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Modeling Driver Behavior and Aggressiveness Using Biobehavioral Methods

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16. Abstract

Mathematical models of car-following, lane changing, and gap acceptance are mostly descriptive in nature and lack decision making or error tolerance. Including additional driver information with respect to behavior and cognitive characteristics would account for these lacking parameters and incorporate a human aspect to these models. Car-following, particularly in relation to the intelligent driver model (IDM), is the primary component of this research. The major objectives of this research are to investigate how psychophysiological constructs can be modeled to replicate car-following behavior, and to correlate subjective measures of behavior and aggressiveness with actual car-following behavior. To accomplish the objectives the following tasks are required: perform a thorough literature review, develop the methodological framework, set up a driving simulator study to collect relevant data, classify drivers with respect to their static and behavioral traits, and calibrate the IDM. This report presents the first part of this study, and includes the thorough literature review, and the methodological framework that will be used to incorporate biobehavioral parameters into the IDM. The data collection plan to execute the methodology involves collecting driving data from 90 participants using a driving simulator, and this will be completed in the second phase of the project. Various car-following tasks will be performed at multiple task difficulties. This will provide data on compensatory and performance effects experienced by drivers. Modification to the IDM will be made to incorporate any observed trends between driver classes, behavior, and performance.

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List of Abbreviations

Detection Response Task (DRT)
Driving Activity Load Index (DALI)
Electrocardiography (ECG)
Electroencephalography (EEG)
Heart Rate (HR)
Heart Rate Variability (HRV)
Human Driver Model (HDM)
Human Research Protection Program (HRPP)
Institutional Review Board (IRB)
Intelligent Driver Model (IDM)
Level of Activation (LA)
Mid-America Transportation Center (MATC)
National Aeronautics and Space Administration (NASA)
Nebraska Transportation Center (NTC)
Peripheral Detection Task (PDT)
Situation Awareness (SA)
Situation Awareness Global Assessment Technique (SAGAT)
Situation Awareness Rating Technique (SART)
Situation Present Assessment Method (SPAM)
Standard Deviation (SD)
The University of Kansas (KU)
Task Load Index (TLX)
Task-Evoked Pupillary Response (TERP)
Useful Field of View (UFOV)
Workload (WL)

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Abstract

Mathematical models of car-following, lane changing, and gap acceptance are mostly descriptive in nature and lack decision making or error tolerance. Including additional driver information with respect to behavior and cognitive characteristics would account for these lacking parameters and incorporate a human aspect to these models. Car-following, particularly in relation to the intelligent driver model (IDM), is the primary component of this research. The major objectives of this research are to investigate how psychophysiological constructs can be modeled to replicate car-following behavior, and to correlate subjective measures of behavior and aggressiveness with actual car-following behavior. To accomplish the objectives the following tasks are required: perform a thorough literature review, develop the methodological framework, set up a driving simulator study to collect relevant data, classify drivers with respect to their static and behavioral traits, and calibrate the IDM.

This report presents the first part of this study, and includes the thorough literature review, and the methodological framework that will be used to incorporate biobehavioral parameters into the IDM. The data collection plan to execute the methodology involves collecting driving data from 90 participants using a driving simulator, and this will be completed in the second phase of the project. Various car-following tasks will be performed at multiple task difficulties. This will provide data on compensatory and performance effects experienced by drivers. Modification to the IDM will be made to incorporate any observed trends between driver classes, behavior, and performance.

Chapter 1 Introduction

1.1 Problem Statement

Driver behavior is a significant contributor to traffic operational quality and safety, and it is also an important element in traffic simulation tools. These tools allow for driver variability through various distributions. In addition, the mathematical models of car-following, lane changing, and gap acceptance are mostly descriptive in nature. As a result, these tools do not accurately describe traffic phenomena such as breakdowns or capacity drop and consequently, calibration efforts to field data are needed. Also, the majority of tools are "collision-free" by default, therefore, estimating surrogate safety measures based on these models would be inaccurate. As such, additional information of driver behavior from the cognitive sciences could significantly enhance the ability of existing models and simulator to replicate field conditions.

Biobehavioral aspects encompass the variability of cognitive workload and situation awareness with the driving behavior of individuals. In this study, variables such as preferred headway, speed, acceleration, and deceleration, are used together with variations in mental workload, changes in situation awareness, and static driver properties to categorize individuals. Although the exact definition for driver behavior will be the outcome of this study, drivers can be generally grouped into three main categories, conservative, average, and aggressive. Where average drivers represent the characteristics exhibited by the majority of the sample population, and conservative and aggressive drivers represent the lower and upper quartiles of the sample population, respectively.

1.2 Objectives

The major goals of this research are to investigate how psychophysiological constructs can be modeled to replicate car-following behavior, and to correlate subjective measures of behavior and aggressiveness with actual car-following behavior. This research is divided in two parts. Part I, which is the focus of this research report, summarizes the literature review comprising of techniques and past studies aimed at incorporating behavioral aspects into traffic models. It also includes the methodological setup of the experiments to be conducted with the use of a driving simulator, as well as survey questionnaires related to driver behavior. Part II of this research project will execute the data collection and model development, and will commence with the completion of Part I.

The specific tasks to be carried out in both parts of this research project are as follows:

- Conduct a thorough literature review comprising of techniques and past studies aimed at incorporating behavioral aspects into traffic models. Including parameters used to categorize drivers into conservative, average, and aggressive;
- Develop the methodological framework to incorporate behavioral aspects into an existing car-following model (i.e., the IDM);
- Classify drivers by self-reported/subjective measures (PANAS, decision making, NASA-TLX (Task load index), attention and executive, and screening questionnaires), biobehavioral measures (level of activation, heart rate, pupil dilation, and gaze fixation), and performance measures (speed, acceleration, headway, standard deviation (SD) steering wheel angle, and SD of lateral position);
- Collect static and dynamic behavioral parameters using a driving simulator study with 90 drivers;
- Analyze data to establish activation level, compensation, and performance thresholds for the different types of driver classifications (conservative, average, and aggressive); and

- Incorporate attained thresholds into the intelligent driver model (IDM) and compare the predictive capability to the unaltered IDM. Validate the feasibility of the modified IDM using data not used for model development.

1.3 Outline of the Report

The report starts by presenting the problem statement and objectives in the first chapter. Chapter 2 presents the literature review findings on car-following models, behavioral components such as situation awareness, workload, and level of activation, experimental techniques, and existing biobehavioral methodologies. The methodological plan is described in Chapter 3, while the data collection plan is presented in Chapter 4. Finally, a short summary is presented along with the future schedule.

Chapter 2 Literature Review

This section provides a detailed review of some of the existing car-following models, especially those that have been used to incorporate some sort of biobehavioral architecture. This chapter also includes literature related to the definitions of several biobehavioral parameters, their measurement methods, and their relationship. Literature were obtained from several journal articles, theses, and publications. Online resources such as Google Scholar, ScienceDirect, University of Kansas (KU) Library resources, WorldCat, and Transportation Research International Documentation (TRID) were used.

2.1 Driver Behavior Models

Driver behavior models have significantly evolved from the first established Greenshields single regime model. The Greenshields model is a starting point for several other more complex traffic flow models such as the Pipes, Lighthill–Whitham–Richards (LWR), Gas kinetic (GK), Edie, Newell, and Drake, listed in a chronological order (Wageningen-Kessels et al. 2015).

Car-following models are an important sub-category of traffic flow. The concept of car-following was first introduced by Pipes in 1953. In 1958, a stimulus-response based approach was developed by Gazis-Herman-Rothery (GHR) in the General Motors laboratories (Saifuzzaman & Zheng 2014). The GHR model relied on a few inaccurate assumptions such as the following driver being able to accurately perceive small changes in speed and react to changes in speed even at very large headways. The need for a more adaptive model that better depicts the car-following behavior led to the establishment of psycho-physical models, that incorporate a certain level of human perspective. This establishes a more realistic approach to model traffic, considering that vehicles are controlled by humans with varying physical and mental restraints.

A discussion consisting of existing psycho-physical models and a few other car-following models such as the intelligent driver model, human driver model, are presented in the sections that follow.

2.1.1 Psycho-Physical Car Following Models

Psycho-physical models, as the name suggests, incorporate both psychological and physical dynamics of drivers into the car following algorithms. They are entirely based on how drivers react to the actions of the lead vehicle and assume similar perception thresholds for all drivers (Schulze & Fliess 1997). This major assumption fails to consider the behavior and driving preferences of the individual operating the vehicle. For example, some individuals prefer maintaining shorter headways and accelerate more rapidly, affecting the overall flow and throughput of the roadway. This section presents a detailed review of the existing psycho-physical car following models and their mechanics.

2.1.1.1 Wiedemann (VISSIM)

This is one of the most well-known psycho-physical models and it acts as the foundation behind the car following algorithm in VISSIM. After first being established in 1974, the model has been constantly modified and calibrated to suit various scenarios.

The Wiedemann model considers six main thresholds as shown in figure 2.1. AX: The desired bumper to bumper spacing between two successive standstill vehicles, BX: The minimum desired headway expressed as a function of AX, speed, and distance, Closing delta velocity (CLDV): Deceleration resulting from the application of brakes because speed of vehicle is greater than the leader, SDV: The point at which the driver perceives a lead vehicle traveling at a slower velocity, OPDV: The point during a drive when the driver realizes that he/she is traveling slower than the lead vehicle and starts to accelerate, and SDX: Perception threshold to model maximum preferred following distance (Saifuzzaman & Zheng 2014).

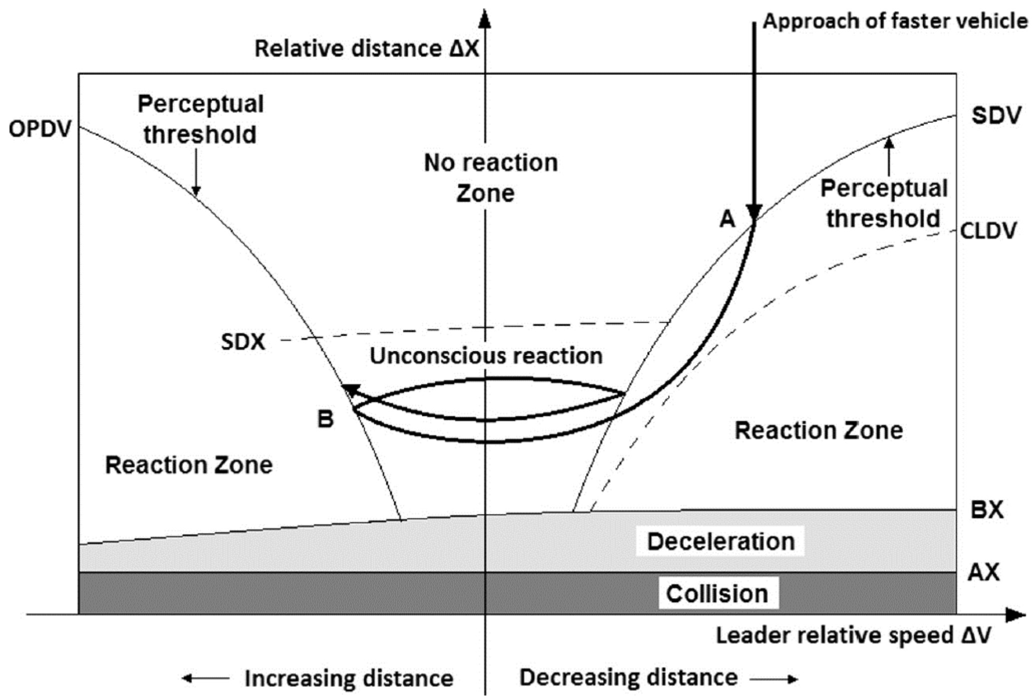


Figure 2.1 Wiedemann car-following model (Wiedemann 1974)

The dark line in figure 2.1 shows the path followed when a fast-moving vehicle approaches a slow leader. The fast-moving vehicle will approach the slower leader until the perpetual threshold of deceleration is reached (SDV), as shown by point A. At this point, the driver of the fast-moving vehicle applies the brakes and decelerates in order to match the velocity of the leader (Saifuzzaman & Zheng 2014). The zone of unconscious reaction is reached because it is very difficult to accurately predict the speed of the lead vehicle, causing an increase in the headway between the two vehicles. However, when the OPDV threshold is reached (point B), the driver realizes he/she is traveling slower than the leader and starts to accelerate. This process is assumed to continue until the destination is reached unless coupled with a lane-changing model. Another iteration of the Wiedemann model was also developed specifically to address driving behavior in a freeway facility (Wiedemann 99). Wiedemann 99 also has nine calibration parameters that allow for a more user adjustable model.

