the state stress increases. This variation in the driving performance reflects the regulatory behavior adopted by the subject when performing an additional cognitive task while driving, particularly at situations requiring more attention and generating more stress. This result is in line with the findings of the statistical analysis that compared the control and treatment phases (within subject comparison) and showed the regulatory behavior of the driver when subjected to the n-back task (at the treatment phase). Studies such as Mandrick et al. (2016) and Zhou et al. (2016) support these findings as well. The positive sign of the reaction time factor loading shows that it will take the driver a longer time to react to roadway hazards under higher conditions of stress. This is also in accordance with the statistical analysis (within subject) that assessed the effect of the secondary task; the reaction time was higher particularly at the treatment phase encountered at the pedestrians and traffic light situations.

Although the coefficients of scenario variables (Ped, TL, Zero, One, Two) in the structural equations of the state stress were statistically significant at the 95% level of confidence (TL was statistically significant at the 90% level of confidence), they were low in magnitude comparing to the constant terms. Therefore, a question of interest would be whether their effect on the driving performance and physiological measures is contextually substantial. In order to address this question, the effects of scenario variables on the indicators are calculated excluding other variable components of the state stress (i.e., agent effect and disturbance) and the error terms in the measurement equations. In the following, we consider the situation whereby the subject encounters the pedestrians event at the 2-back level of the n-back task. Based on the estimated parameters and the considered variables, we calculate the state stress (using the structural equation) and its indicators (using the measurement equations). Table 8 shows the computed measures compared to the baseline phase and to the pedestrians event encountered at the control phase (in order to be able to compare the reaction time since no event occurs at the baseline).

Table 8: Model applied to specific situations considering scenario variables only

Situation	**Baseline**	**Ped + Two**
State Stress	2.23	2.25
Maximum Speed (km/hr)	49.31	49.26
Maximum Acc. Pedal Depression (dimensionless)	0.35	0.34
Maximum Heart Rate (Beats/min)	93	95
Situation	**Ped (Control)**	**Ped + Two**
State Stress	2.16	2.25
Reaction Time (s)	3.26	3.41

Comparing the (Ped + Two) situation to the Baseline, the decrease in the maximum speed and the maximum accelerator pedal depression is minor as is the increase in the maximum heart rate at the $Ped + Two$ situation. This implies that the scenario variables, isolated from all other factors accounted for in the model but not included in the above application (e.g., agent effect, unobserved variables, measurement error terms), do not have substantial effect on the maximum speed, maximum accelerator pedal depression, and maximum heart rate as shown by this example. The comparison between the control and the 2-back level of the secondary task shows the increase in the reaction time at the treatment phase; though it seems low in magnitude, it should not be neglected from the driver safety perspective. The minor effect that scenario variables had on the considered driving performance and heart rate measures might be due to the relatively short length of the experiment and to the analysis being focused on road events particularly with a duration less than 10 seconds that might not be long enough to capture significant variations in the measures of interest. A larger span of analysis whereby the driver is engaged in a secondary task for a longer time might have shown larger effects. Moreover, the types of events encountered and the type of secondary task might be perceived as challenging rather than dangerous when considered in a driving simulation environment, while this might not be the case in real driving situations.

We report in Table 9 results extracted from Mehler et al. (2009) for the purpose of comparison (sample means are reported). The driving simulation experiment did not include any variation in the driving context (i.e., no particular events such as traffic lights or vehicles in the driver's lane of travel were encountered). The n-back task was also used to induce an increase in workload; however, levels were presented for all participants in the same sequence of workload increment (i.e., baseline, 0-back, then 1-back, followed by 2-back). The intervals of time during which the measures were analyzed were 30 seconds for the baseline, and 2 minutes for each level of the secondary task.

Table 9: Measures extracted from Mehler et al. (2009) for comparison

Phase	**Average Velocity (fps)**	**Average Velocity (km/hr)**	**Average Heart Rate (Beats/min)**
Baseline	68.76	75.45	70.5
0-back	68.49	75.15	73.6
1-back	68.09	74.71	78.3
2-back	69.04	75.76	79.4

As shown in Table 9, modest variations in velocity measures were observed, while more substantive changes were observed in terms of the heart rate measures.

It should be noted that the minor effect of the scenario variables particularly on the driving performance measures as shown by the behavioral modeling is in line with the findings of the statistical analysis of Chapter 4 whereby the effect of the secondary task on the driving performance was not substantive at each of the three considered road situations.

Choice Model

The positive sign of the violate alternative specific constant (both ASC_1 and ASC_2) indicates that if everything else is the same, the subject is more likely to violate the red light at the intersection. The higher value of ASC_1 implies that violations are more likely to occur at the first phase than at the second phase. This is in accordance with the observed results of the driving simulation experiment that showed that eleven violations occurred at the first intersection while three violations occurred at the second intersection. This finding highlights the effect of learning as the subject might expect the occurrence of this event again in the drive and crossing the first intersection on red might restore his/her attention to the traffic light at the second intersection.

The negative sign of the state stress in the violate utility function implies that if the subject has a higher state of stress, he/she would be less likely to violate the red light at the intersection, which means that the components of the state stress, i.e., the road events and the secondary task level (if any), have a positive effect on the choice made by the subject at the intersection and serve to alert the driver and increase his/her situational awareness. This impact may be explained by the fact that subjects might not perceive the high cognitive workload arising from the driving task and the secondary task as a “threat” but as a “challenge”, and therefore, the resulting stress reduces the probability of violations. Starcke and Brand (2012) address such outcome of stress.

Model Application

In this section, we apply the estimated model above to the data to predict the various dependent measures of interest and assess how the model predicted measures compare to those observed in the data. First, we use the model to predict red light violations at the two encountered intersections for the traffic light event. In order to calculate the predicted average probability of violating the red light at the intersection, the sample enumeration method is used in PythonBiogeme. Table 10 shows the predicted average probability of violation as well as the observed proportion of violation at the traffic light event (associated with the choice situation). The number of choice situations represents how many times an intersection (a traffic light event) is encountered at a given time period in the sample (N=74). The predicted probabilities of violation by this model reflect the trend of the observed number of violations with a relatively higher tendency to violate at the first phase (at time periods t = 1, 2, 3). This trend reflects the learning and expectation effects that the driver experiences after encountering the first intersection in the driving course, as also demonstrated by the higher alternative (of violation) specific constant estimated for the first phase (ASC_1) than that estimated for the second phase (ASC_2).

Table 10: Observed versus predicted violations using the dynamic HCM with serial correlation

Event Number (Time Period)	Number of Choice Situations	Observed Number of Violations	Observed Proportion of Violations	Predicted Probability of Violations
1	24	3	0.125	0.159
2	25	2	0.080	0.168
3	25	6	0.240	0.197
4	26	1	0.038	0.040
5	13	1	0.077	0.039
6	35	1	0.029	0.051

Second, we use the model to predict the dependent variables that were used as indicators of the state stress, i.e., the driving performance and the physiological measures. Predictions are done at the aggregate level as per the formulation stated below.

The predicted value of each measure of interest is given by equation (39) which expresses the expected value of a lognormally distributed variable ($e^{(\mu+\frac{\sigma^2}{2})}$) (Train, 2009).

$$E(O_{r,t}) = \exp(\alpha_{SS,r} + \lambda_{SS,r}\, SS_t + 0.5 * var(\ln(O_{r,t})) \tag{39}$$

Where $\alpha_{SS,r}$ and $\lambda_{SS,r}$ are estimated parameters output by Biogeme. SS_t is the average value of the state stress of all individuals at time period *t*; its value is also output by Biogeme (in the simulation report). $var(\ln(O_{r,t}))$ is the variance of the logarithm of the measure of interest, and is calculated using equation (40).

$$var\left(\ln\left(O_{r,t}\right)\right) = \lambda_{SS,r}^2 * var(SS_t) + \sigma_{\omega_r}^2 \quad (40)$$

$var(SS_t)$ is the variance of the state stress and is calculated using equation (41.a) for the time period *t=0* and by equation (41.b) for the time periods *t=1,2, … ,6*.

t=0
$$var(SS_t) = \sigma_{AE}^2 + \sigma_{\epsilon_0}^2 \quad (41.a)$$

t=1,2,… ,6
$$var(SS_t) = \beta_{Ped}^2 * var(Ped_t) + \beta_{TL}^2 * var(TL_t) + \beta_{Zero}^2 * var(Zero_t) + \beta_{One}^2 * var(One_t) + \beta_{Two}^2 * var(Two_t) + {\sigma_{AE}}^2 + \sigma_{\epsilon_t}^2 \quad (41.b)$$

In equation (41.b), variances are calculated using data of all individuals in the sample. For example, $var(Ped_1)$ is the variance of the dummy variable Ped in the sample at time period *t=1*.

Figure 23 illustrates the average state stress of all individuals at each time period.

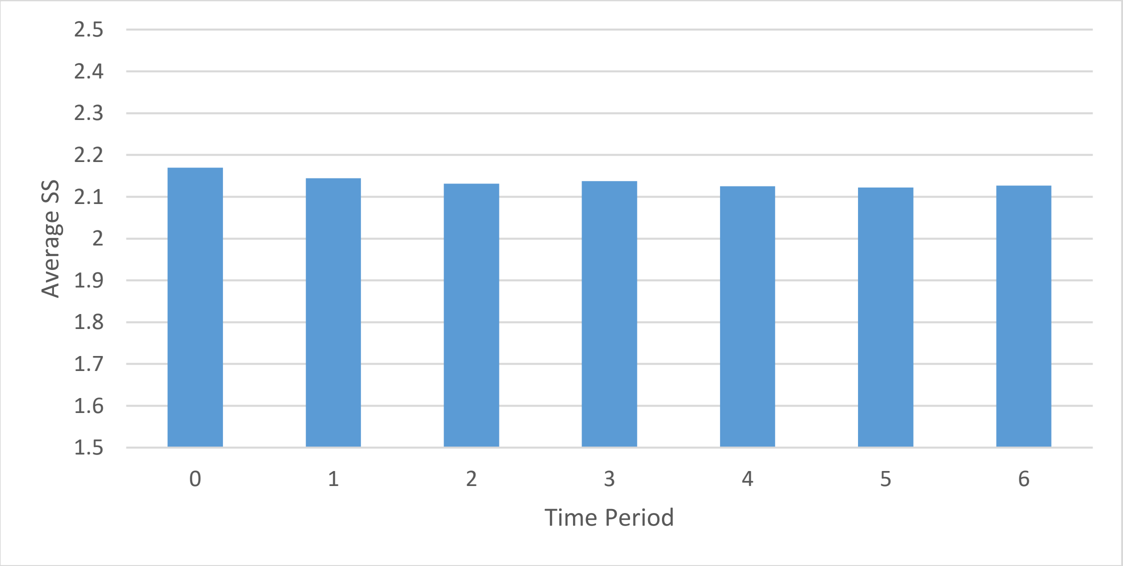

Figure 23: Predicted average state stress at each time period using the dynamic HCM with serial correlation

Figures (24-27) illustrate the average values of the predicted versus the average observed values of each indicator at each time period.

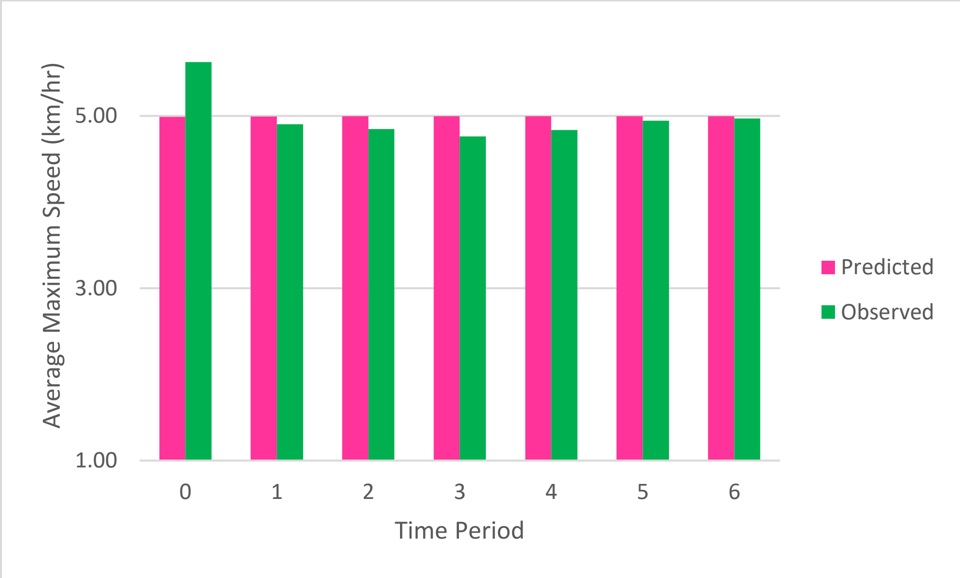

Figure 24: Average observed versus average predicted scaled values of the maximum speed at each time period (scale factor =0.1) using the dynamic HCM with serial correlation

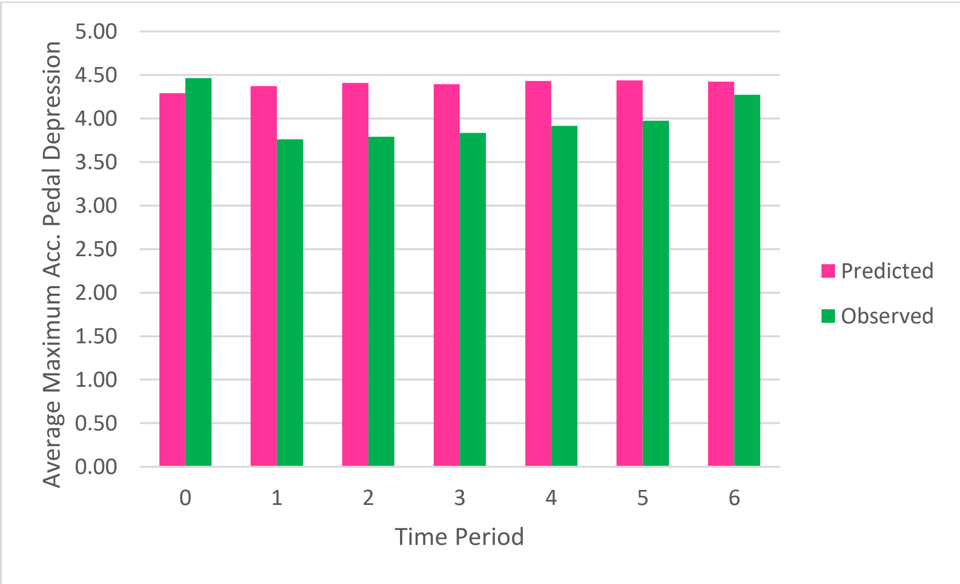

Figure 25: Average observed versus average predicted values of the maximum accelerator pedal depression at each time period (scale factor =10) using the dynamic HCM with serial correlation