In 1998, Fancher and Bareket, proposed a new space known as the “comfort zone” to the Wiedemann model. This zone acts as a threshold for the desired spacing acceptable by the driver as a result of being unable to accurately perceive speed differences (Saifuzzaman & Zheng 2014).

2.1.1.2 Fritzsche (Paramics)

The Fritzsche model is a psycho-physical model first established in 1994. The model has been incorporated in traffic simulation software such as Paramics and is capable of introducing human perception to the car-following (Olstam 2004). There are six main thresholds for this model and they include: perception of negative speed difference (PTN), perception of positive speed difference (PTP), desired speed (AD), risky distance (AR), safe distance (AS), and braking distance (AB). The thresholds together form five regions: free driving, danger, following I, following II, and closing in, as shown in figure 2.2. Each region captures a specific aspect of car-following as experienced by the driver. The Fritzsche model assumes that a driver will only decelerate when in “danger” or “closing in” to the lead vehicle (Saifuzzaman & Zheng 2014).

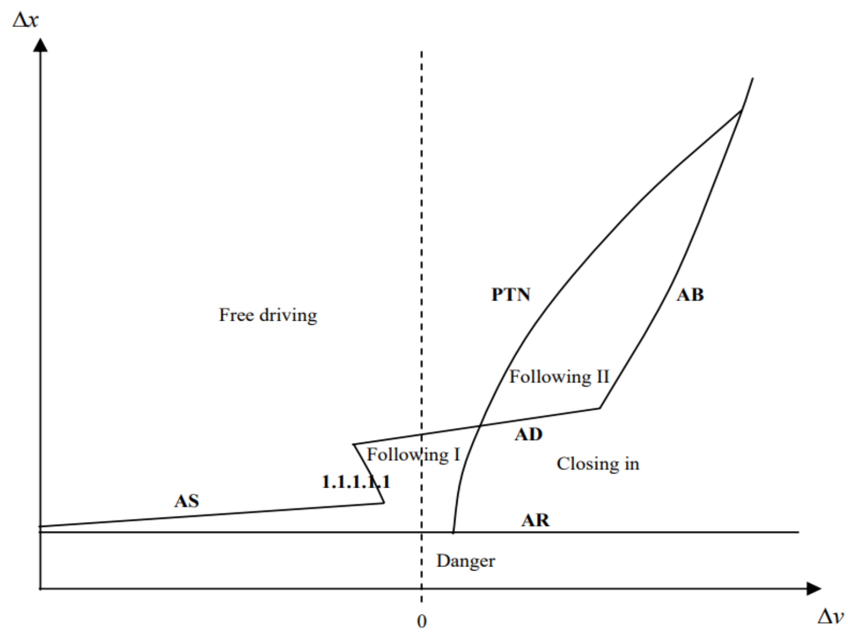


Figure 2.2 Fritzsche car-following model (Olstam 2004)

2.1.1.3 Urban Traffic Psycho-Physical Model

The urban traffic model was established by Schulze and Fliess, in 1997. The phase diagram of the model is shown in figure 2.3 and can be interpreted as a combination of the Wiedemann and the Fritzsche car-following models. The phase diagram shows seven defined regimes, namely: Free driving I, Free driving II, Approximating I, Approximating II, Following I, Following II, and Danger. The green line shows the trajectory of the following vehicle with respect to the changes in the driving regimes.

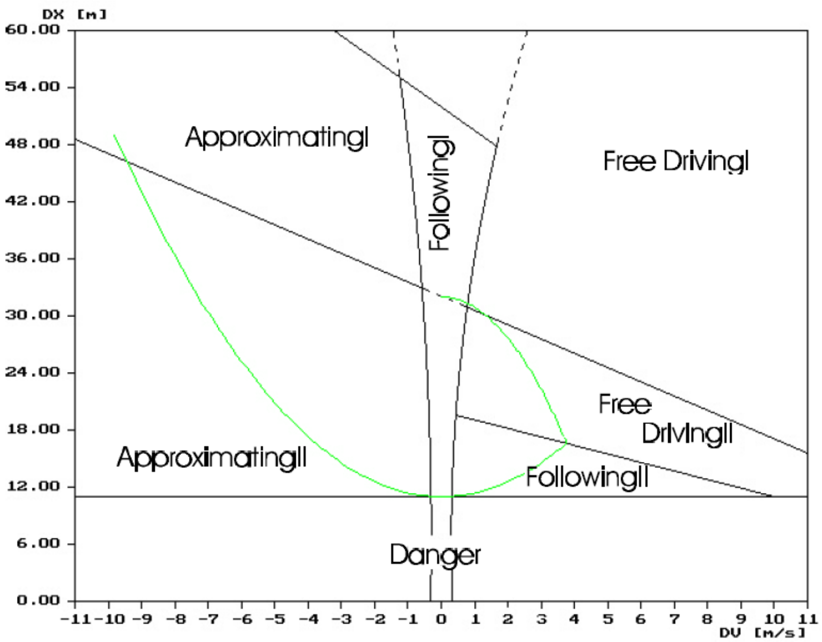


Figure 2.3 Urban traffic psycho-physical model (Schulze & Fliess 1997)

2.1.2 Intelligent Driver Model (IDM)

The IDM model is one of the most commonly used microscopic car-following model. The simplicity of this model with respect to the fewer number of parameters available, makes it easy to apply and calibrate (Hoogendoorn et al. 2012). The IDM captures both the desired speed and desired headway of the driver as shown in equation 2.1 (Saifuzzaman & Zheng 2014).

$$a_n(t) = a_{max}\left[1 - \left(\frac{v_n(t)}{v_0(t)}\right)^{\delta} - \left(\frac{s^*{}_n(t)}{s_n(t)}\right)^2\right] \quad (2.1)$$

$$s^*{}_n(t) = s^*\big(v_n(t), \Delta v_n(t)\big) = s_0 + s_1\sqrt{\frac{v_n(t)}{v_0(t)}} + T_n v_n(t) + \frac{v_n(t)\Delta v_n(t)}{2\sqrt{a_{max}b_{des}}}$$

Where,

$a_n(t)$ is the acceleration of the vehicle at time t

a_{max} is the maximum acceleration of the vehicle

$v_0(t)$ is the desired speed

$v_n(t)$ is the actual speed at time t

$\Delta v_n(t)$ is the approaching rate at time t

$s^*_n(t)$ is the desired minimum gap between two vehicles

s_0 is the minimum spacing at standstill

$s_n(t)$ is the spacing between two vehicles

b_{comf} is the comfortable deceleration

T_n is the desired time headway

δ characterizes how acceleration decreases with speed

Researchers studying the IDM have established typical values for city and highway settings (Kesting & Treiber 2013). However, these values can usually be tweaked within the constraints to provide a better calibrated model. A summary of typical values along with model constraints are shown in table 2.1.

Table 2.1 Typical IDM Constraints (Kesting & Treiber 2013)

Parameter	Typical City Values	Typical highway values	Constraints
Desired speed, v_0	15.0 m/s	33.3 m/s	1 to 70 m/s
Time headway, T_n	1.0 s	1.0 s	0.1 to 5 s
Minimum spacing, s_0	2 m	2 m	0.1 to 8 m
Acceleration component, δ	4	4	1 to ∞
Maximum acceleration, a_n	1.0 m/s^2	1.0 m/s^2	0.1 to 6 m/s^2
Comfortable deceleration, b_{comf}	1.5 m/s^2	1.5 m/s^2	0.1 to 6 m/s^2

The developers of the IDM, Kesting and Treiber, suggested modification to the model that would improve its predictive capabilities by using external visual indicators such as brake lights, turn signals, tailgating, and head light flashes. An example of a binary input to replicate car-following behavior when the brake lights of the lead vehicle are activated and the acceleration ($\dot{v}_l$) is less than the acceleration of the follower (a_c) is shown in equation 2.2.

$$Z_b = \begin{cases} 1 & \dot{v}_l < a_c, \\ 0 & Otherwise. \end{cases} \tag{2.2}$$

A typical value of a_c is -0.2 m/s^2 and it corresponds to the rate of change of velocity when neither the brakes or throttle is applied (vehicle decelerates uniformly) (Kesting & Treiber 2013). Other visual indicators can also be individually represented in similar equations.

A limited number of papers also discuss incorporating behavioral parameters into the IDM. In 2005, Fuller introduced the task capability interface (TCI) model to study the effects of task demand on risk-taking. Hoogendoorn et al. in 2012 combined the task-capability interface model with the IDM to predict changes to driving parameters. Figure 2.4 shows the TCI model that weighs the balance between the capability of the driver (C) and the demand of the task (D).

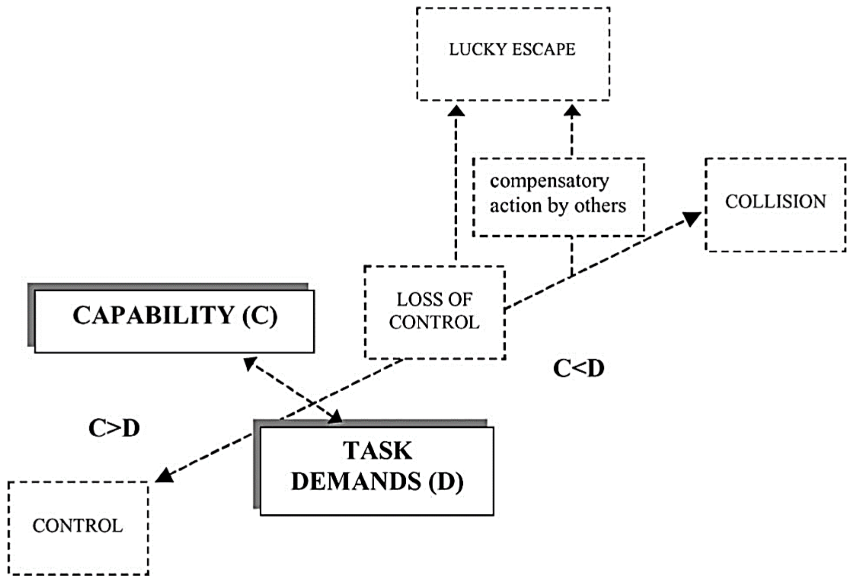


Figure 2.4 Task demand and capability interface (Fuller 2005)

The IDM was modified by incorporating the difference between task demand and the capability of the driver. The task demand and driver capability are applied as a factor scaled between 0 and 1. This implies that the difference between the task demand and capability will range from -1 to 1 as follows:

$$m_d(t) = m_t(t) - m_c(t)\ ; \quad 0 < m_t(t) < 1, 0 < m_c(t) < 1, \text{and} -1 < m_d(t) < 1 \tag{2.3}$$

Where,

$\mathrm{m_t(t)}$ is the task demand

$\mathrm{m_c(t)}$ is the capability of the driver

$\mathrm{m_d(t)}$ is the difference between task demand and driver capability

When the driver's capability is much greater than the demand of the task, the driver will perform better (task is easy), resulting in a negative value for the difference. A theoretical framework of the methodology is shown in figure 2.5. The driver tries to minimize the difference between varying task demand and capability by attempting compensatory actions like reducing speed. However, when compensatory actions alone are not sufficient to neutralize the difference, performance effects can be noticed (changes in workload and situation awareness) (Dee Waard & Brookhuis, 1991).