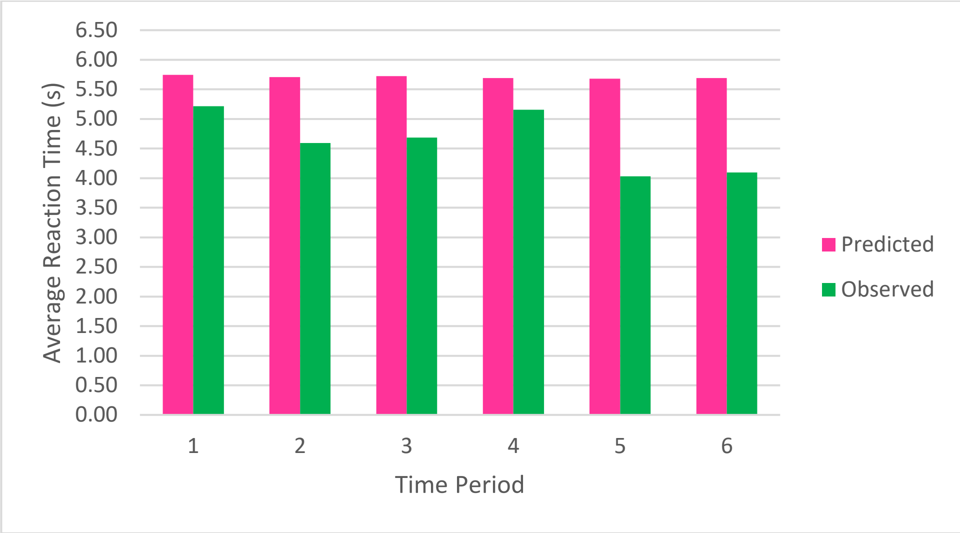

Figure 26: Average observed versus average predicted values of the reaction time at each time period using the dynamic HCM with serial correlation

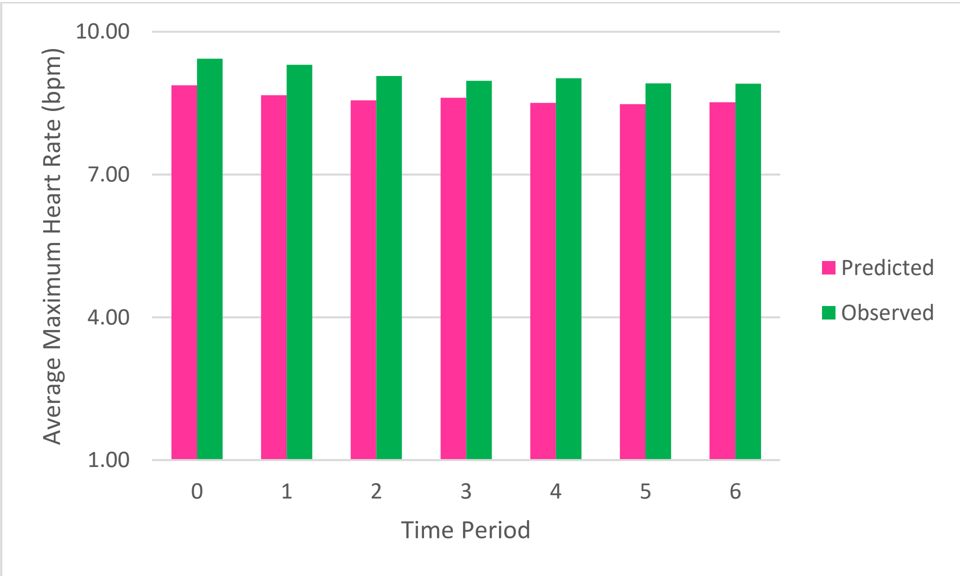

Figure 27: Average observed versus average predicted scaled values of the maximum heart rate at each time period (scale factor =0.1) using the dynamic HCM with serial correlation

Table 11 shows the percentage differences between the average observed values and the average predicted values of the indicators of state stress by the dynamic model with serial correlation using equation (42).

$$\Delta_{O_{r,t}}(\%) = 100 * \left| \frac{O_{r,t_{(observed)}} - O_{r,t_{(predicted)}}}{O_{r,t_{(observed)}}} \right| \tag{42}$$

Table 11: Percentage differences between average observed values and average predicted values of the indicators of state stress by the dynamic model with serial correlation

Time Period	**0**	**1**	**2**	**3**	**4**	**5**	**6**
Maximum Speed	11.3	1.8	3.0	4.9	3.3	1.1	0.5
Maximum Acc. Pedal Depression	3.8	16.2	16.4	14.6	13.1	11.7	3.6
Reaction Time	NA(*)	10.1	24.2	22.1	10.4	40.9	39.0
Maximum Heart Rate	5.9	6.8	5.6	4.0	5.7	4.9	4.4

(*) The reaction time is not used as indicator of state stress at time period $t = 0$ since the baseline does not include road events.

The average predicted values are close to the average observed measures for the majority of the indicators (except for the reaction time indicator at time periods 5 and 6, whereby the model overpredicts the average reaction time by approximately 1.5 s). The model underpredicts the maximum heart rate indicator while it overpredicts the remaining indicators at time t =1,…,6.

5.2.4. State Dependence

This model captures the evolution of the state stress throughout the seven time periods based on the Hidden Markov assumptions presented earlier in this chapter (applied to a continuous latent variable rather than discrete). A new variable is introduced in the structural equation of the state stress representing the state stress of the previous time period. A similar approach is adopted in Danaf (2013) and Danaf et al. (2015) to quantify the driver state anger at signalized intersections.

The framework of the dynamic model with state dependence is illustrated in Figure 28. It is assumed that there is no agent effect.

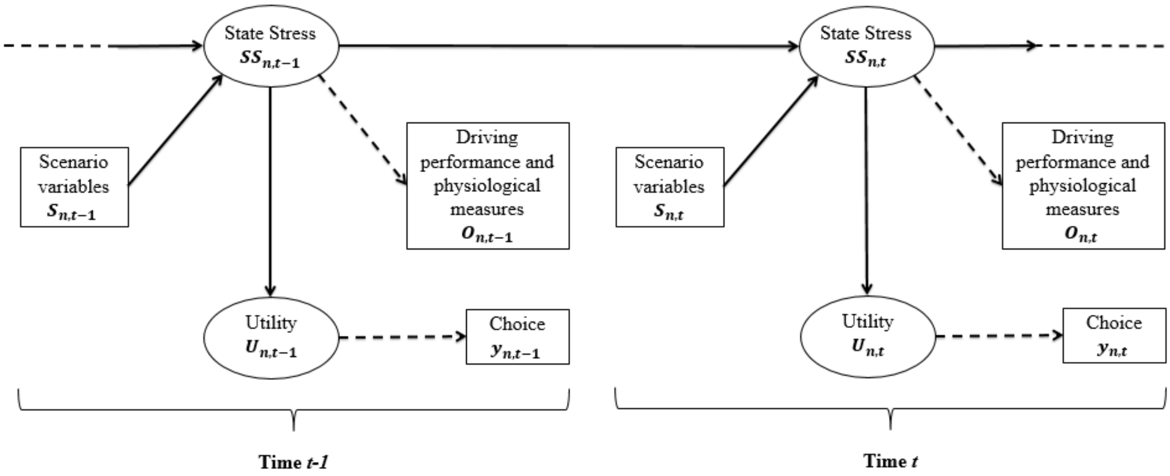

Figure 28: Framework of the HCM with state dependence

5.2.4.1. Model Formulation

Structural Equations of State Stress

Initial conditions of the state stress correspond to the baseline phase and they are given by equation (43).

$$t=0 \qquad SS_{n,0} = Cte_{SS_0} + \epsilon_{n,0} \tag{43}$$

Where Cte_{SS_0} is a constant to be estimated and $\epsilon_{n,0}$ is independently and identically normally distributed as in equation (25) with standard deviation σ_{ϵ_0} to be estimated.

Dynamics in this model arise from the state stress carried over from the previous time period, i.e., $SS_{n,t-1}$. Therefore the current state of stress of individual *n* at time period *t = 1, 2, …,6* is a function of the scenario variables, the accumulated state stress, and a random disturbance $\epsilon_{n,t}$ as shown by equations (44.a) to (44.f).

t = 1

$$SS_{n,1} = Cte_{SS_1} + \beta_{lag}\, SS_{n,0} + \beta_{Ped}\, Ped_{n,1} + \beta_{TL}\, TL_{n,1} + \beta_{Zero}\, Zero_{n,1} + \beta_{One}\, One_{n,1} + \beta_{Two}\, Two_{n,1} + \epsilon_{n,1} \tag{44.a}$$

t = 2

$$SS_{n,2} = Cte_{SS} + \beta_{lag}\, SS_{n,1} + \beta_{Ped}\, Ped_{n,2} + \beta_{TL}\, TL_{n,2} + \beta_{Zero}\, Zero_{n,2} + \beta_{One}\, One_{n,2} + \beta_{Two}\, Two_{n,2} + \epsilon_{n,2} \tag{44.b}$$

t = 3

$$SS_{n,3} = Cte_{SS} + \beta_{lag}\, SS_{n,2} + \beta_{Ped}\, Ped_{n,3} + \beta_{TL}\, TL_{n,3} + \beta_{Zero}\, Zero_{n,3} + \beta_{One}\, One_{n,3} + \beta_{Two}\, Two_{n,3} + \epsilon_{n,3} \tag{44.c}$$

t = 4

$$SS_{n,4} = Cte_{SS} + \beta_{lag}\, SS_{n,3} + \beta_{Ped}\, Ped_{n,4} + \beta_{TL}\, TL_{n,4} + \beta_{Zero}\, Zero_{n,4} + \beta_{One}\, One_{n,4} + \beta_{Two}\, Two_{n,4} + \epsilon_{n,4} \tag{44.d}$$

$t = 5$ $$SS_{n,5} = Cte_{SS} + \beta_{lag}\, SS_{n,4} + \beta_{Ped}\, Ped_{n,5} + \beta_{TL}\, TL_{n,5} + \beta_{Zero}\, Zero_{n,5} + \beta_{One}\, One_{n,5} + \beta_{Two}\, Two_{n,5} + \epsilon_{n,5} \quad (44.e)$$

$t = 6$ $$SS_{n,6} = Cte_{SS} + \beta_{lag}\, SS_{n,5} + \beta_{Ped}\, Ped_{n,6} + \beta_{TL}\, TL_{n,6} + \beta_{Zero}\, Zero_{n,6} + \beta_{One}\, One_{n,6} + \beta_{Two}\, Two_{n,6} + \epsilon_{n,6} \quad (44.f)$$

We assume that the impact of the state stress experienced at the previous time period *t-1* on the state stress at time period *t* is the same across all time periods (designated as β_{lag}). In addition, we assume that the constant term at time period *t=1* is different from the constant terms of all other time periods (*t=2*, *3*, *4*, *5*, *6*). This assumption is made because the stress carried over from the time period $t = 0$ (baseline) to $t = 1$ ($\beta_{lag} * SS_{n,0}$) is not affected by the road events and the n-back task; however, the stress carried over from $t = 1$ to $t = 2$ (and also from $t = 2$ to $t = 3$; from $t = 3$ to $t = 4$; from $t = 4$ to $t = 5$; and from $t = 5$ to $t = 6$) is affected by the road events and/or the n-back levels. Since there is no state dependence in the dynamic model with serial correlation (i.e., no stress is carried over from one state to the following), the structural equations of the state stress at time periods $t = 1,2, \dots ,6$ were assumed to have the same constant. The random disturbances are independently and identically normally distributed given by equations (27.a-27.f).

Measurement Equations of State Stress

As in the first model, the maximum speed, the maximum accelerator pedal depression, the reaction time, and the maximum heart rate are used as indicators of the state stress. The measurement equation associated with each indicator is given by equation (28) and the measurement error term specific for each indicator ($\omega_{r,n,t}$) is independently and identically normally distributed (equation 29) with standard deviation σ_{ω_r} to be estimated.

Choice Model

As in the first model, the utility equations for individual n to violate the red light at the first intersection and the second intersection are given respectively by equations (30.a) and (30.b), while the utility equation to not violate the red light is given by equation (31).

Likelihood Function

The resulting joint probability of choices (violations or non-violations at the two intersections) and the measures of driving performance and physiology (maximum speed, maximum accelerator pedal depression, reaction time, and maximum heart rate) for individual n is given by equation (45).

$$K_n(y_n, O_n|S_n)$$

$$=$$

$$\int_{SS_6=-\infty}^{+\infty} P\left(y_{n,6}\middle|SS_{n,6}\right) * \; g\left(O_{n,6}\middle|SS_{n,6}\right)$$

$$* \int_{SS_5=-\infty}^{+\infty} P\left(y_{n,5}\middle|SS_{n,5}\right) * \; g\left(O_{n,5}\middle|SS_{n,5}\right) * \; f\left(SS_{n,6}\middle|S_{n,6}, SS_{n,5}\right)$$

$$* \int_{SS_4=-\infty}^{+\infty} P\left(y_{n,4}\middle|SS_{n,4}\right) * \; g\left(O_{n,4}\middle|SS_{n,4}\right) * \; f\left(SS_{n,5}\middle|S_{n,5}, SS_{n,4}\right)$$

$$* \int_{SS_3=-\infty}^{+\infty} P\left(y_{n,3}\middle|SS_{n,3}\right) * \; g\left(O_{n,3}\middle|SS_{n,3}\right) * \; f\left(SS_{n,4}\middle|S_{n,4}, SS_{n,3}\right) \tag{45}$$

$$* \int_{SS_2=-\infty}^{+\infty} P\left(y_{n,2}\middle|SS_{n,2}\right) * \; g\left(O_{n,2}\middle|SS_{n,2}\right) * \; f\left(SS_{n,3}\middle|S_{n,3}, SS_{n,2}\right)$$

$$* \int_{SS_1=-\infty}^{+\infty} P\left(y_{n,1}\middle|SS_{n,1}\right) * \; g\left(O_{n,1}\middle|SS_{n,1}\right) * \; f\left(SS_{n,2}\middle|S_{n,2}, SS_{n,1}\right)$$

$$* \int_{SS_0=-\infty}^{+\infty} g\left(O_{n,0}\middle|SS_{n,0}\right) * \; f\left(SS_{n,1}\middle|S_{n,1}, SS_{n,0}\right)$$

$$* \, dSS_0.\, dSS_1.\, dSS_2.\, dSS_3.\, dSS_4.\, dSS_5.\, dSS_6$$

As in the first model, the choice probability density functions are given by equations (33.a) and (33.b), and the joint conditional density function of the indicators is given by equation (34). The density function of $SS_{n,t}$ is presented by equation (46).

t=1,2,…,6 $\quad f\left(SS_{n,t}\middle|S_{n,t}, SS_{n,t-1}\right)$

$$= \frac{1}{\sigma_\epsilon} \emptyset \left[\frac{SS_{n,t} - \; Cte_{SS_t} - \beta_S \, S_{n,t} - \; \beta_{lag} \, SS_{n,t-1}}{\sigma_\epsilon}\right] \tag{46}$$

Equations (37) and (38) are used to derive the log-likelihood for the entire sample.