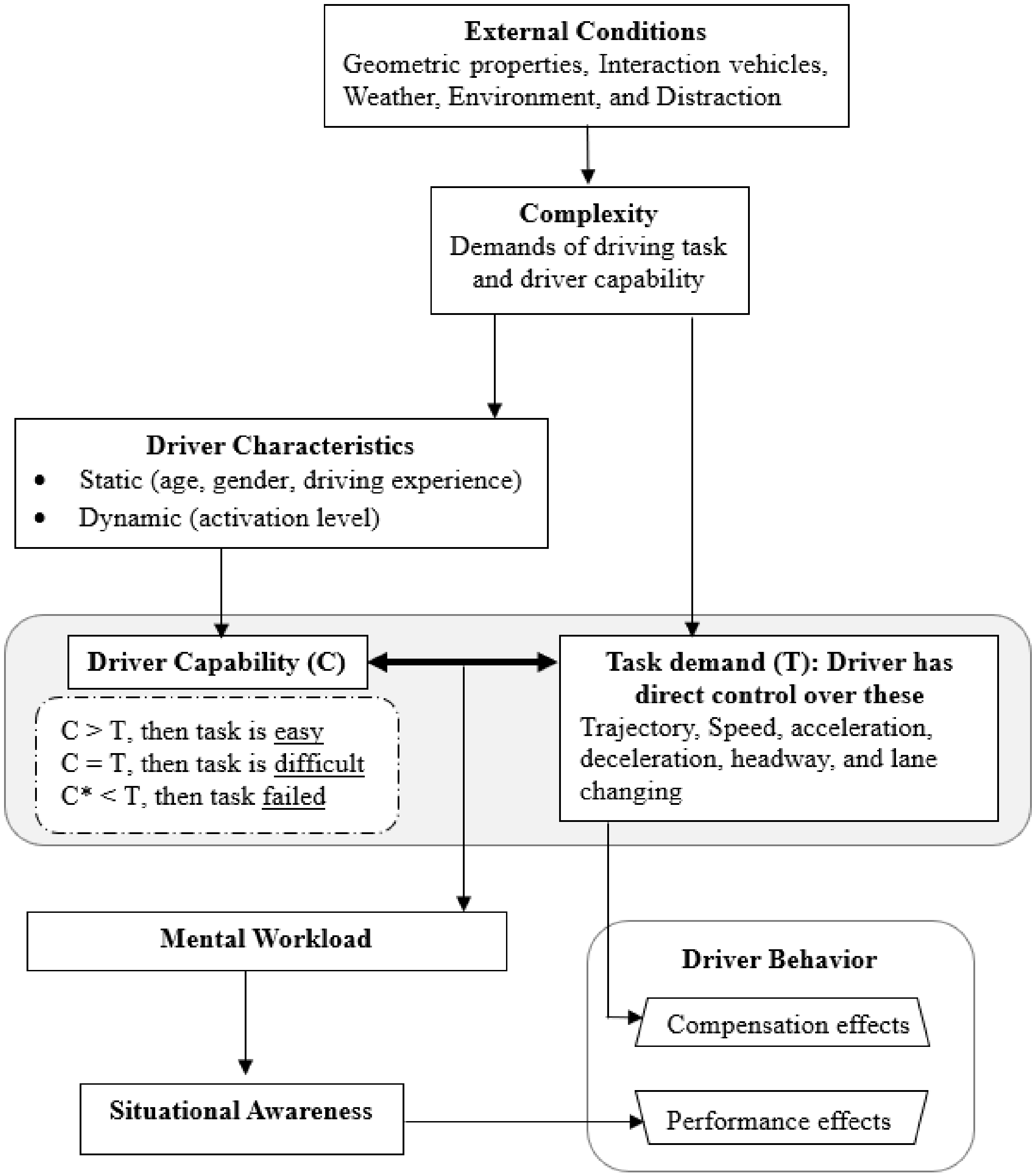


Figure 2.5 Framework developed by Hoogendoorn et al. (2012) to modify the IDM

The a_{max}, b_{comf}, $T_{n,}$ and v_0 parameters were modified to incorporate the difference between task demand and driver capability. When the difference between task demand and driver capability results in a negative value, the a_{max}, b_{comf}, and v_0 parameters increase because of the driver having a greater capability than the required task demand. However, T_n decreases because the driver is assumed to be capable of accepting a smaller time gap as his/her capability is greater than the demand of the task. The difference between task demand and capability was incorporated as a cubic function as shown below in equations 2.4-2.7.

$$a_{max}(t) = (-m_d(t)^3 a_{max}) + a_{max} \tag{2.4}$$

$$b_{des}(t) = (-m_d(t)^3 b_{max}) + b_{max} \tag{2.5}$$

$$v_0(t) = (-m_d(t)^3 v_0) + v_0 \tag{2.6}$$

$$T_n(t) = (m_d(t)^3 T_n) + T_n \tag{2.7}$$

Substituting equations 2.4, 2.5, 2.6, and 2.7 into equation 2.2 results in:

$$a_n(t) = ((-m_d(t)^3 a_{max}) + a_{max}) \left[1 - \left(\frac{v_n(t)}{(-m_d(t)^3 v_0(t)) + v_0(t)}\right)^{\delta} - \left(\frac{s^*{}_n(t)}{s_n(t)}\right)^2\right] \tag{2.8}$$

$$s^*{}_n(t) = s_0 + ((m_d(t)^3 T_n) + T_n) v_n(t) + \frac{v_n(t) \Delta v_n(t)}{2\sqrt{((-m_d(t)^3 a_{max}) + a_{max})((-m_d(t)^3 b_{max}) + b_{\mathrm{max}})}}$$

After incorporating possible compensatory actions, the next step involves incorporating performance effects into the model. De Waard and Brookhuis established that performance effects and demand are related with an inverted parabola function. This relationship was used to establish the following equation, with α, β, and γ being parameters:

$$m_p(t) = -(\alpha m_d(t)^2 + \beta m_d(t) + \gamma) \tag{2.9}$$

Equation 2.9 shows that performance effects will have a greater magnitude if the capability of the driver is less than the demand of the task (if $m_d(t)$ is positive). The following equation (2.10) shows the result of incorporating both performance effects and task-capability interface into the IDM:

$$a_n(t) = (1 - m_p(t))((-m_d(t)^3 a_{max}) + a_{max}) \left[1 - \left(\frac{v_n(t)}{(-m_d(t)^3 v_0(t)) + v_0(t)}\right)^{\delta} - \left(\frac{s^*{}_n(t)}{s_n(t)}\right)^2\right] \quad (2.10)$$

The implementation of models that depend on desired measures such as speed, spacing, and headway, has a limitation that these measures cannot be readily observed in nature (Saifuzzaman & Zheng 2014). A correlation has to be made in order to depict how the desired measures are affected by changes in human factors such as workload, situation awareness, and level of activation.

2.1.3 Human Driver Model (HDM)

The HDM was first proposed by Treiber et al. in 2006. It incorporated four extensions in terms of finite reaction times, imperfect estimation capabilities, spatial anticipation, and temporal anticipation to the IDM (Trieber et al. 2006). The model is based on the reaction time and the number of vehicles ahead for which the drivers can anticipate spatial information. Figure 2.6 shows the relationship between the reaction time and anticipated vehicles on traffic regimes including oscillating congested traffic (OCT), homogeneous congested traffic (HCT), moving and pinned localized clusters (MLC/PLC), and triggered stop-and-go (TSG). It can be seen that the greater the number of vehicles anticipated, the more the reaction time available to mitigate a crash. Anticipation is especially useful in the TSG regime, where predicting behavior of more lead vehicles can be useful to avoid crashes.

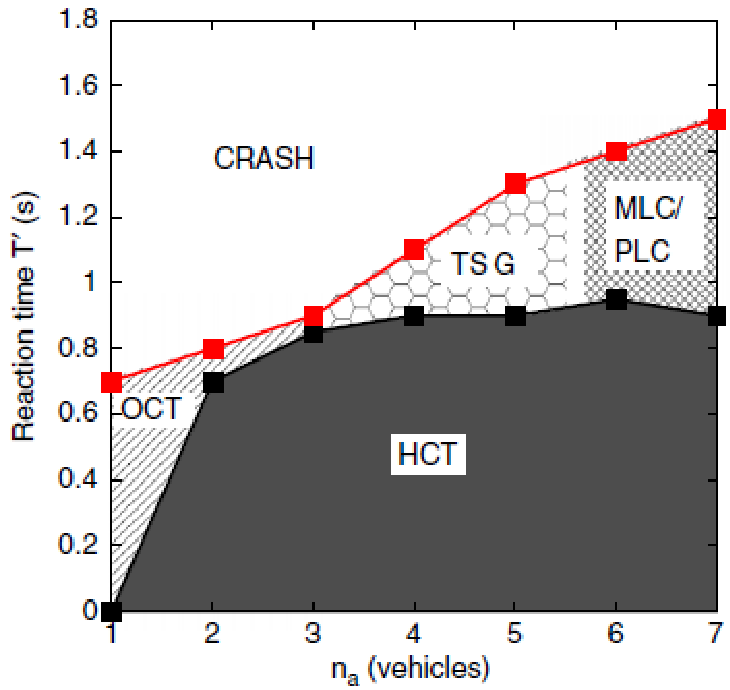


Figure 2.6 Regimes of the HDM

2.2 Situation Awareness, Workload, and Level of Activation

This section summarizes key definitions of the level of activation, situation awareness, and workload. It also discusses the experimental techniques that can be used to collect the respective data.

2.2.1 Situation Awareness (SA)

Situation awareness (SA) has been defined as the ability to perceive (Level 1 SA), comprehend (Level 2 SA), and project future status (Level 3 SA) of elements in an environment (Endsley 1995). A common misconception is that SA is only affected by perception (ability to locate an element). However, comprehension of the situation and the driver's ability to project future scenarios are significant factors where as being able to identify an element without placing where it fits and how it affects an environment is not valuable. The SA of a driver is known to affect his/her capability during a task in that, high SA generally implies a more alert driver unless affected by cognitive overload (Endsley, 1995). Figure 2.7 shows the Endsley, 1995 model developed to process how SA is related to decision making and performance.

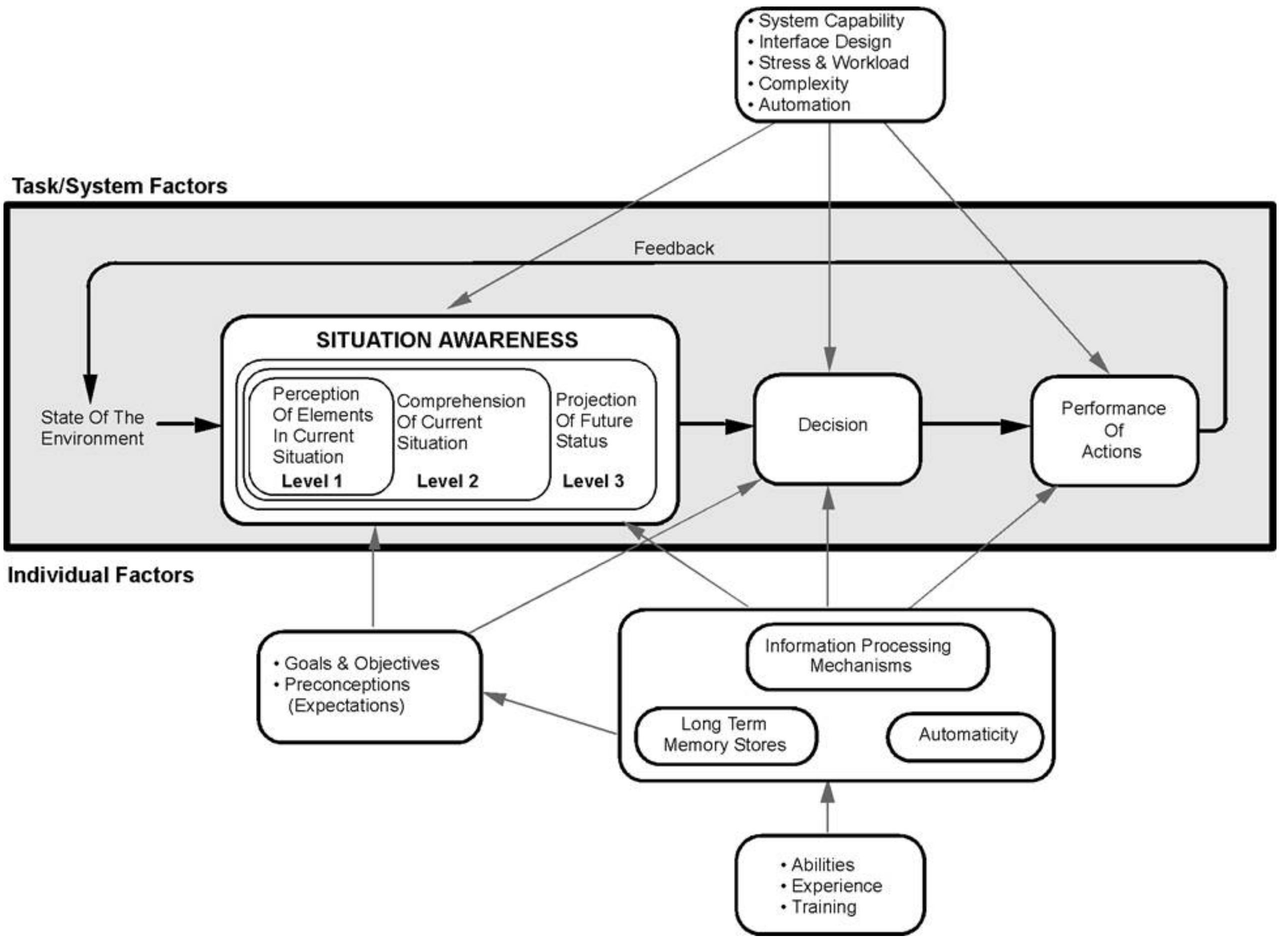


Figure 2.7 Levels of SA in relation to decision making and performance (Endsley 1995)

SA can be measured using several techniques. They can be divided into freeze probe, real-time probe, self-rating, observer-rating, and physiological techniques. A short description about each technique is provided in the sections that follow.

2.2.1.1 Freeze-Probe Technique

These are typically used in a simulation environment, where a scenario is paused and queries about the situation are asked. Usually, all operator displays are blanked and questions related to participant alertness are administered (Salmon et al. 2006). A commonly used freeze probe technique is the situation awareness global assessment (SAGAT) developed by Endsley in 2000. The SAGAT consists of queries designed to assess all three levels of SA. Freeze probe techniques are generally considered as highly intrusive as they interfere with the primary task. However, there has been no conclusive evidence regarding their level of intrusiveness (Salmon et al. 2006).

2.2.1.2 Real-Time Probe Technique

This involves administering the questions targeted at establishing SA without pausing/freezing the simulation. During the task, participants are presented with queries pertinent to the environment and their answers along with response times are noted. A commonly used real-time probe technique is the situation present assessment method (SPAM). Although, generally regarded as less intrusive than the free-probe technique, no conclusive evidence exists to support this claim (Salmon et al. 2006).

2.2.1.3 Self-Rating Technique

This technique involves administering questionnaires about SA after the completion of a task. They are relatively easy and cheap to administer. A commonly used self-rating technique is the situation awareness rating technique (SART). SART is a multidimensional scaling technique that consists of ten subscales each rated from one (low) to seven (high). The subscales include: Instability of situation, variability of situation, complexity of the situation, arousal, spare mental capacity, concentration, division of attention, information quantity, information quality, and familiarity. These ten subscales are categorized in three domains: attentional demand (D), attentional supply (S), and understanding (U). Situation awareness is then calculated by U-(D-S) (Selcon & Taylor 1989).

The main problem associated with self-rating techniques is the susceptibility of the entire results to the last performed task (sensitivity).

2.2.1.4 Observer-Rating Technique

This technique requires the presence of an expert to judge the level of SA of the participant. The observer provides a score based on the tasks performed in the field. The main advantage of this technique is that it is unintrusive. However, multiple observers (experts in SA) are required to ensure accurate results without being subject to individual observer bias. Also, the technique is relatively expensive due to the time required from several observers (Salmon et al. 2006).

2.2.1.2 Physiological Technique

Typical physiological technique used to measure SA is the eye-tracking. SA can be measured using gaze overlays, fixation patterns, and saccades. Studies have shown that analyzing fixation patterns and saccades can provide information on the relation between duration of fixation and the perception of objects/words (Just & Carpenter 1980). Eye-trackers are ideal for a simulation environment and provide real-time continuous data. Also, they are unintrusive and do not affect the performance of the primary task (Salmon et al. 2006). However, devices and relevant software can be very expensive.

2.2.2 Workload (WL)

Workload can be defined as the allocation of attention based on the mental resources available for information processing (Patten et al. 2006). The primary role of any driver is to safely navigate from point A to B. However, depending on environmental conditions, emergency situations that require sudden maneuverability, and driver characteristics like age, experience, and behavior, consume mental resources required by the driver to safely carry out the primary task of driving vary. These changes in WL can be used to represent how the driving performance is affected. WL has been measured using subjective, performance, and physiological methods. A brief description of each of these measures is discussed below along with their respective sensitivities to task demand.

2.2.2.1 Subjective Measures

Subjective measures are a data collection technique that uses questionnaires and surveys to pose questions to participants. Participants reply based on their individual experience on the topic in question. Questionnaires and surveys can be administered before, during, or after the study. Three most commonly used techniques to measure subjective WL are the NASA-task load index (TLX), driver activity load index (DALI), and the rating scale mental effort (RSME). Each technique is briefly discussed in the sections that follow.

2.2.2.1.1 NASA- Task Load Index (TLX)

The NASA-TLX is one of simplest and the most widely used subjective measure. The NASA-TLX questionnaire calculates WL experienced by participants as a weighted average of six subscales: mental demand, physical demand, temporal demand, performance, effort, and frustration experienced during the task, each on a 20-point scale ranging from “very low” to “very high” (Stojmenova & Sodnik 2015). Participants are then required to assign a weight, from 0 to 5, to a pair of subscales shown on flash cards (6 subscales resulting in 15 possible pairwise combinations). It is usually administered after the completion of a task or event and has been used in several WL studies. However, it has been shown that the answers to the questionnaire are strongly influenced by the last task performed (Stojmenova & Sodnik 2015). Also, the NASA-TLX does not provide time-varying data but instead relies on participant's memory and ability to recall events that have already occurred.

2.2.2.1.2 Driver Activity Load Index (DALI)

The NASA-TLX was specifically designed to capture WL of pilots. However, a modified version known as DALI was developed by Pauzie around 1994 to assess WL related to driving with and without secondary tasks. The DALI replaces some subscales from the NASA-TLX not applicable to driving. The six subscales for the DALI are: effort of attention, visual demand, auditory demand, temporal demand, interference, situational stress (Pauzie et al. 2008). Although the DALI was developed for driving, NASA-TLX is still more commonly cited and used to measure WL in simulation studies (Stojmenova & Sodnik 2015).

2.2.2.1.3 Rating Scale Mental Effort (RSME)

The RSME is conceptually similar to the NASA-TLX and DALI, however, it consists of a nine-point scale ranging from "absolutely no effort" to "extreme effort" (Sartang 2017). Participants mark their level of effort after completion of each task. It is relatively easier and cheap to use. However, not a lot of studies utilize RSME to compute WL with respect to driving thus not favored over the NASA-TLX.

2.2.2.2 Performance Measures

Performance measures are based on changes to variables collected from the drive. Examples of performance measures during the drive include; lane keeping ability, speed control, and car-following ability (De Waard 1996). De Waard in 1996 concluded that varying WL results in changes to speed, car-following parameters such as standard deviation of headway deviation, and lane keeping parameters such as standard deviation of lateral position (SDLP) and steering wheel movement. The main issue with performance measures is that they vary by task and the same measure sometimes cannot be used as a basis for comparison of WL (Sirevaag et al. 1993). For example, a driver might choose to slow down when observing a crash near the roadway, however, when driving through a work zone he/she might choose to focus more on keeping in their lane (SDLP). Ideally, performance measures should be coupled with other WL measures to provide a more holistic picture.

2.2.2.3 Physiological Measures

Physiological measures are used to assess mental workload from reactions within the human body. This type of measure provides exact results without interaction from other variables other than those being examined (De Waard 1996). Participants also do not need to reflect and fill questionnaires as data is continuous and readily available for the entire task. Most physiological measures focus on these four areas: heart, brain, eyes, and muscles. A brief description of measures in these areas is presented.

2.2.2.3.1 Heart

Electrocardiography (ECG) is primarily used in health care centers to monitor electrical activity in the heart and diagnose critical heart conditions such as attacks and arrhythmias. The ECG can be used to provide a continuous stream of data showing the impact of various driving tasks on the electrical activity of the heart expressed over a defined time period. ECG captures several variables than can be analyzed to assess workload and they include: heart rate (HR), heart rate variability (HRV), and Inter-Beat-Interval (IBI). Other devices such as heart rate monitors and chest straps can also be used to track changes to HR. However, they may be less accurate due to the lower sampling frequency. Both the ECG equipment and heart rate monitors/chest straps are considered as intrusive techniques because electrodes or contact points must be placed on the participant.

2.2.2.3.2 Brain

Electroencephalography (EEG) is a clinical technique used to measure changes in electrical activity in the brain. The brain is a complex organ that controls most of the functions in the human body. The EEG device uses electrodes attached to the scalp of an individual to detect changes in electrical charges arising from the activity in the brain cells. The following paragraphs discuss the various regions of the brain and their functions. The EEG electrode positions corresponding to the regions of the brain are discussed.

The brain can be divided into six regions: frontal lobe, parietal lobe, occipital lobe, cerebellum, temporal lobe and the brain stem, each responsible for different functions. The frontal lobe is the most anterior region of the brain, located in the forehead. It is responsible for problem solving, emotions, response, reasoning, and consciousness. The parietal lobe is located at the same level behind the frontal lobe. The parietal lobe is responsible for controlling sensory functions such as voluntary movements, touch, and visual attention. The occipital lobe is the most posterior region of the brain and is responsible for anything related to vision. The cerebellum is located at the base, in line with the ears and is responsible for coordination and balance. The brain stem is located deep in the center of the brain and links directly to the spinal cord. Figures 2.8a and 2.8b show the different regions of the brain.

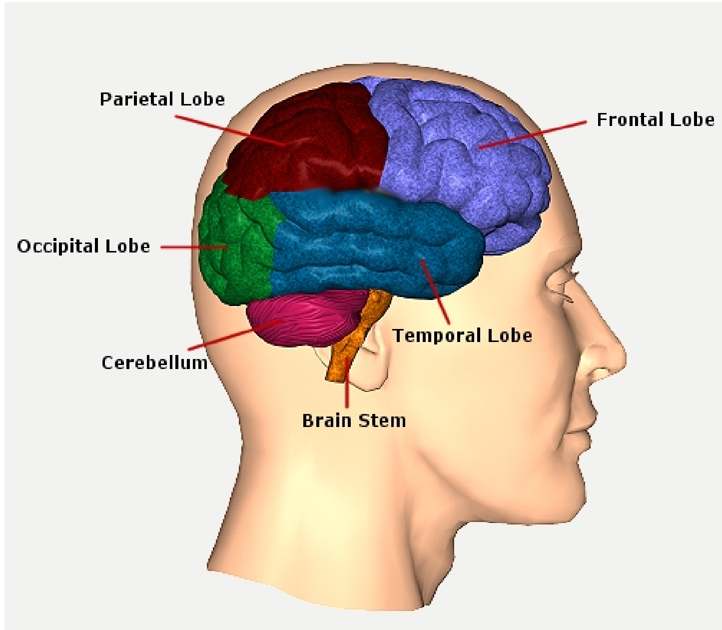


Figure 2.8a Regions of the brain (Lehr 2015)

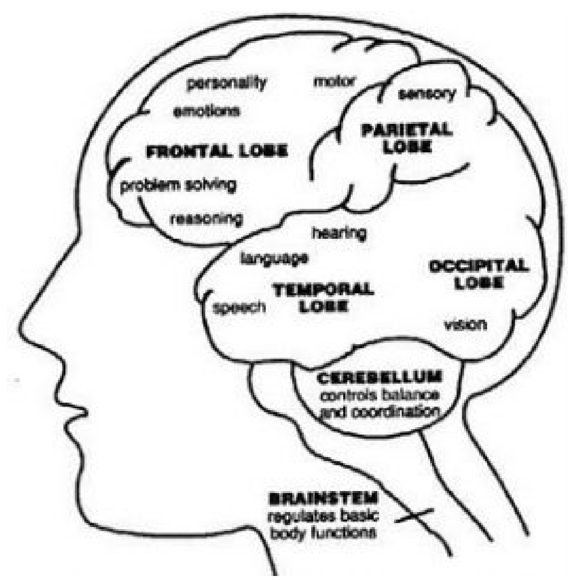


Figure 2.8b Regions of the brain (Lehr 2015)

The EEG electrodes are placed in positions shown in figure 2.9. The first alphabet in each position refers to a region of the brain. For example: the frontal lobe is represented by the letter

“F”, parietal lobe by the letter “P”, temporal lobe by the letter “T”, occipital lobe by the letter “O”. However, the letter “C” does not represent the cerebellum. Other letters such as “FP” represent the frontopolar and “A” represents the auricular (ear electrode).