5.2.4.2 Model Estimation

As in the first model, two parameters were fixed: $\alpha_{SS,4}$ is fixed to 0, and $\lambda_{SS,4}$ is fixed to 1. Restrictions 2, 3, and 4 of the first model were also assumed. Results of this model are presented in Table 12.

Table 12: Estimation results of the dynamic HCM with state dependence

State Stress – Structural Equations				
Variable/Parameter	**Parameter Estimate**	**Robust Standard Error**	**Robust t-test**	**p-value**
Constant (*t=0*)	2.22	0.0136	162.60	0.00
Constant (*t=1*)	-0.0333	0.0466	-0.72	0.47
Constant (*t=2, … ,6*)	-0.0198	0.0428	-0.46	0.64
Ped	0.0215	0.0124	1.73	0.08
TL	0.0395	0.0140	2.82	0.00
Zero	-0.0246	0.0153	-1.61	0.11
One	0.00786	0.0114	0.69	0.49
Two	0.0360	0.0124	2.91	0.00
Previous Stress	0.995	0.0202	49.20	0.00
State Stress – Measurement Equations				
Variable/Parameter	**Parameter Estimate**	**Robust Standard Error**	**Robust t-test**	**p-value**
$\alpha_{SS,1}$ (Constant – Max. Speed)	1.70	0.177	9.57	0.00
$\alpha_{SS,2}$ (Constant – Max. Acc. Pedal depression)	2.88	0.655	2.88	0.00
$\alpha_{SS,3}$ (Constant – Reaction Time)	-0.0204	0.837	-0.02	0.90
$\alpha_{SS,4}$ (Constant – Max. Heart Rate)	0.00	-	-	-
$\lambda_{SS,1}$ (Factor loading – Max. Speed)	-0.0464	0.0811	-0.57	0.57
$\lambda_{SS,2}$ (Factor loading – Max. Acc. Pedal Depression)	-0.732	0.305	-2.40	0.02
$\lambda_{SS,3}$ (Factor loading – Reaction Time)	0.555	0.379	1.47	0.14
$\lambda_{SS,4}$ (Factor loading – Max. Heart Rate)	1.00	-	-	-
Choice Model				
Variable/Parameter	**Parameter Estimate**	**Robust Standard Error**	**Robust t-test**	**p-value**
ASC_1 (Violate Constant at *t=1, 2, 3*)	9.28	5.53	1.68	0.09
ASC_2 (Violate Constant at *t=4, 5, 6*)	7.59	5.55	1.37	0.17
State Stress	-5.08	2.58	-1.97	0.05

Table 12 (cont.): Estimation results of the dynamic HCM with state dependence

Standard Deviations of Error Terms				
Variable/Parameter	**Parameter Estimate**	**Robust Standard Error**	**Robust t-test**	**p-value**
σ_{ϵ_0} (SS – Structural) at $t=0$	0.143	0.0128	-11.20	0.00
σ_{ϵ} (SS – Structural)	0.0421	0.00557	7.55	0.00
σ_{ω_1} (S.D. Max. Speed)	0.134	0.00700	19.14	0.00
σ_{ω_2} (S.D. Max. Acc. Pedal Depression)	0.564	0.0681	8.28	0.00
σ_{ω_3} (S.D. Reaction Time)	1.07	0.125	8.51	0.00
σ_{ω_4} (S.D. Max. Heart Rate)	0.0675	0.00546	12.38	0.00
Model Statistics				
Final Log-Likelihood	-3491.255			
Final Gradient Norm	+5.056e-04			

Analysis of Results

The coefficient of the $Previous\ Stress$ variable (β_{lag}) is positive and statistically significant at the 95% level of confidence, implying that the state stress experienced at a time period $t-1$ and the state stress at the following time period t vary in the same direction. More specifically, the state stress from the previous time period $t-1$ carries over the following time period t but in a slightly damping manner (coefficient slightly smaller than 1).

As in the first model, results show that the Ped and TL events generate more stress than the Truck event (Ped is statistically significant at the 90% level of confidence, TL is statistically significant at the 95% level of confidence). Also, the difference between the effects of Ped and TL on the state stress is statistically insignificant at the 95% level of confidence (t-statistic = 0.118). Unlike the first model, the coefficients of $Zero$ and One are not statistically significantly different from the

$Control$ at the 95% level of confidence. Comparing to the $Control$, only the 2-back level contributes to a higher level of stress (Two is statistically significant at the 95% level of confidence).

The main difference in the structural equations of the state stress between the two models is in the estimated constants, particularly in the constants at time periods $t = 1,2, \ldots ,6$; the estimated constant at time $t = 0$ does not differ between the two approaches (it is estimated to be 2.23 in the dynamic model with serial correlation, and 2.22 in the dynamic model with state dependence). In the dynamic model with serial correlation the constant at time periods $t = 1,2, \ldots ,6$ is estimated to be 2.14 and is statistically significant at the 95% level of confidence, while the estimated constants at time $t = 1$ (equal to -0.0333) and $t = 2, 3, \ldots ,6$ (equal to -0.0198) are not statistically significant at the 95% level of confidence. The amount of stress that was captured by the constant at $t = 1,2, \ldots ,6$ in the dynamic model with serial correlation is rather explained in the dynamic model with state dependence by the stress accumulated or carried over from the previous state (as $\beta_{lag} * SS_{n,t-1}$) at the time periods $t = 1,2, \ldots ,6$.

Conclusions derived from the measurement equations of the state stress and the choice model for the dynamic model with state dependence are similar to that of the first model with serial correlation.

Model Application

The dynamic model with state dependence is used to predict the probability of violation at each time period. Table 13 shows the predicted average probability of violation versus the observed proportion of violation at the traffic light event. Similarly to the dynamic model with serial correlation, higher probabilities of violations are predicted for the first phase ($t = 1, 2, 3$) than those predicted for the second phase ($t = 4, 5, 6$).

Table 13: Observed versus predicted violations using the dynamic HCM with state dependence

Event Number (Time Period)	Number of Choice Situations	Observed Number of Violations	Observed Proportion of Violations	Predicted Probability of Violations
1	24	3	0.125	0.112
2	25	2	0.080	0.159
3	25	6	0.240	0.164
4	26	1	0.038	0.028
5	13	1	0.077	0.042
6	35	1	0.029	0.046

This model is also used to predict the driving performance and heart rate measures at each time period. The formulation presented earlier in the dynamic model with serial correlation applies for the dynamic model with state dependence (equations 39-40) with slight variations in the equations used to calculate the variance of the state stress (41.a-41.b). For the dynamic model with state dependence, the variance of the state stress is calculated using equations (47.a) and (47.b) below.

t=0 $$var(SS_t) = \sigma^2_{\epsilon_0} \tag{47.a}$$

t=1,2,… ,6 $$var(SS_t) = \beta^2_{Ped} * var(Ped_t) + \beta^2_{TL} * var(TL_t) + \beta^2_{Zero} * var(Zero_t) + \beta^2_{One} * var(One_t) + \beta^2_{Two} * var(Two_t) + \sigma^2_{\epsilon_t} \tag{47.b}$$

Figure 29 illustrates the average state stress of all individuals at each time period.

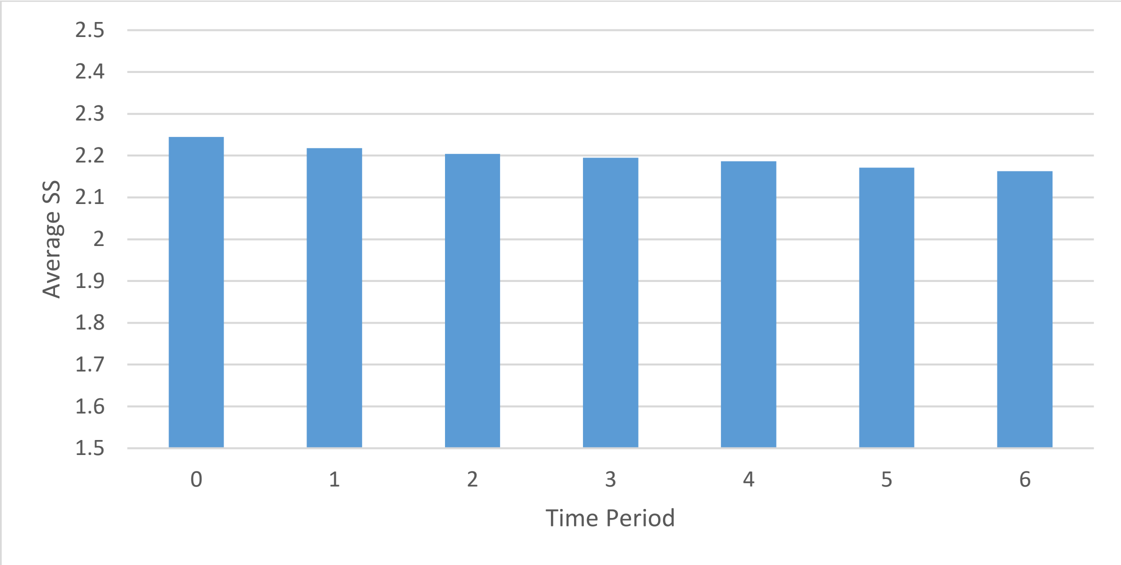

Figure 29: Predicted average state stress at each time period using the dynamic HCM with state dependence

The decreased pattern observed in the state stress over time is attributed to the fact that the coefficient of the Previous Stress (β_{lag}) is less than 1, which implies that the state stress from the previous time period $t-1$ carries over the following time period t but in a damping manner. Since this coefficient (0.995) is not statistically significantly different from 1 ($|t\ statistic| = 0.247 < 1.96$), the decreased pattern of the state stress over time is modest.

Figures (30-33) illustrate the average values of the predicted versus the average observed values of each indicator at each time period using the dynamic model with state dependence.

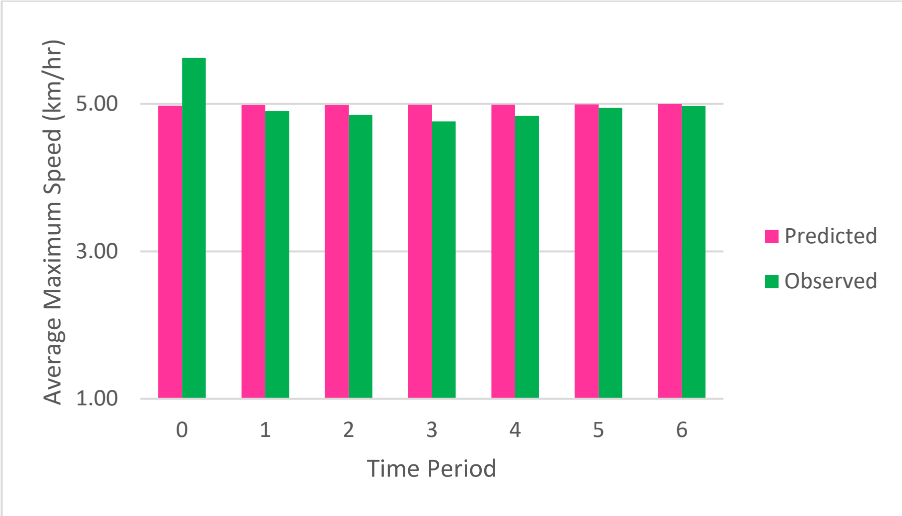

Figure 30: Average observed versus average predicted scaled values of the maximum speed at each time period (scale factor =0.1) using the dynamic HCM with state dependence

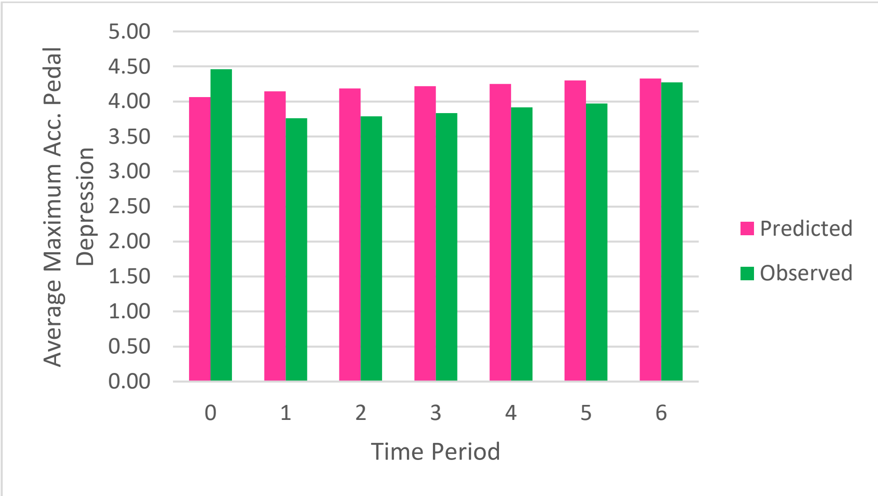

Figure 31: Average observed versus average predicted values of the maximum accelerator pedal depression at each time period (scale factor =10) using the dynamic HCM with state dependence