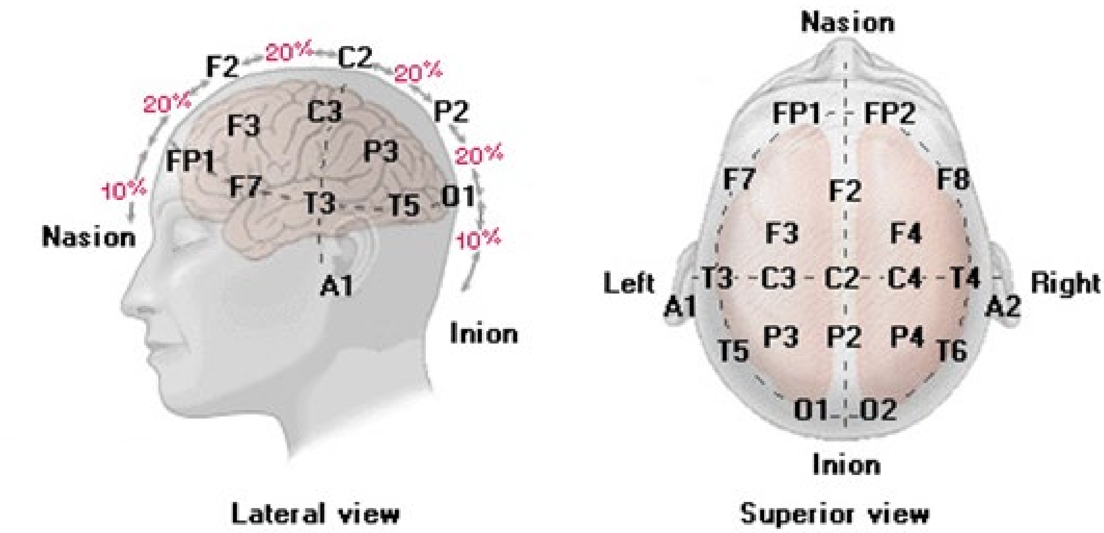


Figure 2.9 EEG electrode positions

2.2.2.3.3 Eyes

Eye-tracking devices that track eye movement of the driver without disrupting the primary task of driving are very useful in determining the areas of focus of the driver. Some advanced devices are also capable of tracking pupil dilation—the phenomenon causing changes to the pupil diameter due to varying levels of cognitive workload, also known as task-evoked pupillary response (TEPR) (Devos et al. 2017, Strayer et al. 2013). This can be used to assess cognitive workload continuously throughout a drive. Software analyze the patterns observed and compare it to baseline conditions to identify any changes resulting from the task.

2.2.2.3.4 Coordination between Vision and Muscles

These measures typically require participants to react to a visual or sensory stimulus. Common measures include:

The peripheral detection task (PDT) presents visual stimuli throughout various locations in a driving scenario. Stimuli are presented as small colored squares or circles. Participant's reaction time to detect and respond to the task by pressing a button (coordination between vision and muscle), usually on the steering wheel, is measured (Patten et al. 2004).

The detection response task (DRT) is a more refined version of the PDT and was primarily devised to determine the effect of a secondary task on WL. The DRT equipment presents frequent artificial stimuli during a task and records participant performance in the form of response time, hit rate, and miss rate (ISO 17488 2016). There are three types of DRT stimuli commonly used in studies. The head-mounted light-emitting diode (LED), fixed LED location mounted inside a vehicle, and a tactile electrical vibrator attached to the driver's shoulder (ISO 17488 2016). As the stimuli are presented, participants are required to acknowledge them using a micro-switch, typically attached to the thumb. Changes to the response time, hit rate, and miss rate of stimuli are analyzed to determine the intensity of WL being experienced. However, because both the PDT and DRT present simultaneous alternative tasks for the driver to complete, they compete with the primary task of driving thus not very effective in establishing actual WL.

2.2.2.4 Sensitivity of the Various Measures

De Waard observed that some WL measures were sensitive at a particular intensity of the task demand than others. This can be clearly observed in figure 2.10. However, it can also be noted that most measures are only sensitive at high WL and not during low WL. De Waard concludes that one measure of WL might not be a sufficient representation for the entire task and multiple measures would provide a better basis for comparison.

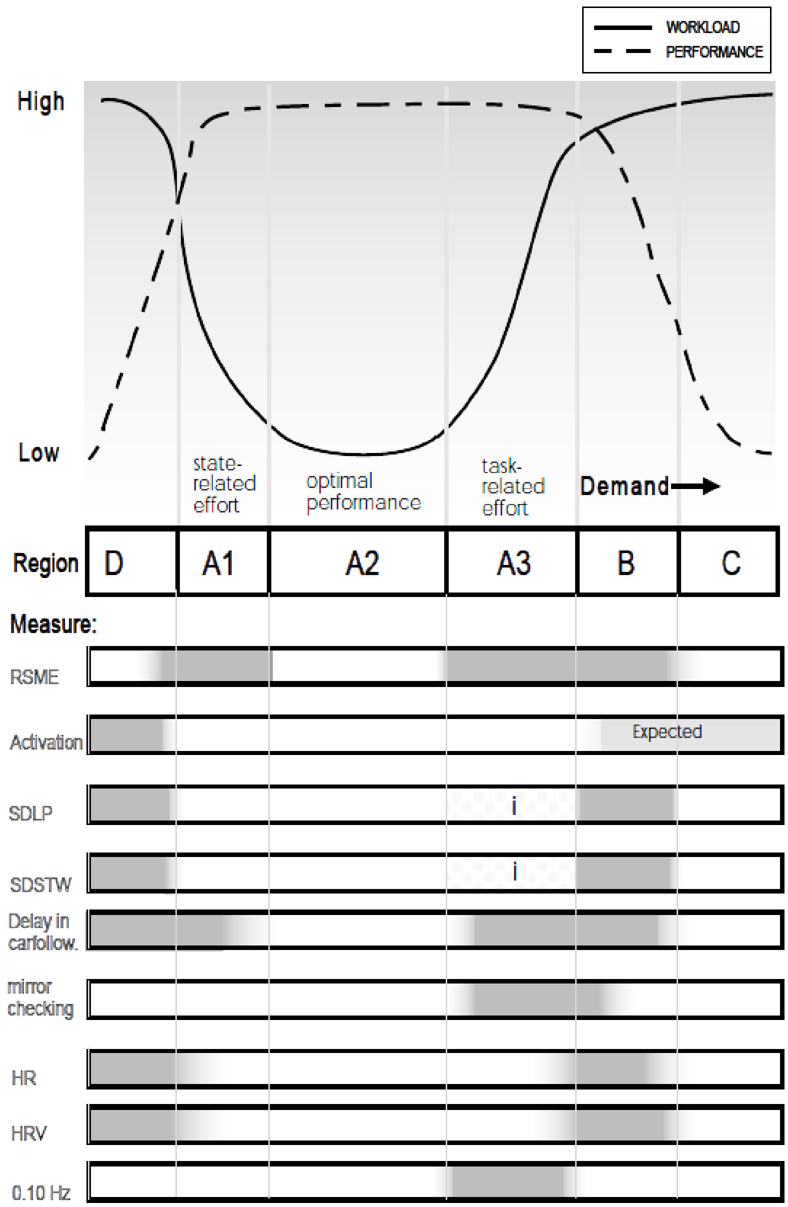


Figure 2.10 Sensitivity of workload measures (De Waard 1996)

Where, SDLP is the standard deviation of lateral position and SDSTW is the standard deviation of steering wheel movements.

2.2.3 Level of Activation (LA)

The level of activation or arousal has been identified by several researchers as a key measure of engagement, motivation, and enthusiasm involved in responding to a task. The LA is directly related to the ability of an individual to perform the task of driving (Tampere et al. 2009). However, the LA is not only affected by the primary task of driving, but also by secondary tasks such as cell phone use and operating the media controller or navigation system (Tampere et al. 2009).

De Waard and Brookhuis (1991), suggested measuring LA using the three classic EEG bands: theta, alpha, and beta, representing the frequency ranges 4-7 HZ, 8-13 HZ, and 14-30 HZ, respectively. To prevent susceptibility to isolated changes, De Waard and Brookhuis proposed combining the spectral power of all three bands (filtered and divided into epochs) using the formula $(\alpha+\theta)/\beta$ (De Waard & Brookhuis 1991). Prinzel III et al. in 2001, identified the electrode positions P3, PZ (P2), P4, CZ(C2) to capture the "engagement index" of a driver, also known as the LA.

A study by Tejero and Choliz in 2002 used the EEG Fourier spectral power analysis suggested by De Waard and Brookhuis in a real-world driving study. Participants were required to drive 90 km on a highway while being monitored by researchers. The study showed that LA increased with varying speed than when keeping at a constant speed. They concluded that the act of modifying speed creates a source of engagement thus increasing the LA of the driver.

2.3 Relationship Between WL, SA, LA and Performance

The relationship between WL and task demand is well established by several studies. De Waard suggests a U-function as shown in figure 2.10, where WL initially starts off at high and decreases as the task gets familiar. As the task difficulty gradually increases, there might not be any significant changes to WL until a threshold is reached (region A3). After, WL increases steeply with increase in task demand (regions with high sensitivity and easy measurability of WL) and performance slump is recorded (De Waard 1996).

From figure 2.11, it can be seen as WL increases, the LA also increases. However, the relationship is not entirely linear.

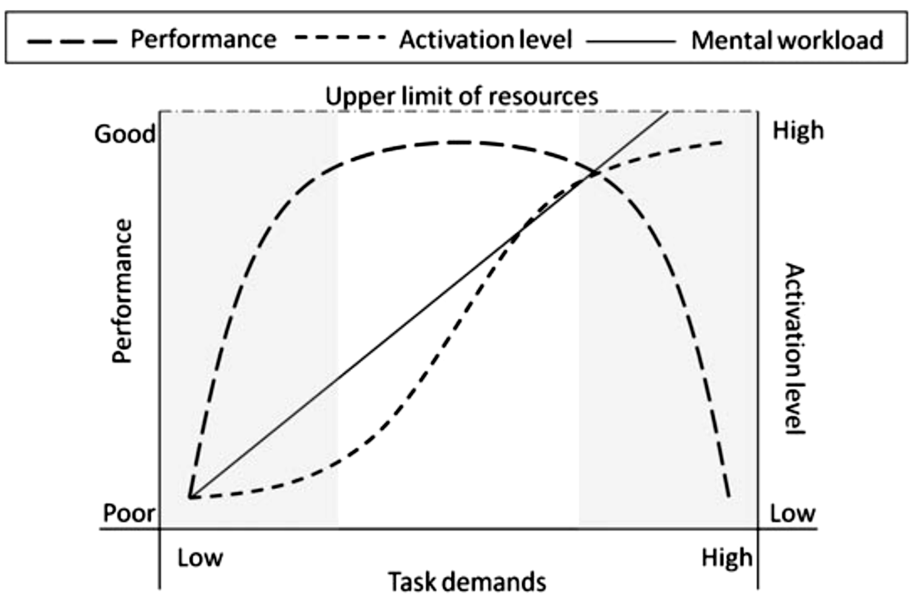


Figure 2.11 Relationship of WL, LA, and performance (Young et al. 2015)

Zhang and Kumada, in 2017, studied the relationship between WL and mind wandering. The experiment was performed in a low-fidelity driving simulator. 40 participants drove a 25-minute scenario with car-following tasks. A real-time probe was applied randomly and participants rating of mind wandering was recorded. After the completion of the scenario, NASA-TLX was completed to establish the WL. The study also correlated the measured WL to performance measures such as the standard deviation of lateral position (SDLP) and standard deviation of steering wheel movement (SDSTW). No significant relationship was seen between the performance measures and WL.

From figure 2.12, it can be clearly established that as WL increases, mind wandering decreases. Mind wandering can be directly attributed to SA. However, from this experiment, the levels of WL are not clear. It would seem that it only captures the region between low and high WL.

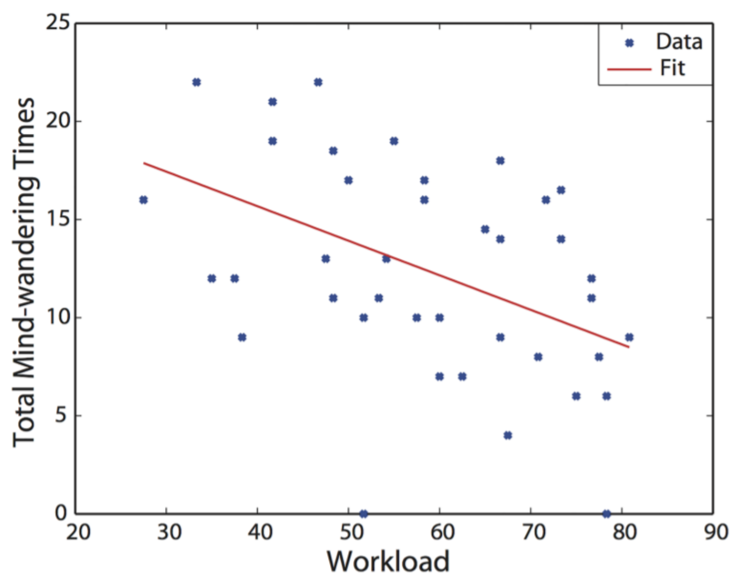


Figure 2.12 Mind wandering and WL (Zhang & Kumada 2017)

In general, it can be theorized that high levels of WL indicate low SA, but low levels of WL do not necessarily indicate a high level of SA. In situations with low to medium WL, SA increases gradually before reaching an optimum and decreasing sharply. Also, both WL and SA are dependent on LA.

Chapter 3 Methodology

The methodology is divided into two main phases. The first phase involves a simulator study to establish different levels of driver classification through performance parameters and biobehavioral trends and the second phase incorporates the classifications with their subsequent biobehavioral parameters into car following models. A framework for the proposed methodology is provided in figure 3.1.

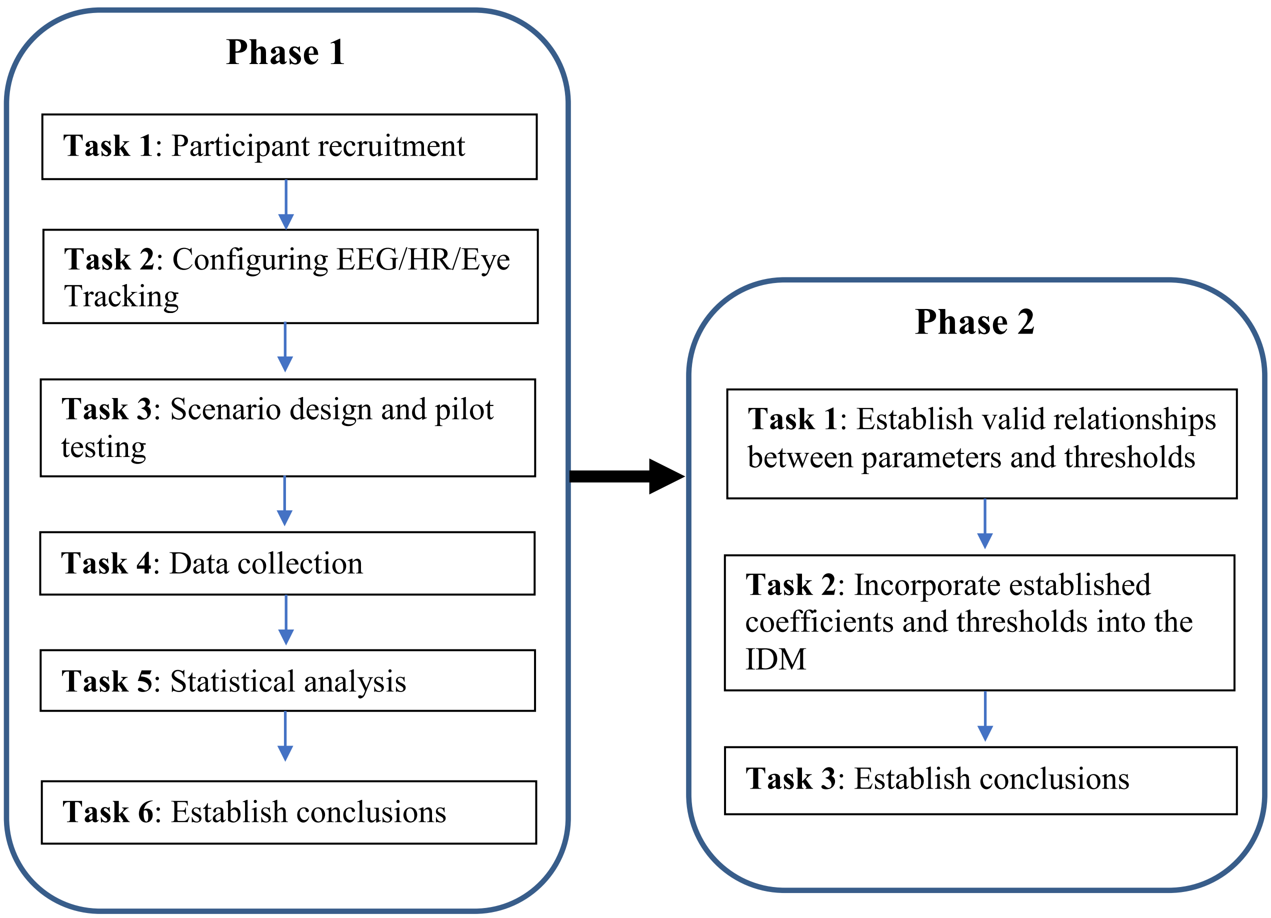


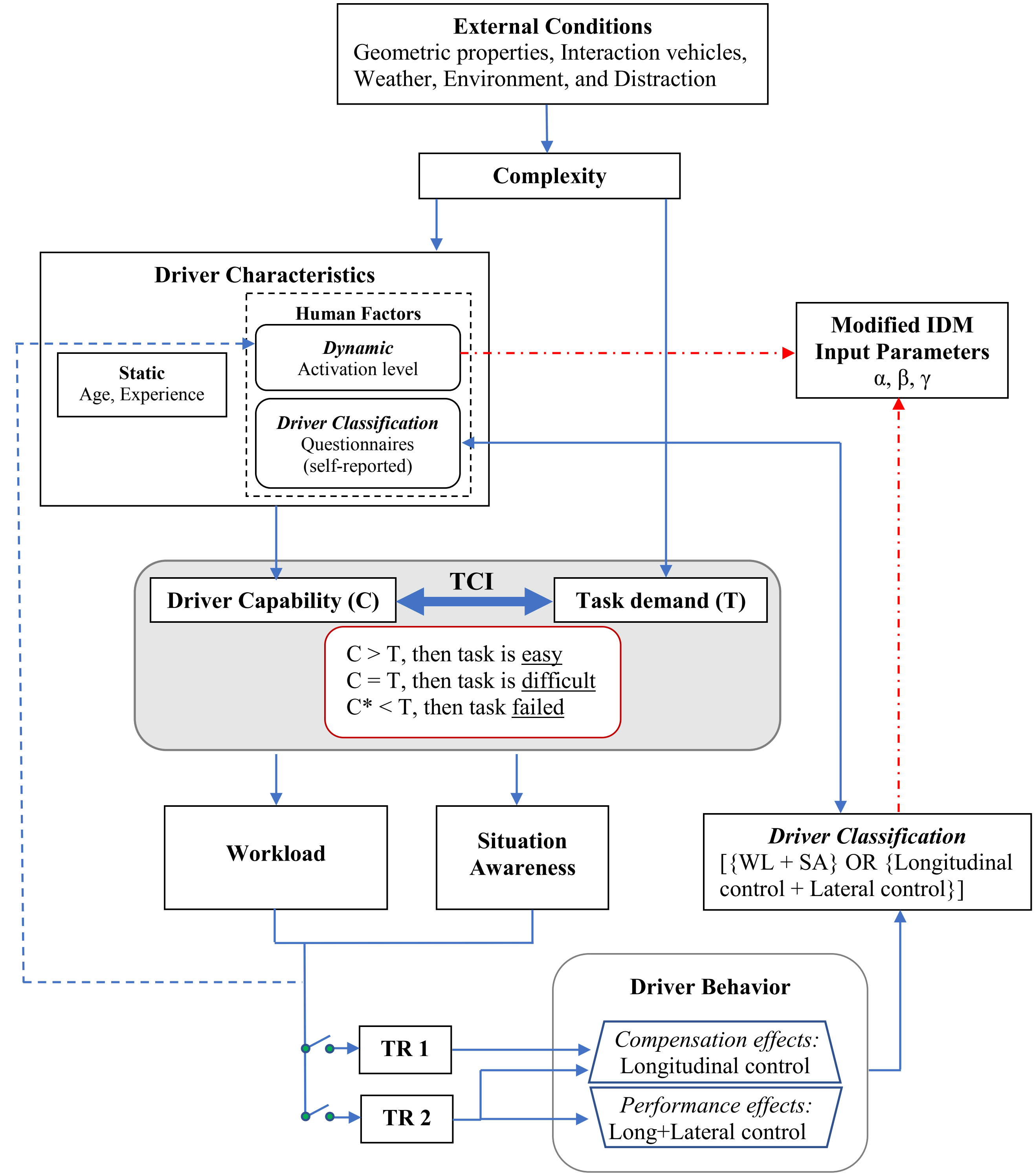
Figure 3.1 Methodological framework

The theory behind developing a framework that can be used to incorporate biobehavioral parameters such as LA, WL, and SA, with respect to changes in driving performance is explained in the paragraphs that follow.

The external conditions in a specific scene contribute towards the complexity of the driving task at hand. Differences in conditions, such as the geometric properties, weather, number of interaction vehicles, and sources of distraction, add a complexity to the driving environment. The capability of the driver to handle tasks of varying complexity, mostly depend on his/her physical and mental characteristics. For example: it can be expected that older drivers have slower reaction times than younger drivers due to their diminishing physical capabilities. Also, some individuals may prefer to drive faster and follow smaller headways (aggressive), while others tend to be more conservative. Static and dynamic characteristics are identified as distinguishable variables between drivers. Where the age and experience of the driver coupled with the activation level can affect driving performance. Activation level describes the driver arousal state before and during the drive e.g. a drowsy or less motivated driver will have a lower activation level than an active driver.

Also, the capabilities of the driver and the demands of the task are closely related. If the capabilities of the driver are greater than those required by the task, then the task will be easily completed (Hoogendoorn et al. 2012). It also means that, drivers can complete this task at a lower activation level and by utilizing fewer mental resources (WL). If the capability of the driver is equal to the task demand, the task becomes difficult as the driver is using all the available capabilities to successfully complete the task (Hoogendoorn et al. 2012). The driver will require a higher LA and alertness to complete this task. However, if the capability of the driver is less than that required by the task, then the driver will fail to complete the task. The capability of the driver is also constrained by the physical capability/condition of the vehicle.

The interaction between driver capability and demand can be quantified with respect to the changes in WL and SA. Slight imbalance between the WL and SA can result in the driver compensating by adjusting longitudinal control variables such as speed, acceleration, and headway. For example: if a task is challenging (increased WL), the driver might choose to reduce his/her overall speed or increase his/her headway in order to be safe and maintain a comfortable level of SA. In essence, he/she is compensating for the lack of capabilities at that instance, by making these changes to the driving. This leads to a trigger that is activated through small imbalances between WL and SA (TR 1) as seen in figure 3.2. However, if the imbalance between driver capability and task demand is high, e.g. task is hard to be successfully completed by the driver's current capability, the driver tries to restore this imbalance resulting in both compensatory and performance effects (setting off TR 2). Compensation effects are theorized to only affect longitudinal driving variables while performance effects are theorized to affect longitudinal and lateral (standard deviation of lateral position, standard deviation of the steering wheel position) driving variables.



C* = min {VC_{max} or C}. Where VC is the capability of the vehicle.

Figure 3.2 Theoretical framework for classifying drivers and incorporating biobehavioral parameters

Drivers will also be categorized by behavioral (LA, WL, SA) and static characteristics (age, experience, number of speeding tickets, number of accidents), into three groups: conservative, average, and aggressive. The resulting effect of the driver trying to match his/her capability to the task demand will be used to establish how a conservative or aggressive driver will react to a task when compared to an average driver. Will the aggressive driver experience lower workload, implying lower compensation and performance effects, while completing a difficult task? Or will aggressive drivers increase the speed and follow shorter headways during an easy task, to increase the level of difficulty to match their capability accordingly? The established classifications will also be compared to the driving performance variables such as average speed, average headway, and maximum acceleration, to measure the accuracy of self-perception in driver classification.

Based on this description, the theoretical framework in figure 3.2 for classifying drivers using characteristics, physiological, and behavioral parameters is established.