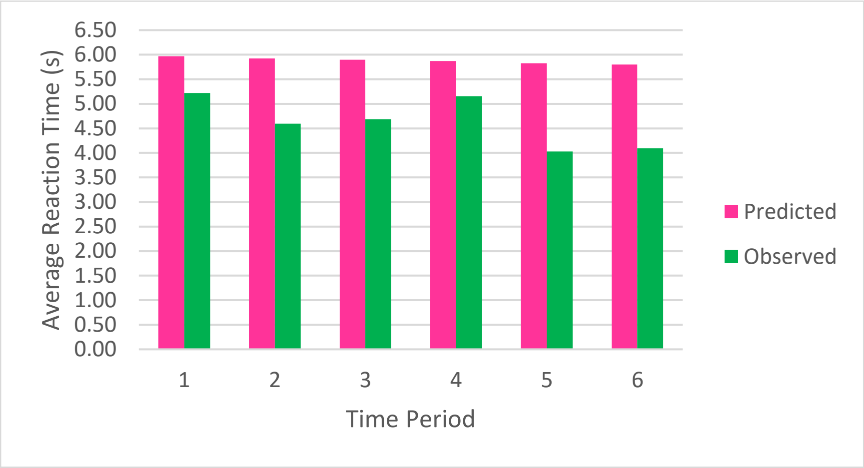

Figure 32: Average observed versus average predicted values of the reaction time at each time period using the dynamic HCM with state dependence

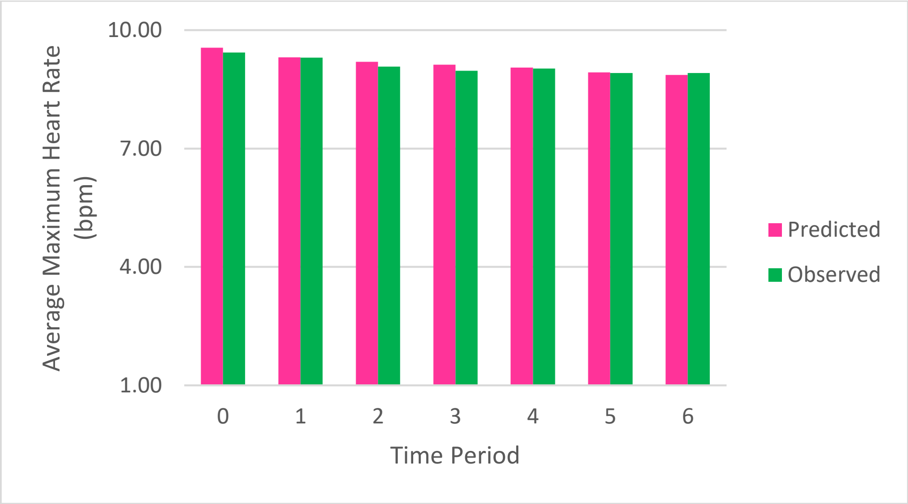

Figure 33: Average observed versus average predicted scaled values of the maximum heart rate at each time period (scale factor =0.1) using the dynamic HCM with state dependence

Table 14 shows the percentage differences between the average observed values and the average predicted values of the indicators of state stress by the dynamic model with state dependence using equation (42).

Table 14: Percentage differences between average observed values and average predicted values of the indicators of state stress by the dynamic model with state dependence

Time Period	**0**	**1**	**2**	**3**	**4**	**5**	**6**
Maximum Speed	11.5	1.6	2.8	4.8	3.2	1.0	0.5
Maximum Acc. Pedal Depression	9.0	10.2	10.5	10.1	8.5	8.2	1.3
Reaction Time	NA(*)	14.4	28.9	25.8	13.9	44.4	41.6
Maximum Heart Rate	1.3	0.1	1.4	1.7	0.3	0.1	0.5

(*) The reaction time is not used as indicator of state stress at time period $t = 0$ since the baseline does not include road events.

Trends of predictions by this model are relatively similar for the maximum speed, maximum accelerator pedal depression, and reaction time to those obtained by the first model with serial correlation. The dynamic model with state dependence gives better predictions of maximum heart rate than the dynamic model with serial correlation. It should be noted that accounting for individual differences among subjects such as gender and driving experience did not improve the patterns of predictions for both models.

5.3. Conclusion

In this chapter, we represented dynamically the driving behavior in a hybrid choice model whereby the driver stress is introduced as a latent variable affected by the scenario variables (i.e., road events and levels of the n-back task), and manifested in the driving behavior (e.g., speed, reaction time) and the heart rate. Two approaches were used to model the evolution of the state stress over time. In the first approach, dynamics were captured through serial correlation expressed by an agent effect representing the individual trait. The latter is found to significantly affect the state stress at each time period considered in the experiment. In the second approach, dynamics were captured through state dependence using Hidden Markov Chains. The state stress at a specific time period was found to significantly affect the state stress at the following time period. Both models reflected the regulatory behavior adopted by the driver in response to an increase in cognitive workload/stress. The dynamic model with state dependence performed better than the dynamic model with serial correlation in terms of predictions, particularly for the maximum heart rate and the maximum accelerator pedal depression (for $t = 1, 2, \ldots, 6$). Table 15 compares the goodness-of-fit of the two developed models based on the Akaike Information Criterion (AIC) that accounts for model complexity by penalizing the models for additional estimated parameters as shown in equation (48):

$$AIC = -2L(\beta^*) + 2K \tag{48}$$

where $L(\beta^*)$ is the final log-likelihood and K is the number of the estimated parameters.

Table 15: Comparison between the two dynamic models

Statistic	Serial Correlation	State Dependence
Number of parameters K	23	24
Final log-likelihood $L(\beta^*)$	-3463.637	-3491.255
Akaike Information Criterion AIC	6973.274	7030.509

Based on this comparison, the dynamic model with serial correlation has a better goodness-of-fit than the dynamic model with state dependence (lower AIC). It should be noted that ideally the two models would be combined (i.e. state dependence with an agent effect). Such model was tested, and the estimated coefficient of the Previous Stress was not statistically significant (p-value = 0.71). However, this combined model may suffer from endogeneity if the agent effect also influences the initial state stress, which would need to be corrected using the Wooldridge approach (Ben-Akiva, 2013; Wooldridge, 2003).

CHAPTER 6

CONCLUSION

This chapter concludes the thesis. It is organized as follows. The first section summarizes the findings of the research. The second section suggests a potential application of the models developed in Chapter 5. The third section highlights the contributions of the thesis. The fourth section states the research limitations. Finally, the fifth section presents recommendations for future research.

6.1. Summary of Findings

This study aimed at quantifying the effects of an increase in the driver cognitive workload on driving performance and physiological measures in a city driving environment based on a driving simulation experiment with physiological sensors. A secondary cognitive task (n-back) that systematically increases the driver cognitive workload was used to simulate auditory-vocal distraction. Cognitive workload was additionally induced by contextual variations manifested by the occurrence of three road events frequently encountered in an urban context such as sudden crossing of pedestrians, sudden truck stop, and traffic light. The driving simulation experiment involved three phases: a baseline, a control phase whereby the subject encountered the three road events without being assigned the n-back task, and a treatment phase whereby the subject encountered the three road events while also being required to perform one level of the n-back task at each encountered road situation. Driving performance measures such as speed, lane position, pedal depression, brake, and reaction time were extracted/calculated from the driving simulator output. Physiological measures such as heart rate and skin conductance level were monitored throughout the experiment using EKG and skin conductance sensors. All these measures were analyzed at each road situation. The driver state stress as an outcome of the driver distraction was also modeled.

In Chapter 4, we performed a static analysis at each road situation separately, and we aimed to answer the below questions:

1. *How does the secondary task affect driving performance and physiological measures?*
2. *To what extent may there be self-regulation in driving to allow the performance of the secondary task?*
3. *Do the levels of the secondary task have different effects on driving performance and physiological measures?*
4. *Do the drivers ignore the secondary task when its level of difficulty increases?*

In order to answer the first two questions, we used Wilcoxon Signed-Ranks test to compare driving performance and physiological measures of each subject at the control phase and at the treatment phase (paired comparison). Results showed that the average and maximum speed, the maximum pedal depression, the maximum brake, the standard deviation of the lane position, the standard deviation of brake, and the standard deviation of the pedal depression statistically significantly decrease at the treatment phase. These variations indicate that the driver adopts a regulatory behavior at the operational level in order to perform the n-back task and drive simultaneously, as if he/she compensates the unsafe behavior of being engaged in distracting tasks by giving additional control over the driving task. Putting this in perspective, these findings would raise the question whether being engaged in secondary tasks while driving, particularly auditory-vocal tasks, leads to improving or deteriorating the driving behavior. We highlight first that, though differences in the driving behavior between the control and treatment phases were statistically significant, their impact is modest, that is, the difference between the medians of one driving performance measure at the treatment phase and the control phase is minor (e.g., the median of the maximum speed at the control phase of the pedestrians event is 51.39 km/hr, while the median of the maximum speed at the treatment phase of the same event is 50.55 km/hr). Second, evidence from the literature characterizes regulatory behavior as a risky or unsafe behavior since resources available to keep control of the driving task will be exhausted over time while performing a secondary task simultaneously. Moreover, the literature mentions that drivers with compensatory beliefs (i.e., they believe that they are capable of compensating an unsafe behavior such as being distracted while driving by a regulatory behavior such as reducing the speed) are more likely to be involved in road accidents. Third, we showed that the effect of the regulatory behavior on driving safety is limited as evidenced by the longer time taken to implement a reaction in response to a sudden road event encountered for the first time at the treatment phase compared to the control phase. Therefore, self-regulatory behavior, in response to competing activities, should be cautiously perceived when addressing driving safety. In terms of the physiological measures, the impact of the n-back task was substantive. Heart rate and skin conductance level (average, minimum, and maximum) statistically significantly increased at the treatment phase with the additional workload of the secondary task.

In order to answer the third question, we used Kruskal-Wallis H test to compare driving performance and physiological measures between subjects across the levels of the n-back task. Results of this analysis did not show strong evidence of variations with respect to the driving performance and physiological measures across the three levels. This might be justified by the fact that the analysis was conducted on a short period of time (at the road event particularly) that did not capture significant differences in the driver behavior and physiology between subjects across the levels of the n-back task. This could further imply that the effects of a distracting task on driving performance and physiological measures particularly when assessed at critical road situations (such as those studied in this thesis) do not depend on its level of difficulty, i.e., whether it is judged as an easy or difficult task.

In order to answer the fourth question, we used Mann-Whitney U-Test to compare driving performance measures at the three road situations between the subjects who perfectly performed the n-back task and those who at least had one error in the performance of the n-back task. Results showed that there are no statistically significant differences between the compared groups of subjects in terms of driving performance measures. If we consider the similarities between the n-back task and real distracting activities such as conversing with passengers, the findings imply that some subjects might ignore or pay less attention to conversations in order to maintain control of the driving task, while others might succeed in regulating their driving behavior and being engaged with deep conversations at the same time.

In Chapter 5, we performed a dynamic analysis. The driver behavior was modeled in a dynamic hybrid choice model whereby the driver state stress was introduced as a latent variable that evolves over time. Seven time periods of the driving course (baseline and six road events) were considered. Maximum speed, maximum accelerator pedal depression, reaction time, and maximum heart rate were used as indicators of the state stress. The traffic light event was associated with the choice of whether to violate red light or not and the utility of the choice was expressed as a function of the state stress. Scenario variables (road events and levels of the n-back task) were used as predictors of the state stress. We aimed to answer two main questions:

1- *Do the individual traits affect the actual state stress of the driver?*
2- *Does stress carry over from one time period to another while driving?*

In order to answer the first question, we modeled dynamics by including serial correlation expressed by a time-invariant agent effect that influences the state stress across the seven time periods. The model results showed that the individual trait (agent effect) significantly affects the state stress at each time period. This model represents the mathematical conceptualization of the transactional approach of the driver stress (Lazarus, 1999; Matthews, 2002). In order to answer the second question, we captured dynamics through state dependence whereby the state stress at one time period is assumed to be affected by the state stress experienced at the previous time period. Results of this model showed that the state stress at a specific time period is significantly affected by the stress experienced at the previous time period. Results derived from both models (serial correlation and state dependence) reflected the regulatory behavior of the driver: as the driver state stress increases, the maximum speed and the maximum accelerator pedal depression decrease, while the reaction time increases. A higher state stress was also found to decrease the probability of violating the red light at the intersection indicating that the high stress level served to alert the driver. The two models were used to predict driving performance and heart rate.

6.2. Potential Technology Application

This section presents a potential technology application of the model developed in this thesis for enhancing road safety. As introduced in the first chapter of this thesis, detecting the driver state in real time can be integrated within in-vehicle systems to help the driver improve his/her driving performance. The developed dynamic model can be used for this purpose. Inputs for this model include driver-related conditions that might be provided by physiological sensors (e.g., by monitoring heart rate) that allow classifying the workload/distraction level, in addition to contextual-related conditions that might be provided by communication technologies of connected vehicles such as Vehicle to Infrastructures or V2I (providing information about traffic lights for example), Vehicle to Pedestrians or V2P (providing information about pedestrians, bicyclists, etc.), and Vehicle to Vehicle or V2V (providing information about surrounding vehicles). Accordingly, updated dynamic information on the driver state helps in-vehicle systems perform in the appropriate direction, i.e., to reduce stress or increase alertness. For instance, if the driver is found inattentive to the roadway situations, the integrated system could alert the driver to retrieve his or her attention/focus on the primary driving task. If the driver is found overloaded and stressed, the integrated system could reduce the stress level by recommending relaxing conditions (music, lightening) or reduce the cognitive workload temporarily by taking control of the driving task (the car switches to the autonomous mode for example). Therefore, such system enhances the driver safety and well-being.

Furthermore, the developed model can help increase the predictability of crash occurrence by integrating the state detection in the design of accident avoidance safety systems (introduced in Chapter 1 of this thesis). Given the state-integrated framework of VCAS presented in Figure 7 (b), the developed dynamic model could also be implemented in the design of safety systems based on the accident avoidance technology to increase the predictability of crash involvement.

Our model utilizes the n-back task levels (0-back, 1-back, and 2-back) as predictors of the driver state stress (included in the structural equation of the state stress). These levels could be generalized to classify the workload induced by any distracting activity that the driver could be engaged with while driving such as low, medium, and high. Classification of workload/distraction could be done using machine learning techniques and algorithms (see as examples of workload classification Solovey et al. (2014); Streiffer et al. (2017)) based on inputs provided by sensing devices located in the vehicle (e.g., speed, heart rate). For the purpose of an adequate/practical real-time physiological monitoring in the driving context, Ford Motor Company developed a prototype of physiological sensors embedded within the vehicle (Figure 34) (Ridella et al., 2015). The MIT Media Lab also demonstrated that physiological measures such as heart rate and respiration rate can be remotely monitored using a camera installed on the steering wheel (Figure 35). They introduced potential stress indicators embedded in the car (Figure 36) and suggested several interactions to help manage the stress such as adaptive music, calming temperature, empathetic GPS, and corrective headlights (Hernandez et al., 2014).

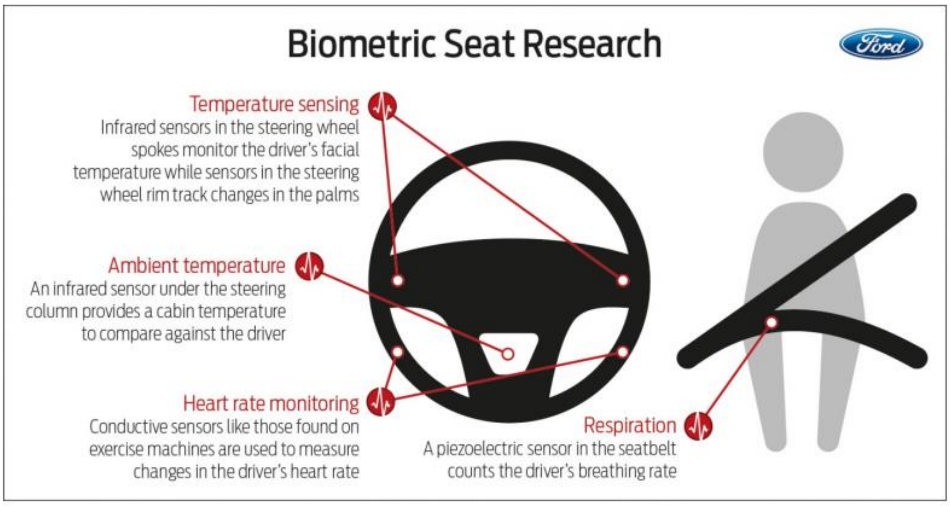

Figure 34: Prototype sensors installed within the vehicle components (Ridella et al., 2015)

Figure 35: Camera installed on the steering wheel to measure heart rate (Hernandez et al., 2014)

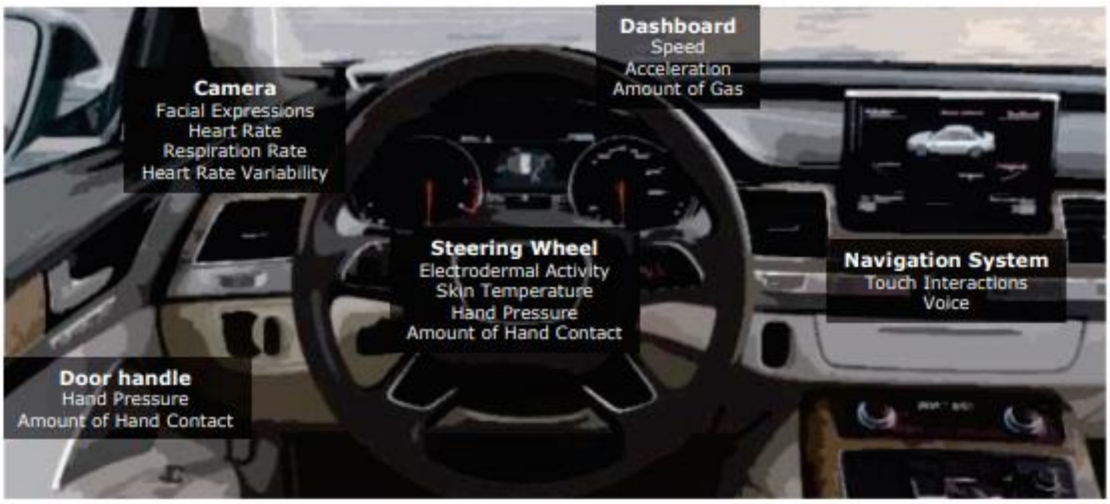

Figure 36: Potential on-board stress indicators (Hernandez et al., 2014)

In this context, the model developed in this thesis could be integrated in the design of safety systems and play an important role in terms of state stress detection. Moreover, the implementation of physiological indices as objective assessment of the driver cognitive workload in the development of new safety technologies can be used to evaluate and rate the effectiveness of available/new safety systems (Mehler et al., 2014).

6.3. Contributions

The findings of this study contribute to a better understanding of the impacts of auditory-vocal distraction at frequently encountered road situations in urban settings with implications for road safety. Physiological measures, such as heart rate and skin conductance level, can be used as objective tools to dynamically monitor the evolution of the driver's cognitive workload in real time when engaged with auditory-vocal tasks.

The theoretical contribution of this study consists of modeling the driver stress in a dynamic hybrid choice model. The transactional model of driver stress that has been widely used in the literature to account for both situational and individual factors has been implemented in this thesis in a mathematical model that treats the state stress as a latent variable manifested by variations in the driver behavior and heart rate.

6.4. Research Limitations

This study has several limitations. First, it is based on a driving simulation experiment that might not necessarily replicate real driving conditions. The subjects might be involved in a more risky behavior in the virtual environment of the experiment than they actually do in real life. The n-back task would also be perceived more dangerous if it was assigned to subjects in real driving situations and scenario variables would have a more substantial impact if they were considered under real driving conditions. The simulator used nonetheless is a mid-level simulator with relative validity, so results are expected to hold on a relative basis. Second, road directions presented to the subjects in the driving simulation experiment by means of billboards might have caused a visual distraction and therefore interfered with the cognitive workload tested in this experiment. Third, the findings are specific only to the population of young students and might not be generalized to all demographic segments. Fourth, subjects were volunteering to participate in this experiment and they might have a different driving behavior from those who did not participate; therefore, the sample could be biased by self-selection.

6.5. Recommendations for Future Research

Future research may improve the design of the scenario variables adopted in this thesis such as including car following, heavy traffic, honking, other types of secondary tasks, etc. The effect of scenario variables may also be analyzed in longer time periods (not just at the event itself) in order to determine if stress carries over or dissipates after the occurrence of the event. Workload monitoring may include additional measures such as eye tracking (that could detect visual distraction and account for the issue of its interference with the cognitive workload), respiration rate, and electroencephalogram or EEG (that measures the brain activity). Also, data collection may be extended to increase the sample size and include other segments from the general population (not only students). As for the model, future extensions of this work should further investigate how the model developed in this thesis may relate to algorithms for driver state detection that are incorporated into certain types of in-vehicle systems in the auto manufacturing sector. The patterns of overprediction and underprediction of the behavioral models developed in this thesis should be further explored. Finally, the model estimation in this thesis was done using the data of all subjects that participated in the experiment. We recommend that in future extensions of this work, the model should be estimated on a training sample (say 80%), with a hold-out sample (e.g. 20%) left for model validation.

APPENDIX A: EKG WAVE EDITING[10]

This appendix presents an overview of the EKG editing process. This documentation is based on the user manual provided by NeuroDyne Medical, Corp. (NeuroDyne Medical, 2009). NeuGraph software (version 4.6) is used to collect data (sampling rate = 250 Hz) and display physiological signals in real-time. MEDAC System/3 instrumentation is configured as MEDAC Custom (61) - Board USB-1608FS. EKG Wave Editor 1.8 is used for editing[11].

EKG Signal

An EKG signal (ideal) is shown in Figure 37. It consists of five waves: P, Q, R, S, and T. The R-wave (also known as R-spike) can be approximated to an actual heart beat.

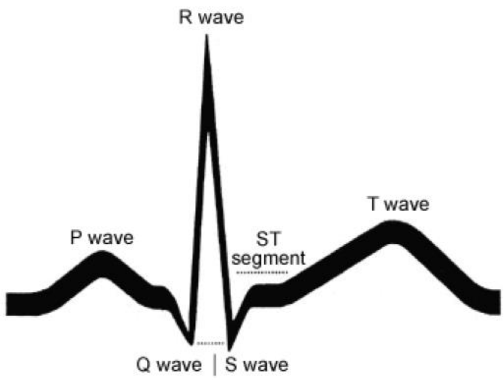

Figure 37: An idealized example of EKG signal

An example of EKG signal as displayed by the EKG Wave Editor is presented in Figure 38. This signal is provided by the EKG of MEDAC System/3 instrumentation.

---

[10] This process is adopted by the MIT AgeLab in several research projects such as Mehler et al. (2009, 2012) and Reimer and Mehler (2011).

[11] The editing algorithm of EKG Wave Editor was implemented and tested in LabView. Results output by both programs were the same.

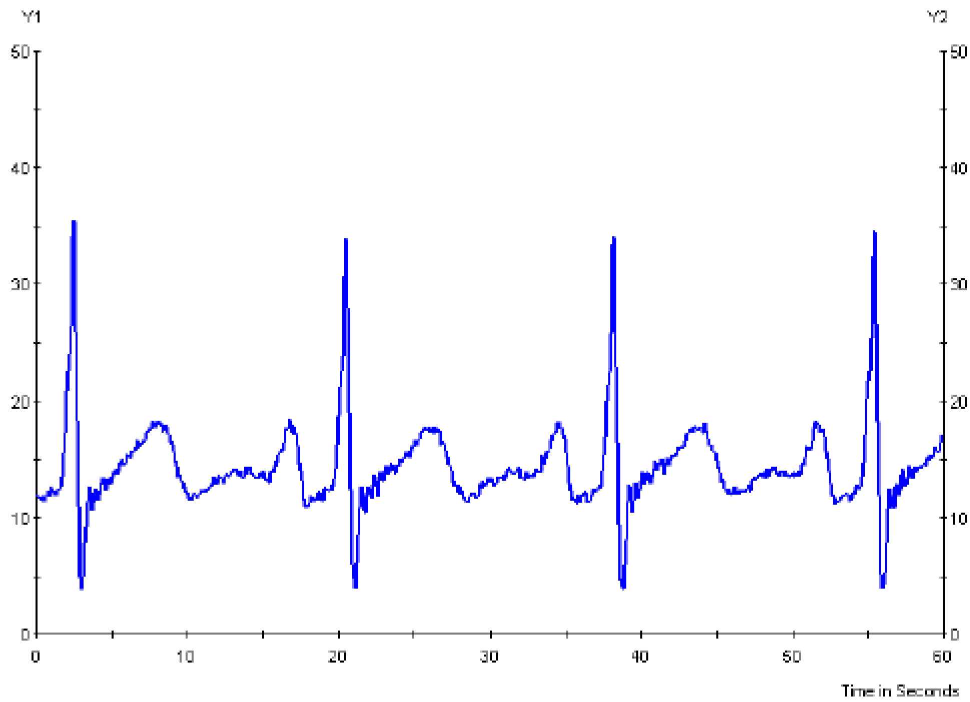

Figure 38: MEDAC System/3 EKG signal

Editing Concept

EKG Wave Editor automatically detects R-waves and calculates the time interval between peaks or the period between heart beats, known as inter-beat interval (IBI). Heart rate values can be derived from the IBI value using equation (49).

$$HR = \frac{1}{IBI} * 60 \tag{49}$$

where HR is the heart rate (in beats/min), and IBI is the inter-beat interval (in seconds).

Based on a predefined threshold (can be adjusted by the user), the automatic detection routine of the EKG Wave Editor detects R peaks and places a marker on each R-spike (Figure 39).

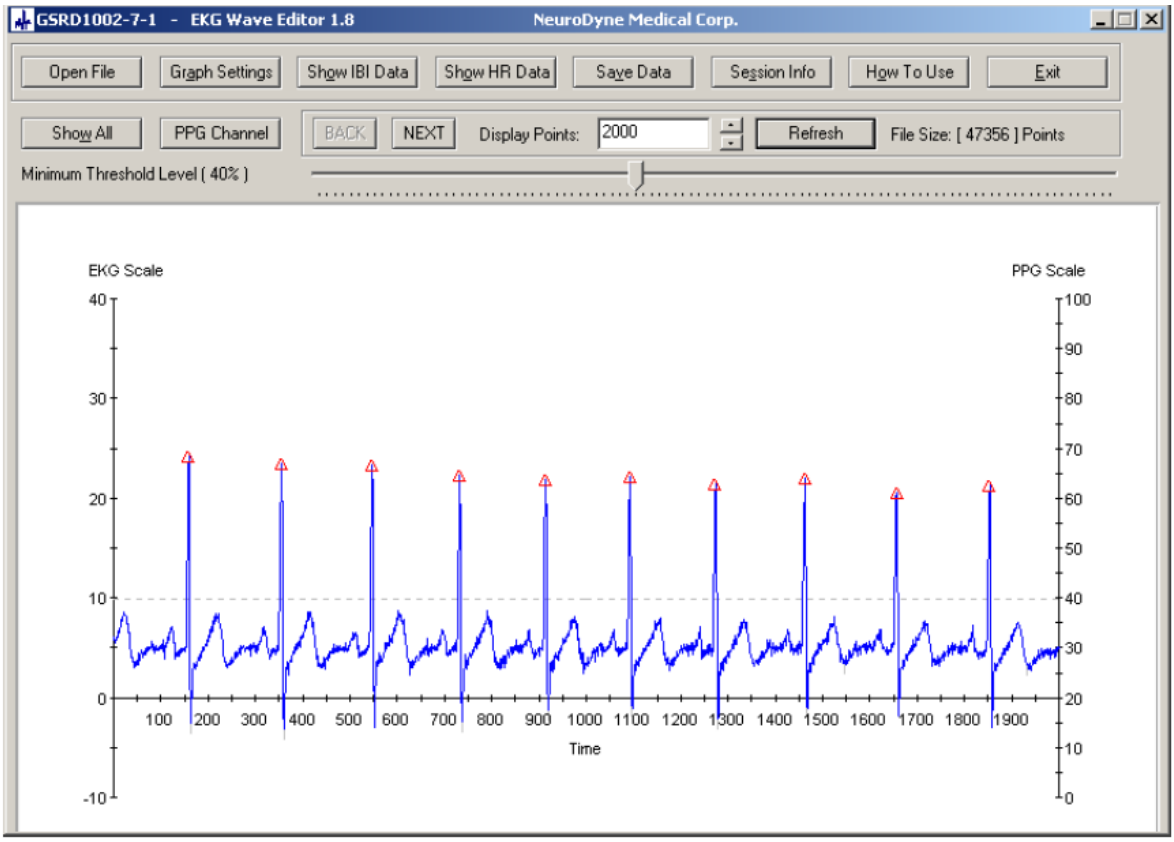

Figure 39: An example of a processed EKG data signal: R-spikes are detected by the automatic routine detection of EKG Wave Editor

However, R-spikes might be inaccurately identified by the automatic detection routine (e.g., the automated routine misses an R-spike or marks a P-wave or a T-wave instead of an R-wave) because of movement artifacts (e.g., movements of the driver). The EKG Wave Editor processes a raw data file[12] provided by NeuGraph (i.e., runs the automatic detection routine to identify R-spikes) and displays the processed EKG signal where R-spikes are automatically marked. As such, the EKG Wave Editor allows the user to visually examine the processed record of EKG and correct or clean potential inaccuracies/errors of the automatic detection routine. The correction or cleaning process is referred to as editing and it consists of adding or deleting R-peak markers.