3.1 Proposed Modification to the IDM

In order to incorporate the theoretical framework shown in figure 3.2, modifications to the IDM are required. The IDM parameters that can be affected by an imbalance in the task-capability interface are assumed to be the desired speed and desired time gap. This assumption is made because the desired variables capture what the driver wants to do at that moment but is not able to due to a higher than normal task demand. Equations 3.1 and 3.2 show how the overall acceleration of the IDM will be modified when triggers 1 or 2 are activated.

Compensation only (TR 1):

$$a_n(t) = a_{max}\left[1 - \left(\frac{v_n(t)}{(\alpha + \beta)v_0(t)}\right)^{\delta} - \left(\frac{s^*{}_n(t)}{s_n(t)}\right)^2\right] \tag{3.1}$$

$$s^*{}_n(t) = s_0 + (\alpha + \beta)T_n v_n(t) + \frac{v_n(t)\Delta v_n(t)}{2\sqrt{a_{max}b_{comf}}}$$

Where,

α = Compensation coefficient

β = Activation level coefficient

Compensation and Performance (TR 2):

$$a_n(t) = a_{max}\left[1 - \left(\frac{v_n(t)}{(\{\alpha + \gamma\} + \beta)v_0(t)}\right)^{\delta} - \left(\frac{s^*{}_n(t)}{s_n(t)}\right)^2\right] \tag{3.2}$$

$$s^*{}_n(t) = s_0 + (\{\alpha + \gamma\} + \beta)T_n v_n(t) + \frac{v_n(t)\Delta v_n(t)}{2\sqrt{a_{max}b_{comf}}}$$

Where,

γ = Performance coefficient

Together with incorporating compensation, LA, and performance coefficients, a visual cue parameter that incorporates the effect of active brake lights (*bl*) on the lead vehicle is implemented to the model. When brake lights are activated on the leader and the time-gap ($T(t)$) between the leader and follower at time (t) is less than the desired time-gap (T_n), the modified IDM model recalculates the car-following trajectory using the acceleration/deceleration ($a(t)$) at that instance. However, if $T(t)$ is greater than T_n, it can be assumed that the driver does not apply brakes or accelerate, resulting in a uniform deceleration of -0.2m/s^2 (Kesting & Treiber 2013). $T(t)$ and T_n are used to establish constraints because it can be assumed that drivers can more readily perceive time-gaps than the acceleration of the leader. Equation 3.3 shows the implementation of brake light parameter along with the resulting acceleration/deceleration.

$$bl = \begin{cases} 1 & On, \\ 0 & Off. \end{cases}$$

$$\text{If } bl \; = \; 1 \text{ then, } \; a_n(t)^* = \begin{cases} a(t) & 0 \leq T(t) \leq T_n \\ -0.2\, m/s^2 & T_n \leq T(t) \leq 5 \end{cases} \tag{3.3}$$

Where, $a_n(t)^*$ describes the starting acceleration/deceleration during car-following computations. Any brake light observed from a time-gap of greater than five seconds will not be considered as this will be the threshold to represent active car-following.

3.2 Data Collection Techniques

A list of the techniques that will be used during data collection to establish the coefficients α, β, and γ are listed in table 3.1.

Table 3.1 Measuring techniques aggregated by the coefficient

Coefficient	Methodological Definition	Measuring Event/Technique
α	Compensation coefficient	*Measuring WL:* • HR • Pupil dilation • NASA-TLX *Measuring SA:* • Gaze overlay *Measuring longitudinal control:* • Speed • Headway • Acceleration
β	LA coefficient	EEG
$\alpha + \gamma$	Compensation + Performance coefficient	*Measuring WL:* • HR • Pupil dilation • NASA-TLX *Measuring SA:* • Gaze overlay *Measuring longitudinal control:* • Speed • Headway • Acceleration *Measuring lateral control:* • SD of steering wheel position • SD of lateral position

Chapter 4 Data Collection Plan

This section discusses the design of the scenarios and the strategies that will be followed during data collection.

4.1 Participant Recruitment

The study was first submitted to the Human Research Protection Program (HRPP) at the University of Kansas (KU), for approval. The study was then advertised to attract potential participants through flyers around Lawrence, social media websites, and email announcements. 90 participants will be recruited to participate in this research, equally split between males and females. The participants will be divided into three age groups 18-24, 25-49, and 50-65 years. Participants will be screened using a questionnaire to determine their age, driving experience, susceptibility to motion sickness, health conditions, and other aspects of driving such as gap acceptance, merging behavior, speed preferences, and lane changing preferences. Based on static and dynamic characteristics, drivers will be divided into the following three categories: conservative, average, and aggressive. This information will later be used to check if participants are able to correctly gauge their driver classification level.

Participants are required to complete a 45-minute screening questionnaire, covering the demographic information, medical conditions, driving preferences and history, mood and personality measure, empathy and moral decision-making measures, and attention and executive function measures. The internet information statement for this survey is shown in Appendix A.

4.1.1 Mood and Personality Measure

There are several measures available through the literature that provide mood and personality assessments such as:

- Positive and Negative Affect Schedule (PANAS): The PANAS is a self-report measure designed to assess both positive and negative affect (Watson et al. 1988). The PANAS consists of 20 adjectives pertaining to negative affect (i.e., distressed or nervous) and positive affect (i.e., excited or proud), with ten items for each subscale. Items are rated on a five-point Likert scale: 1 = "Very slightly or not at all" to 5 = "Extremely." The subscales are obtained by taking the average of each item within that subscale.
- Need for Cognition: This test is designed to assess the tendency to engage in and enjoy effortful cognitive endeavors (Cacioppo et al. 1984).
- Cognitive Reflection Task: This questionnaire assesses individuals' ability to suppress an intuitive and spontaneous wrong answer in favor of a reflective and deliberative right answer (Frederick 2005).
- Neuroticism-Extroversion-Openness Five Factor Inventory: this is a 60-item survey to measure the five primary personality characteristics of openness, conscientiousness, extraversion, agreeableness, and neuroticism (Costa & McRae 1989).

4.1.2 Empathy and Moral Decision-Making Measures

- Interpersonal Reactivity Index (Davis 1983). This questionnaire measures individual differences in empathy.
- The Empathy Quotient (Baron-Cohen & Wheelwright 2004): This questionnaire also measures individual differences in empathy.
- Psychological Entitlement Scale (Campbell et al. 2004): This scale measures psychological entitlement, which refers to the stable and pervasive sense that one

deserves more and is entitled to more than others. This sense of entitlement will also be reflected in desired or actual behaviors. The concept of psychological entitlement is intrapsychically pervasive or global; it does not necessarily refer to entitlement that results from a specific situation (e.g., “I am entitled to social security because I paid into the system,” or “I deserve an ‘A’ because I performed well in class”). Rather, psychological entitlement is a sense of entitlement that is experienced across situations.

- Ethical dilemmas such as the Trolley/Footbridge Dilemmas: These are short vignettes describing different scenarios and the participant has to decide or evaluate the 'right' course of action. The tasks are meant to measure moral decision making in context.

4.1.3 Attention and Executive Function Measures

- Stroop Task (Stroop 1935): This is a classic measure of cognitive inhibition in cognitive control.
- Eriksen Flanker task (1979): This is a classic measure of attention.

4.2 Configuring the EEG, HR Monitor, and Eye Tracker

The LA (arousal) is a key variable in this research. Changes in the LA has been directly associated with the changes in neural activity occurring in the driver’s brain (Brookhuis et al. 1991). The EEG will be used to monitor any changes in activation level associated with the various tasks presented during the drive. It will also be used to capture an initial state of mind of the driver at the beginning of the drive.

During the drive, participants’ overall attentional trajectory will be captured using the EEG at a sampling frequency of 500 HZ. A portable, lightweight, wireless, and rechargeable system for EEG recording is available for this project. The system (Enobio) allows for the reliable reproduction of EEG, EOG, and EMG signal with a rapid setup that takes less than 5 minutes and is optimal for multi-component, multi-method studies. The accompanying software allows for visualization of time-frequency 2D/3D features (3D EEG scalp map) in real time, including the power spectrum and spectrograms, as well as easy channel labeling. The software further provides continuous online EEG signal quality.

The HR monitor used is the Polar H10 chest strap that collects heart rate at 1 HZ. Participants will be shown how to properly place the device along their chest to ensure accurate data collection.

Fovio-FX3 eye tracker is installed inside along the dashboard of the simulator chassis. This collects cognitive workload through TERP at 60 HZ. Also, SA is tracked by overlaying the gaze of the participants with respect to the object in sight, fixation patterns, and saccades.

4.3 Scenario Design and Pilot Testing

A preliminary driving scenario is designed with two phases: free driving and following. The free driving phase captures the participant's desired speed and maximum acceleration components on an empty highway, while the following phase captures the participant's desired time-gap. Each phase is designed to be driven at both 55 mph and 75 mph speed limit, to capture the variability.

The actual driving scenario is designed to last 35 minutes and consists of approximately 40 miles of roadway. A breakdown of the full appointment schedule of the participant is shown in table 4.2.

Table 4.2 Time breakdown by activity

Description	Expected Time
Consent form explanation	**3 minutes**
Equipping participants with EEG & HR	**5 minutes**
Baseline EEG data: Watching short video	**5 minutes**
Introduction to simulator driving	**2-7 minutes**

Preliminary scenario:

Free driving (no other roadway traffic) with 55 mph and 75 mph speed limits	5 minutes
Following (one lead vehicle): lead speed changes from 55 mph to 75 mph	5 minutes
Total time	**10 minutes**

Actual scenario:

Traffic density	**Scenario Type**		
	1	**2**	**3**
Level 1 (Medium)	2 mins no weaving activity + 5 mins	5 minutes	5 minutes
Level 2 (High)	2 mins no weaving activity + 5 mins	5 minutes	5 minutes
Total time	**35 minutes**		

NASA-TLX + SA Questionnaires	**15 minutes**

Total anticipated duration = 80 minutes

The actual scenario incorporates six tasks with varying levels of difficulty (three types and two levels of traffic density) on a four lane-divided highway with a grass median. The participant is asked to follow the lead vehicle in each of these tasks. At the completion of each task, the participant is required to fill out the NASA-TLX and SA questionnaire.

Type 1: Low weaving activity

The first type is designed to capture driving performance at lower task difficulty. Participants are required to follow a car ahead of them at 75 mph while driving on the right lane. Low weaving activity occurs in the left lane with approximately three cars per mile changing lanes ahead of the car-following lead vehicle.

Type 2: Active work zone-left shoulder closed and medium weaving activity

The second type is designed to capture driving performance at a slightly higher task difficulty with an active work zone that closes the left shoulder of the roadway. The idea is to alter the driver's WL and SA. Participants are also required to follow a car ahead of them at 75 mph while sticking to the right lane. Medium weaving activity occurs in the left lane with approximately five cars per mile changing lanes ahead of the car-following lead vehicle.

Type 3: Active work zone-left shoulder closed and high weaving activity

The third type is designed to capture driving performance at a higher task difficulty with an active work zone that closes the left shoulder of the roadway. However, high weaving activity occurs in the left lane with approximately ten cars per mile changing lanes ahead of the lead vehicle.

Each scenario type is driven at two levels of traffic density, to further increase the number of task difficulty variations. The actual scenario is counter balanced by randomizing the order in which the scenario types and traffic density levels appear to each driver. Figure 4.1 shows the layout of the designed highway (T1, L1 represents scenario type 1 and traffic density level 1).