[12] Raw data collected by NeuGraph software (source data file) are known as GSRD which stands for NeuGraph Standard Raw Data file. EKG Wave Editor opens GSRD files for processing and editing.

Examples of manual editing of peak points are illustrated in Figures 40 and 41. In Figure 40, the R-wave is below the defined threshold and it is therefore not detected by the automatic routine (this point needs to be added). In Figure 41, a T-wave is detected instead of an R-wave (this point needs to be deleted).

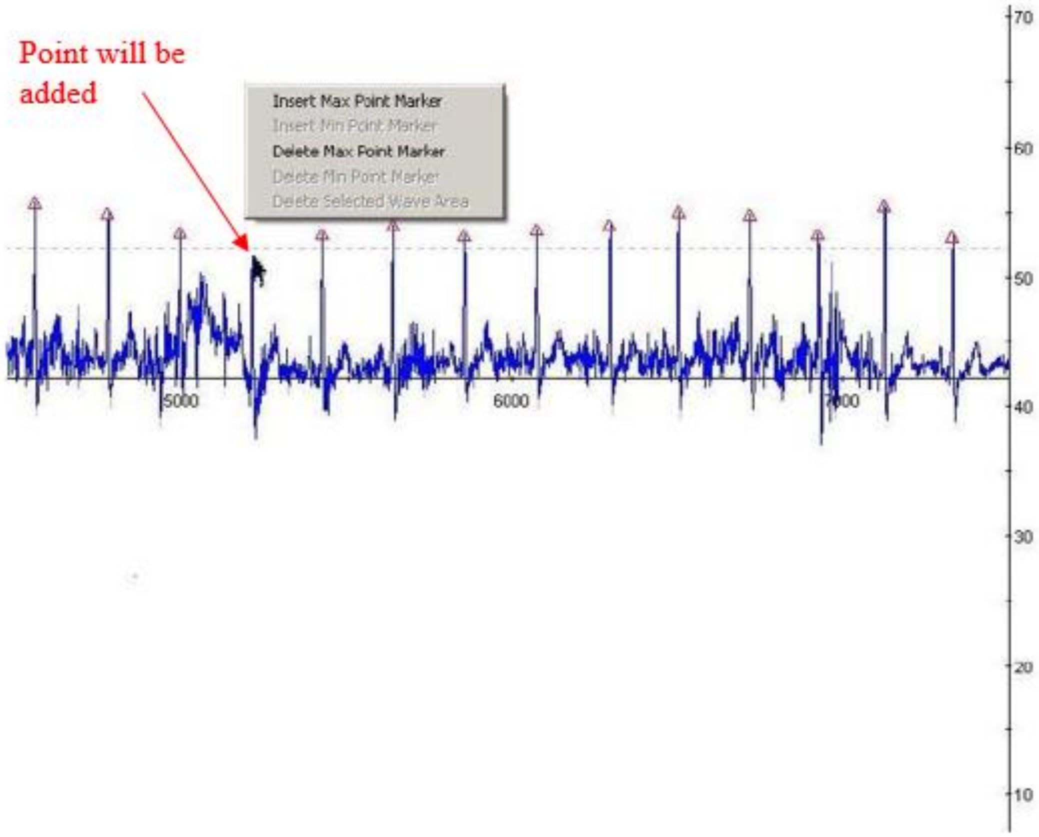

Figure 40: Adding an R-spike (peak) marker

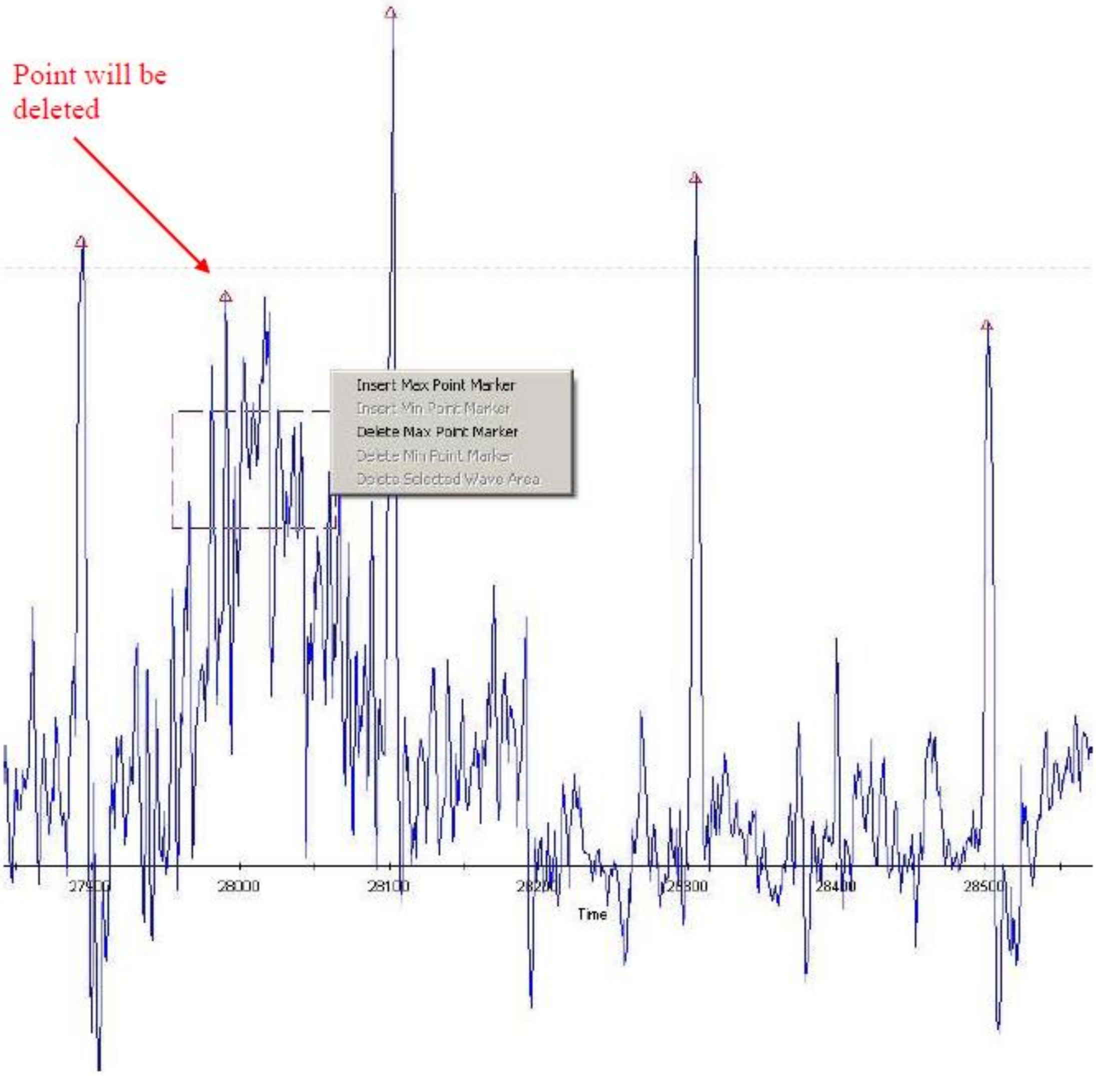

Figure 41: Deleting an R-spike (peak) marker

APPENDIX B: SCREENING INTERVIEW

Driving Behavior Study Using a Driving Simulator and Physiological Measurements

Screening Interview

Subject ID [Filled out by Research Associate]:

…………………………………………………

Interview Date [Filled out by Research Associate]:

……………………………………………

We will ask you now a few questions to make sure you are eligible to participate in this study.

1. **Do you have a driver's license?**
   - ☐ Yes
   - ☐ No

   [If "No", interviewer thanks the subject and tells him/her that he/she is not eligible to participate in the study; otherwise, interviewee is asked to kindly show his/her driver's license before proceeding to Question 2.]

2. **Have you ever participated in a driving simulation experiment?**
   - ☐ Yes
   - ☐ No

3. **Do you currently drive?**
   - ☐ Yes
   - ☐ No

   [If "Yes", interviewer proceeds to Question 3a; if "No", interviewer proceeds to Question 3b.]

   3a. For how long have you been driving?

   ……………………………………………………………………………

   3b. How long has it been since you stopped driving?

……………………………………………………………………………………

[If answer to Question 3b is 3 years or more, interviewer thanks the subject and tells him/her that he/she is not eligible to participate in the study; otherwise, interviewer proceeds to Question 4.]

4. What type of roads do you drive more often?

- ☐ Highway
- ☐ Urban (city driving)
- ☐ Rural

5. Where do you usually drive?

- ☐ Lebanon, Greater Beirut
- ☐ Lebanon, Outside Greater Beirut
- ☐ Outside Lebanon
  Please Specify:
  …………………………………

6. [Health related issues]

a. Are you on medications?

- ☐ Yes
- ☐ No

If "Yes", please specify: …………………………………

[If the specified medication is mentioned in the list of medications that are under exclusion, interviewer thanks the subject and tells him/her that he/she is not eligible to participate in the study; otherwise, interviewer proceeds to Question 6.b.]

b. Have you ever complained of dizziness?

- ☐ Yes
- ☐ No

c. Do you have any ear or eye problem?

- ☐ Yes
- ☐ No

d. Do you have any motion sickness?

- ☐ Yes
- ☐ No

e. **Have you had any recent sleep deprivations (i.e., sleeping for less than 6 hours a day, having sleep disorder causing a poor quality of sleep)?**
   - ☐ Yes
   - ☐ No

f. **Do you have any active medical problems such as heart problems, epilepsy, respiratory problems, etc.?**
   - ☐ Yes
   - ☐ No

g. **Do you have any active psychiatric problems such as anxiety, panic disorder, etc.?**
   - ☐ Yes
   - ☐ No

h. **Do you have a fear of being enclosed in a small space or room and having no escape?**
   - ☐ Yes
   - ☐ No

i. **Do you have Alzheimer's disease?**
   - ☐ Yes
   - ☐ No

j. **Do you have any mental health condition that would make you feel uncomfortable participating in this experiment?**
   - ☐ Yes
   - ☐ No

k. **Do you currently feel exhausted?**
   - ☐ Yes
   - ☐ No

l. **Have you had a main meal shortly before coming to the experiment?**
   - ☐ Yes
   - ☐ No

[If subject answers "Yes" to any of the questions from 6.b to 6.l, interviewer thanks the subject and tells him/her that he/she is not eligible to participate in the study; otherwise, interviewer proceeds to Question 7.]

7. [Interviewer notes respondent's gender.]

- ☐ Male
- ☐ Female

[If subject is female, interviewer proceeds to Question 8; otherwise, interviewer proceeds to Question 9].

8. Are you pregnant?

- ☐ Yes
- ☐ No

[If subject is pregnant, interviewer thanks the subject and tells her that she is not eligible to participate in the study]

9. What is your age?

………………………………………………

[If age is less than 18, interviewer thanks the subject and tells him/her that he/she is not eligible to participate in the study]

10. a. What is your occupational status?

- ☐ Student at AUB
- ☐ Employee at AUB
- ☐ Other
  Please specify: ....

b. If student, what are your faculty and major of study?

Faculty:

…………………………………………………………………………………………

Major of study:

…………………………………………………………………………………………

c. If student, what is your current educational status?

- ☐ Sophomore (first year)
- ☐ Junior (second year)
- ☐ Senior (third year or above)
- ☐ Graduate (Masters or Ph.D student)

d. If employee, what is your job type?

- ☐ Academic
- ☐ Management
- ☐ Non-academic, non-management

11. What is your nationality?

………………………………………………………………………………………
…………

APPENDIX C: CONSENT FORM

Consent Form/Information Sheet

Driving Behavior Study Using a Driving Simulator and Physiological Measurements

Subject ID [Filled out by Research Associate]: ………………………………

Investigator: Dr. Maya Abou-Zeid
Address: American University of Beirut
Department of Civil and Environmental Engineering
P.O.Box 11-0236 / FEA-CEE, Room 527
Riad El-Solh / Beirut 1107 2020, Lebanon
Phone: (01) 350 000 ext 3431
Email: ma202@aub.edu.lb

You are being asked to participate in a research study conducted at the American University of Beirut. Please take time to read the following information carefully before you decide whether you want to take part in this study or not. Feel free to ask the principal investigator if you need more information or clarification about what is stated in this form and the study as a whole.

The information procedure may take about 4-5 minutes.

Site where the study will be conducted

Transportation Lab, Irani-Oxy Engineering Building

Inclusion/Exclusion criteria

You are eligible to participate in this research study if you are an AUB student (aged above 18) or staff, have a driving license, and are currently driving.

You are not allowed to drive the simulator if you suffer from at least one of the following health-related issues:

- If you are on medications
- If you have ever complained of dizziness
- If you have an ear or eye problem
- If you have any motion sickness
- If you had any recent sleep deprivations
- If you have any active medical problems such as heart problems, epilepsy, respiratory problems, etc.
- If you have any active medical problems such as anxiety, panic disorder, etc.
- If you have a fear of being enclosed in a small space or room and having no escape
- If you have Alzheimer's disease
- If you have any mental health condition that would make you feel uncomfortable participating in this experiment
- If you currently feel exhausted

Purpose of the Research Study and Overview of Participation

This research study is conducted by faculty and students in the Department of Civil and Environmental Engineering at the American University of Beirut. The purpose of the study is to analyze the driving behavior under different scenarios in a driving simulator and using physiological measures (sensors will be attached to measure the heart rate and the skin conductance). The study may not benefit you directly, but the information we collect from you will help us better understand driving behavior and suggest ways to improve road safety. Your participation in this study is completely voluntary. There is no monetary reimbursement for participation in the study.

The duration of your participation in this study will be about 30-45 minutes. Approximately a total of 100 subjects will be recruited by means of flyers distributed on campus, mainly at the entrance of Jafet Library, and at AUB gates to students who enter or leave AUB, in addition to personal approaches and announcements.

The study consists of three phases. In the first phase, we will conduct a brief interview with you to see if you are eligible to participate. In the second phase, the research associate will explain the secondary cognitive task to be performed while driving as part of this study. You will also be trained on how to perform this task. Then, the research associate will show you on a map a route that you need to drive in the simulator. Afterwards, he/she will attach the physiological sensors (EKG, to measure the heart rate, and skin conductance sensors, to measure the skin conductance). Please note that no risk will be induced by the attachment of these sensors which are intended for research use. The research associate will show you how to use the driving simulator. You will test it in a training environment in order to get used to the simulator. The test will take about 5 minutes. After this training, you will be given a break of 2 minutes. Then you will start the actual driving experiment which will take about 12 minutes. You will be asked to drive the same route that the research associate showed. Also, you will hear auditory messages that ask you to accomplish the secondary task explained in the second phase. You should drive normally as you drive in real life, while accomplishing the secondary assigned task, without exceeding speed limits (shown in signs on the road), without hitting other cars and pedestrians, without hitting the sidewalk, without running red lights, etc. In the third phase, we will ask you to fill out a survey about your driving history, attitudes towards driving, some other information about you, and how you felt while driving the simulator.

Your participation in this study may be terminated by the principal investigator if you were not serious during the experiment procedure.

Overall findings from this study will be conveyed to you and to the public at large.

Potential Risks

Driving the simulator may cause dizziness in an estimated 10% of subjects. Participants are advised not to have eaten a main meal right before conducting the experiment. If you feel dizzy at any time or feel discomfort due to any unforeseeable reasons, please notify the research associate and stop the experiment immediately. The principal investigator will terminate your participation if you suffer from a severe motion sickness/dizziness due to the driving simulator. There will be no loss of benefits to you due to stopping the experiment.

In order to surpass any negative feeling induced by the simulator (e.g., dizziness), participants are recommended to:

- Sit or lie down immediately for at least 1-2 minutes, or until the dizziness has passed
- Breathe deeply
- Drink water (or hot tea with a little sugar)
- Have something to eat (e.g., quick snack, chocolate, banana)
- Avoid bright lights or light from a laptop (or closing their eyes for 1-2 minutes)

Benefits

The study may not benefit you directly, but the information we collect from you will help us better understand driving behavior and suggest ways to improve road safety.

Confidentiality

If you agree to participate in this research study, the information will be kept confidential. Unless required by law, only the study principal investigator and designee and the ethics committee will have direct access to the data collected from you in this study.

Please note that records may be monitored by the Institutional Review Board (IRB) while assuring confidentiality.

Data will be stored for three years after the study completion.

Investigator's Statement:

I have reviewed, in detail, the information document for this research study with _ ______________________________ (name of participant, legal representative, or parent/guardian) the purpose of the study and its risks and benefits. I have answered to all the participant's questions clearly. I will inform the participant in case of any changes to the research study.

Maya Abou-Zeid ________________

Name of Investigator or designee **Signature**

____

Date

American University of Beirut, Riad El-Solh / Beirut 1107 2020, Lebanon

Participant's Participation:

I have read and understood all aspects of the research study and all my questions have been answered. I voluntarily agree to be a part of this research study and I know that I can contact Dr. Maya Abou-Zeid at 01-350000 Ext. 3431 or by email (ma202@aub.edu.lb) or any of her designee involved in the study in case of any questions. If I feel that my questions have not been answered, I can contact the Institutional Review Board for human rights at 01-350000 Ext. 5445, 5454, or 5455. I understand that I am free to withdraw this information sheet and discontinue participation in this project at any time, even after signing this form, and it will not affect my care or benefits. I know that I will receive a copy of this signed document.

______________________________ __________________

Name of Participant **Signature**

____

Date

APPENDIX D: IN-LABORATORY N-BACK TRAINING

(These instructions are derived from Mehler et al. (2011))

The Research Associate used the text below in instructing participants. During actual evaluation trials, all instructions were presented from recordings to provide consistency of presentation.

Part of the experiment will involve performing a set of number tasks. You are going to learn how to perform a few versions of these tasks and practice each with a few trials. This sheet provides an overview of the task.

(Direct the subject's attention to the *N-back Instructions* sheet.)

Please follow along as I explain each version.

The first version is called the **0- back**. During this task, I will read a list of ten single digit numbers. As I read each number, you are to repeat out loud the last number that you've heard. For example, if I were to say the number 3, you would say 3; then if I said 2, you would say 2; then if I said 6, you would say 6, and so on. Try to be as accurate as you can be.

(Point to the appropriate "I say" and "you say" squares on the sheet as you read the above.

I say:	3	2	6	7	1
You say:	3	2	6	7	1

Let's practice with an actual set of numbers:

7	4	6	8	9	0	5	2	1	3

(If the subject misses more than 1 response, repeat up to four more trials. Write the numbers in the trial above on a separate sheet backwards and then in the same order as they appear alternating up to twice. Present one trial at a time trying to improve the subject's understanding to the point where they respond correctly to seven of ten stimuli.)

The second version of the task is called the **1- back**, which simply means that as I read each list of ten numbers, you are to repeat out loud the number before the last number that you heard. For example, if I said 3, you would say nothing, then if I said 2, you would say 3, then if I said 6, you would say 2, and so on. Try to be as accurate as you can be.

(Point to the appropriate “I say” and “you say” squares on the sheet as you read the above.)

I say:	3	2	6	7	1
You say:	nothing	3	2	6	7

Let’s practice with an actual set of numbers:

9	2	0	7	1	4	6	3	9	8

Let’s try that again. Just repeat out loud the number before the last number that you’ve heard. For example, if I were to say the number 1, you would say nothing, then if I said 2, you would say 1, then if I said 3, you would say 2, and so on. Try to be as accurate as you can be.

Let’s practice:

1	7	3	8	9	0	5	4	6	2

(If the subject misses more than 2 in the last practice trial repeat up to four more trials. Write the numbers in the two trials above on a separate sheet backwards and then in the same order as they appear. Present one trial at a time trying to improve the subject’s understanding to the point where they respond correctly to seven of ten stimuli.)

The final version of the task is called the **2- back**, which simply means that as I read each list of ten numbers, you are to repeat out loud the number that was read two numbers ago. For example, if I were to say the number 3, you would say nothing, then if I said the number 2, you would say nothing, then if I said 6, you would say 3, then if I said 7, you would say 2, and so on. Try to be as accurate as you can be.

(Point to the appropriate “I say” and “you say” squares on the sheet as you read the above.)

I say:	3	2	6	7	1
You say:	nothing	nothing	3	2	6

Let’s practice with an actual set of numbers:

5	0	6	7	1	4	2	3	9	8

Let’s try another example. Just repeat out loud the number that was read two numbers ago. For example, if I were to say the number 1, you would say nothing, then if I said 2, you would say nothing, then if I said 3, you would say 1, then if I said 4, you would say 2, and so on. Try to be as accurate as you can be.

Let’s practice:

6	5	3	4	7	2	1	8	0	9

Let’s try another one. Just repeat out loud the number that was read two numbers ago. For example, if I were to say the number 0, you would say nothing, then if I said 9, you would say nothing, then if I said 1, you would say 0, then if I said 5, you would say 9, and so on. Try to be as accurate as you can be.

Let’s practice:

0	9	1	5	8	2	4	6	3	7

(If subjects miss more than 4 in the last practice trial repeat up to six more trials. Write the numbers in the three trials above on a separate sheet backwards and then in the same order as they appear to form the six trials. Present one trial at a time trying to improve the subjects understanding to the point where they respond correctly to four of ten stimuli)

Good job!

APPENDIX E: IN-VEHICLE TRAINING

(These instructions are derived from Mehler et al. (2011))

[The Research Associate explains to the subject while being in the vehicle that he/she will hear audio messages of the secondary task, and each level of this task will include 2 sets of 10 numbers. Sets are separated by the word "Next set", and levels of this task might not be ordered 0-1-2. Subjects are encouraged to listen well to the instructions at the beginning in order to determine which level of the secondary task is being tested with each audio message.

One practice test shall be performed in-vehicle (before starting the drive and while sensors are attached) to ensure that subjects are comfortable with the n-back task in the experiment conditions. In this practice test, levels of the secondary task shall not be ordered 0-1-2 and subjects shall be told that they might have different sequence of the n-back levels in the experiment.]

[0-back]

We are now going to complete two sets of trials of the 0-back task. Remember that in this task, you are to repeat out loud the number that you just heard. Please, try to be as accurate as you can be.

3	0	8	4	6	1	7	2	9	5

Next Set

2	5	3	4	8	0	7	1	9	6

[1-back]

We are now going to complete two sets of trials of the 1-back task. Remember that in this task, you are to repeat out loud the number before the number that you just heard. Please, try to be as accurate as you can be.

4	7	0	9	5	3	6	2	1	8

Next Set

1	6	7	0	3	9	4	5	2	8

[2-back]

We are now going to complete two sets of trials of the 2-back task. Remember that in this task, you are to repeat out loud the number that you heard two numbers ago. Please, try to be as accurate as you can be.

9	0	1	7	3	2	6	8	4	5

Next Set

3	5	8	1	9	6	0	4	2	7

APPENDIX F: POST-DRIVING SURVEY

Post-Driving Survey

This survey is intended to study the driving behavior of the participants and their opinions about driving safety. All your answers will remain confidential.

Subject ID [Filled out by Research Associate]: …………… Survey Date and Time [Filled out by Research Associate]: ……………

Please answer each of the following items as honestly as possible. Please read each item carefully and then select or write down the answer. If none of the choices seems to be your ideal answer, then select the answer that comes closest. THERE ARE NO RIGHT OR WRONG ANSWERS. Select your answers quickly and do not spend too much time analyzing your answers. The expected completion time of this survey is 10 minutes.

Section I: Driving Behavior

<u>Question 1:</u>

Please check one of the following numbers from **0 (Not at all)** to **10 (Very much)** to the right of each of the below statements on the basis of your **<u>usual</u>** or **<u>typical</u>** feelings about driving.

Statement	Not at all										Very much
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1. It annoys me to drive behind a slow moving vehicle.	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
2. I'm annoyed when the traffic lights change to red when I'm approaching them.	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
3. I find it difficult to control my temper when driving.	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
4. I think I don't have enough experience and training to deal with risky situations on the road safely.	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
5. I feel more anxious than usual when I have a passenger in the car.	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
6. I feel more anxious than usual when driving in heavy traffic.	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
7. I always keep an eye on parked cars in case somebody gets out of them, or there are pedestrians behind them.	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
8. I make a special effort to be alert even on roads I know well.	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
9. I make an effort to see what is happening on the road a long way ahead of me.	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

10. I would like to risk my life as a racing driver.	□	□	□	□	□	□	□	□	□	□	□
11. I like to raise my adrenaline levels while driving.	□	□	□	□	□	□	□	□	□	□	□
Statement	**Not at all**										**Very much**
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
12. I would enjoy driving a sports car on a road with no speed limit.	□	□	□	□	□	□	□	□	□	□	□
13. Think about how you feel when you have to drive for several hours, with few or no breaks from driving. How do your feelings change over the course?											
a- **I become more uncomfortable physically (e.g., headache, muscle pains).**	□	□	□	□	□	□	□	□	□	□	□
b- **I become more drowsy or sleepy.**	□	□	□	□	□	□	□	□	□	□	□
c- **I become increasingly inattentive to road signs**	□	□	□	□	□	□	□	□	□	□	□

Question 2:

This question is concerned with how you usually deal with driving when it is difficult, stressful or upsetting. Think of those occasions during the last year when driving was particularly stressful. Perhaps you nearly had an accident, or you were stuck in a traffic jam, or you had to drive for a long time in poor visibility and heavy traffic. Use your experiences of driving during the last year to indicate how much you usually engage in the following activities when driving is difficult, stressful or upsetting, by checking one of the numbers from 0 to 10 to the right of each statement.

Statement	Not at all										Very much
	0	1	2	3	4	5	6	7	8	9	10
1. **I relieved my feelings by taking risks or driving fast.**	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
2. **I flashed the car lights or use the horn in anger.**	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
3. **I tried to make other drivers more aware of me by driving close behind them.**	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
4. **I made sure I kept a safe distance from the car in front.**	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
5. **I made an effort to stay calm and relaxed.**	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
6. **I made a special effort to look out for hazards.**	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
7. **I cheered myself up by thinking about things unrelated to the drive.**	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
8. **I refused to believe that anything unpleasant had happened.**	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
9. **I thought about good times I have had.**	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

10. **I wished that I found driving more enjoyable.**	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
11. **I criticized myself for not driving better.**	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
12. **I wished that I was a more confident and forceful driver.**	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
Statement	**Not at all**										**Very much**
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
13. **I felt I was learning how to cope with stress.**	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
14. **I looked on the drive as a useful experience.**	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐
15. **I learnt from my mistakes.**	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐	☐

Section II: Evaluation of the Driving Activity

Please evaluate the driving activity in this experiment:

A- When you were driving without performing the n-back task

Factor	Very Low	Below Average	Average	Above Average	Very High
1. **Effort of attention required by the driving activity (e.g., to think about, to decide, to choose)**	☐	☐	☐	☐	☐
2. **Visual demand necessary for the driving activity**	☐	☐	☐	☐	☐
3. **Situational stress while driving (e.g., fatigue, insecure feeling, irritation, discouragement)**	☐	☐	☐	☐	☐

B- When you were driving and performing the n-back task at the same time

Factor	Very Low	Below Average	Average	Above Average	Very High
1. **Effort of attention required by the driving activity (e.g., to think about, to decide, to choose)**	☐	☐	☐	☐	☐
2. **Visual demand necessary for the driving activity**	☐	☐	☐	☐	☐
3. **Interference or disturbance when driving simultaneously with the n-back task**	☐	☐	☐	☐	☐
4. **Situational stress while driving (e.g., fatigue, insecure feeling, irritation, discouragement)**	☐	☐	☐	☐	☐

Section III: Driving Experiment Using a Driving Simulator and Physiological Measurements

12. Have you ever participated in a driving simulation experiment?
    - ☐ Yes
    - ☐ No

If "Yes", please indicate when you have participated in that experiment. ____

13. Overall, to what extent did driving in the simulator feel like real world driving?

Not at all close	Somewhat close	Very close
☐	☐	☐

14. How realistic did the driving speed in the simulator feel to you?

Very unrealistic	Somewhat realistic	Very realistic
☐	☐	☐

15. To what extent did you feel dizzy while driving the simulator?

Not at all	A little	Very much
☐	☐	☐

16. Do you believe that dizziness or other factors affected your driving behavior in the simulator to differ from your actual driving behavior on the roads?

Not at all	A little	Very much
☐	☐	☐

17. To what extent did the attachment of physiological sensors affect your behavior while driving?

Not at all	A little	Very much
☐	☐	☐

Section IV: General Driving Patterns

1. How many hours did you drive today? ________________
2. How many of these were in heavy traffic? ________________
3. How many hours do you drive on an average weekday? ________________
4. How many days a week do you drive on average? ________________
5. Do you own the vehicle you drive? ________________
6. How many major accidents in the past 3 years have you been involved in as a driver? ________________
7. How many moving violation tickets (speeding tickets, tickets for crossing red lights, etc., but not including tickets obtained for not wearing the seatbelt) have you been given in the past 3 years as a driver? ________________

Section V: Comments

If you have any comments about this survey or the drive in the driving simulator, please write them below:

____

____

APPENDIX G: SUBJECTIVE WORKLOAD ASSESSMENT

Evaluation of the Driving Activity (Section II of the post-driving survey)

Design

Items of this section were derived from the DALI (Driving Activity Load Index), a subjective tool to assess the driver cognitive workload while driving under different conditions (with and without secondary tasks). This index is a revised version of the NASA-TLX[13], adapted to the driving task. Factors of the DALI and their description are presented in Table 16 (Pauzie, 2008).

The driving activity of the simulation experiment conducted in this study did not require auditory demand; road directions were provided on billboards (the audio messages were not related to the driving activity but to the secondary task), and there were no timing constraints imposed (the driving simulation experiment is set for the day-time). Therefore, items related to auditory and temporal demands required by the driving activity were removed in the post-driving survey for this study. The subject was required to evaluate the driving activity in the experiment under the “control” condition, i.e., when he/she was driving without performing the n-back task, and under the “treatment” condition, i.e., when he/she was driving and performing the n-back task at the same time. The “Interference” item is only assessed under the “treatment” condition (since the control phase does not involve the secondary task). The scale rates the

[13] The NASA-TLX was originally created to evaluate the workload of the pilots in the aviation domain and it has been tested and used by the army. Factors affecting workload in the NASA-TLX were mental demand, physical demand, temporal demand, performance, frustration level and effort. Using this tool, the subject rates the magnitude of each of these factors on a scale, then he/she conducts pairwise comparisons between all these factors; for each pair, the subject identifies the highest source of workload. The final index that quantifies the workload level combines the scale rating and the relative weight computed from the pairwise comparison. The NASA-TLX is revised and enhanced in the DALI to particularly evaluate the driving task (Pauzie, 2008).

magnitude of each factor demanded by the driving activity as Very Low, Below Average, Average, Above Average, and Very High.

Table 16: DALI factors and their description (Pauzie, 2008)

Item	Description
Effort of Attention	To evaluate the attention required by the driving activity – to think about, to decide, to choose, to look for, etc.
Visual Demand	To evaluate the visual demand necessary for the driving activity
Auditory Demand	To evaluate the auditory demand necessary for the driving activity
Temporal Demand	To evaluate the specific constraint owing to timing demand when running the driving activity
Interference	To evaluate the possible disturbance when running the driving activity simultaneously with any other supplementary task such as phoning, using systems or radio, etc.
Situational Stress	To evaluate the level of constraints/stress while conducting the driving activity such as fatigue, insecure feeling, irritation, discouragement, etc.

Analysis of Results

Responses of the subjects were compared between the "control" and "treatment" conditions for the Effort of Attention, Visual Demand, and Situational Stress factors using paired t-test[14]. Results showed that, for each factor, the responses between the "control" and "treatment" conditions were statistically significantly different at the 95% level of confidence with higher responses[15] under the "treatment" condition ($\text{t-statistic}_{(\text{Effort of Attention})} = -8.87$; $\text{t-statistic}_{(\text{Visual Demand})} = -6.87$; $\text{t-statistic}_{(\text{Situational Stress})} = -9.20$).

Figures 42-45 represent the subjects' rating of each workload factor of the driving activity.

[14] Responses were assumed to be normally distributed.

[15] The scale extending from "Very Low" to "Very High" was digitized from *1* to *5*, with *1* designating the "Very Low" end and *5* designating the "Very High" end.

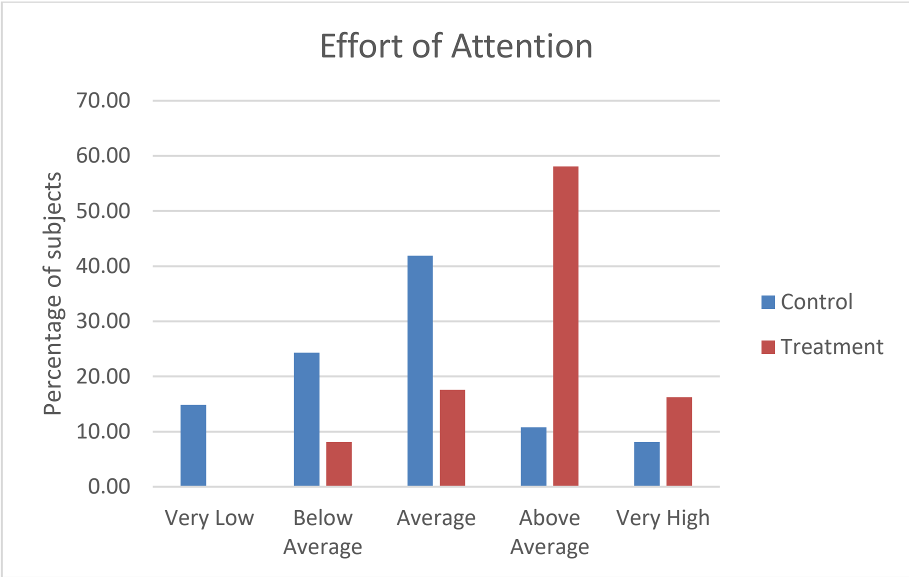

Figure 42: Rating the effort of attention required by the driving activity

Under the "control" condition, approximately 19% of the subjects evaluated the effort of attention as "Above Average" or "Very High". Under the "treatment" condition, approximately 74% of the subjects evaluated the effort of attention as "Above Average" or "Very High".

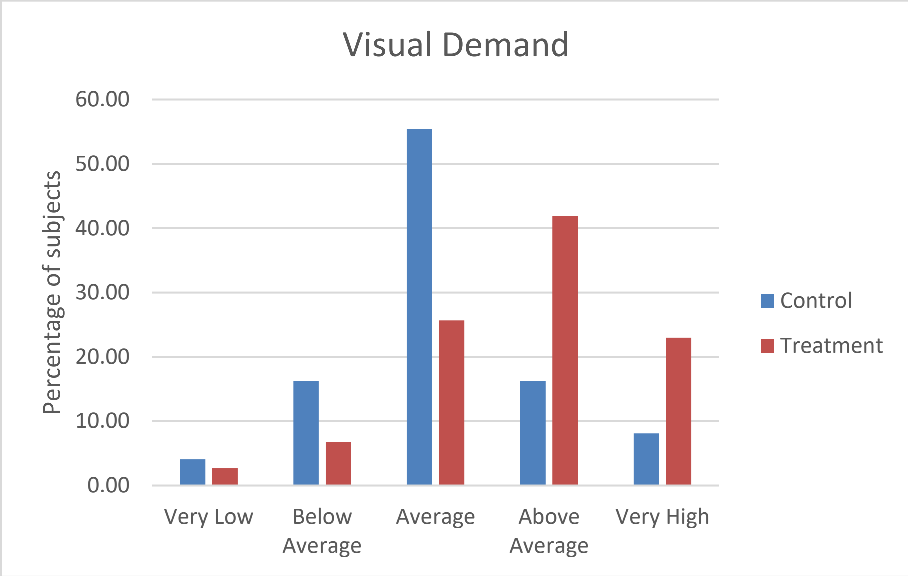

Figure 43: Rating the visual demand required by the driving activity

Under the "control" condition, approximately 24% of the subjects evaluated the visual demand as "Above Average" or "Very High". Under the "treatment" condition, approximately 65% of the subjects evaluated the visual demand as "Above Average" or "Very High".

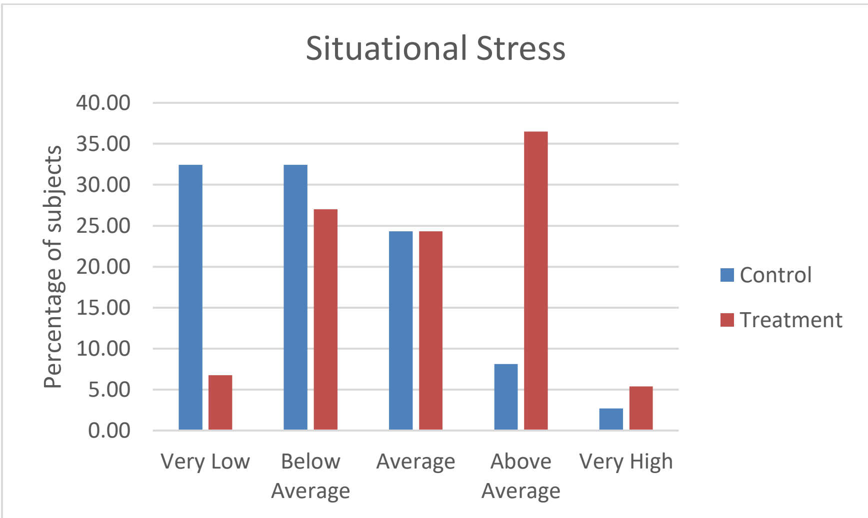

Figure 44: Rating the situational stress required by the driving activity

Under the "control" condition, approximately 11% of the subjects evaluated the situational stress as "Above Average" or "Very High". Under the "treatment" condition, approximately 42% of the subjects evaluated the situational stress as "Above Average" or "Very High".

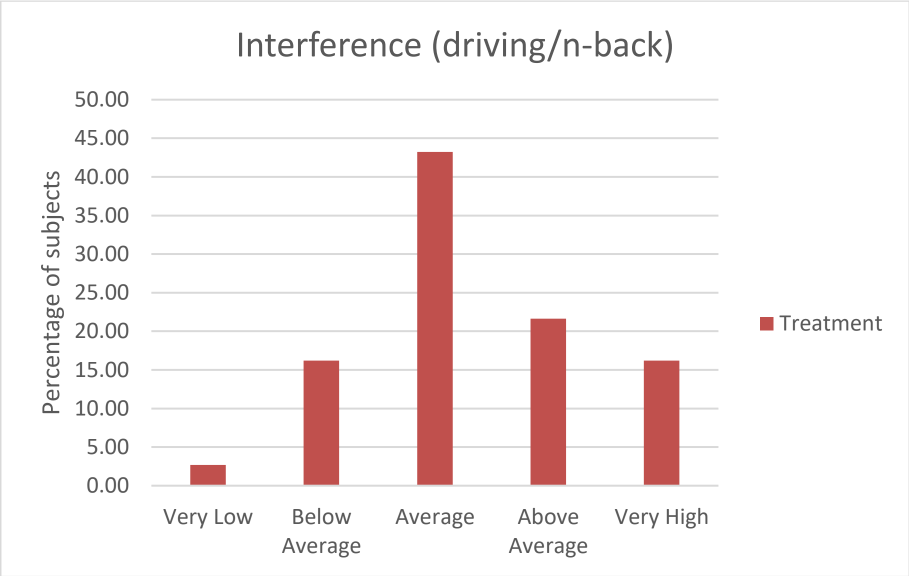

Figure 45: Rating the interference of the driving task and the secondary n-back task

Approximately 38% of the subjects evaluated the interference between the driving task and the secondary n-back task as "Above Average" or "Very High".

Based on the above results, subjects were subjectively reporting a higher workload (effort of attention and visual demand) required at the treatment phase than at the control phase. Subjects also subjectively reported that a higher situational stress was induced at the treatment phase than at the control phase. The majority of the subjects reported that the driving activity was disturbed by the n-back task at the treatment phase. This implies that the n-back task requires additional effort from the subjects.

APPENDIX H: EXPERIMENT SHEET

[This experiment sheet is filled out by the Research Associate. It is specific to each subject. The Research Associate notes the driving simulation run time and the physiological session start time. The subject's performance on the secondary task is evaluated off-line (i.e., after the actual experiment ends, the Research Associate corrects the subject's answers based on the audio record specific to each subject).]

Subject ID: _________________

Simulation start time (run time): ____

Physiological session start time: ____

Records of the secondary task: (0-1-2 order)

0-back **Score: / 20**

8	7	4	5	2	3	1	9	6	0

7	3	6	4	0	5	8	1	9	2

1-back **Score: / 20**

6	5	7	0	1	2	9	8	3	4

9	2	5	3	7	8	1	6	0	4

2-back **Score: / 20**

7	6	0	2	1	3	5	9	4	8

0	4	3	7	5	9	8	1	2	6

Notes from the driving simulation experiment

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