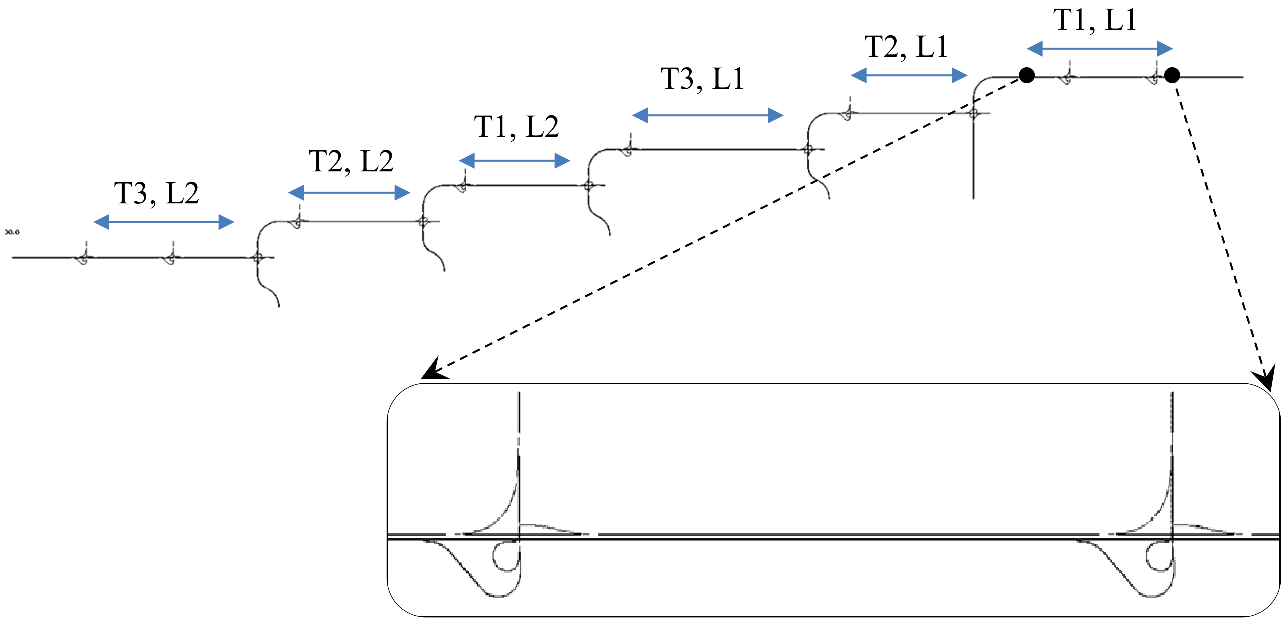


Figure 4.1 Highway layout of the actual scenario

Pilot testing will be carried out on five participants to establish any design flaws in the scenario and assess the quality of data output. Any identified flaws will be corrected to ensure a smoother experiment.

4.4 Data Collection

The data will be collected using the KU driving simulator, a fixed-based simulator in an Acura MDX chassis (half cab). The simulator provides a 170° horizontal field of view as shown in figures 4.2 and 4.3, with three forward screens and one rear screen. The rear screen renders the view of both side-view mirrors and the rear-view mirror, providing an immersed driving experience.

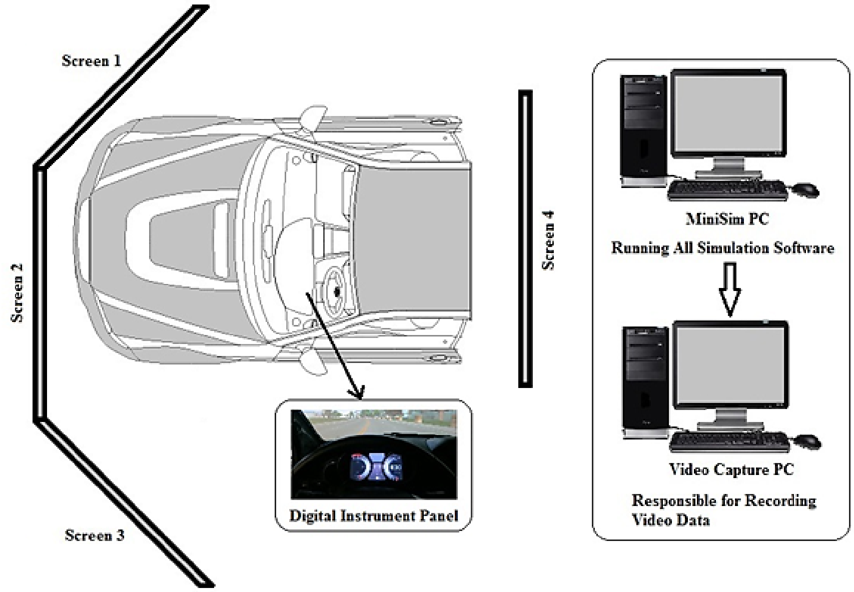


Figure 4.2 Layout of the KU driving simulator

The simulation run and respective data are recorded on the MiniSim computer while the video of the participant's drive is captured on the video capture computer.

Figure 4.3 KU driving simulator in action

Data will be obtained in three formats: subjective, driving variables, and physiological. The subjective data will be collected using paper and online questionnaires such as the screening questionnaire, NASA-TLX, and SA questionnaires. Driving variables will be the outputs from the simulator and they include: average speed, maximum speed, average headway, minimum headway, maximum acceleration, maximum deceleration, standard deviation (SD) of lateral position, SD of steering wheel position, number of collisions, maximum brake force, and average brake force. Physiological variables will be obtained using the EEG, HR monitor, pupillometry, and gaze overlay.

4.5 Analysis Plan

All participants are required to complete all six driving tasks that represent increasing task difficulty. This represents a within-subjects design with the independent variable being task difficulty. The dependent variables will be the output from the driving simulator and physiological variables.

The null hypothesis for this research is that changes in task difficulty do not result in changes to WL and SA and cannot be directly correlated to performance measures thus providing no basis for incorporating these into the IDM. A significance level of 95% will be used to substantiate any evidence. A paired t-test will be used to compare variables obtained at each difficulty level with those obtained from a baseline difficulty consisting of no significant visual or mental load.

The analysis plan involves performing a cluster analysis to establish the different behavioral thresholds for the drivers that participated in the study. First, the clusters will be created using subjective data from self-reported questionnaires. These clusters will then be correlated to those obtained by using performance measures collected from the drive.

The level of activation, compensation, and performance coefficients will be obtained by normalizing the data obtained from each technique listed in table 3.1. Various variable interactions will be tested to determine those which result in the best goodness of fit to the simulation data. Data from 69 drivers will be used for model development (determining which combination of measurement techniques yields the best results for the modified IDM used to better approximate simulation collected results) while the remaining 21 drivers will be used for validation.

Chapter 5 Summary and Future Plan

In summary, the previous chapters provide a comprehensive literature review of existing car-following models with specific attention to the IDM and how it has been previously modified to incorporate biobehavioral parameters along with the strategies to collect and measure these parameters. The proposed methodology and developed framework of the theoretical model is then discussed in chapter 3. A detailed section describing the data collection plan with respect to the driving simulator, questionnaires, and physiological measures is presented in chapter 4. Appendix A, B, C, D consist of the internet information statement, IRB approval letter, flyer to recruit participants, and the informed consent form, respectively.

Table 5.1 shows the proposed timeline for all remaining tasks. The timeline accounts for unforeseen changes that might be made to the statistical analysis to provide a better representation of the data. A final report detailing all the tasks performed during the next year will be submitted in December.

Table 5.1 Timeline for the next year

	2018	2019											
Tasks	DEC	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
Pilot Testing													
Design Adjustment													
Finalizing Participants													
Data Collection													
Statistical Analysis													
Unforeseen Changes													
Draft Final Report													
Deliverables	**FR1**	**QR**			**QR**			**QR**			**QR**	**DFR**	**FR2**

Where, DFR: Draft report, QR: Quarterly updates, FR1: Final report phase 1, FR2: Final report phase 2.

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Appendix A: Internet Information Statement

Internet Information Statement

The Department of Civil, Environmental and Architectural Engineering at the University of Kansas supports the practice of protection for human subjects participating in research. The following information is provided for you to decide whether you wish to participate in the present study. You should be aware that even if you agree to participate, you are free to withdraw at any time without penalty.

The research is part of a Mid-America transportation Center (MATC) project and will be used to analyze driver behavior and aggressiveness. The findings of this research will help us better understand how driver behaviour and aggressiveness are linked to changes in driving performance and workload. The study will entail your completion of a questionnaire. The questionnaire packet is expected to take approximately 45 minutes to complete.

The content of the questionnaire should cause no more discomfort than you experience in your everyday life. Additionally, we believe that the information obtained from this study will help us gain a better understanding of how people behave when they drive. Your participation is solicited, although strictly voluntary. Your name will not be associated in any way with the research findings. It is possible, however, with internet communications, that through intent or accident someone other than the intended recipient may see your response.

If you would like additional information concerning this study before or after it is completed, please feel free to contact us by phone or mail.

Completion of the survey indicates your willingness to participate in this project and that you are at least age eighteen. If you have any additional questions about your rights as a research participant, you may call (785) 864-7429, write the Human Research Protection Program (HRPP), University of Kansas, 2385 Irving Hill Road, Lawrence, Kansas 66045-7563,
or email irb@ku.edu.

Eligibility Criteria:

Participants are required to be between the ages of 18 and 65 years. Participants are selected based on possession of a valid US driver's license with at least 3 years of driving experience and no less than 5000 miles of annual driving. Participants with any significant heart conditions or at any stage of pregnancy will not be approved for the study. Also, participants with medical conditions such as severe motion sickness or a history of seizures will not be approved for participation in the study.

Sincerely,

Dr. Alexandra Kondyli, PhD
Principal Investigator
Department of Civil, Environmental, and Architectural Engineering
1530 W. 15th Street | 2159A Learned Hall
University of Kansas, Lawrence, KS 66045
(785) 864-6521

KU Lawrence IRB # STUDY00142724 | Approval Period 7/17/2018 – 7/16/2019

Appendix B: IRB Approval Letter

THE UNIVERSITY OF KANSAS
Research

Date: July 17, 2018

TO: Vishal Chandra Kummetha, (kummetha@ku.edu)

FROM: Jocelyn Isley, MS, CIP, IRB Administrator (785-864-7385, irb@ku.edu)

RE: **Approval of Initial Study**

The IRB reviewed the submission referenced below on 7/17/2018. The IRB approved the protocol for one year, effective 7/17/2018. Approval expires on 7/16/2019.

IRB Action: APPROVED	**Effective date: 7/17/2018**	**Expiration Date : 7/16/2019**
STUDY DETAILS		
Investigator:	Vishal Chandra Kummetha	
IRB ID:	STUDY00142724	
Title of Study:	Modeling Driver Behavior and Driver Aggressiveness Using Biobehavioral Methods	
Funding ID:	Name: US Dept of Transportation, Funding Source ID: 69A3551747107	
REVIEW INFORMATION		
Review Type:	Initial Study	
Review Date:	7/17/2018	
Documents Reviewed:	• Enobio 8 (EEG device manual).pdf, • Flyer_study advertising, • Hear rate monitor manual (polar HR10).pdf, • HIPAA completion-vishal.pdf, • HRPP_Consent form_amended , • Human Research Protocol_Aggressiveness Study_Amended, • Internet information statement_amended, • NASA TLX (Workload questionnaire), • Participant selection email.pdf, • Pre-screening and post screening surveys, • Social and behavioral research completion-vishal.pdf, • Wellness Questionnaire.pdf	
Expedited Category(ies):	• (6) Voice, video, digital, or image recordings • (4) Noninvasive procedures • (7)(b) Social science methods • (7)(a) Behavioral research	
Special Determinations:		
Additional Information:		

Appendix C: Flyer for Recruiting Participants

KU SCHOOL OF ENGINEERING
The University of Kansas

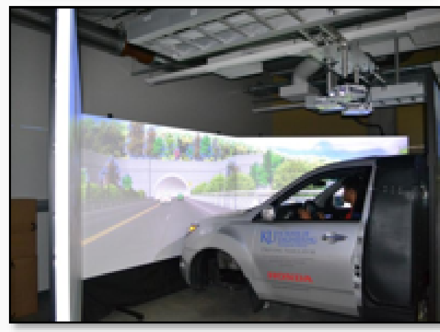
Participants Needed for Driving Simulator Research

Study sponsored by:

MID-AMERICA TRANSPORTATION CENTER

Title:
Modeling Driver Behavior and Aggressiveness Using Bio-Behavioral Methods

Flyer valid from **10/01/2018 to 04/31/2019**



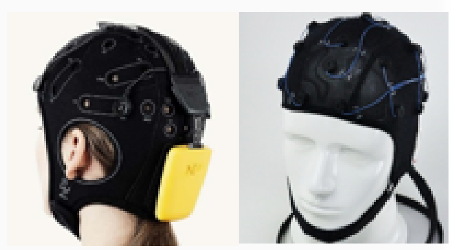
Experimental Procedure:
90 participants are required to drive specific simulated scenarios designed to study driving preferences and behavior.

Participants will be required to drive for no more than **70 minutes**. Information on braking, reaction time, lateral position, speed, time gap, acceleration, and electrical activity in the brain will be collected using electroencephalogram (EEG), heart rate monitoring chest strap, software, questionnaires, and video cameras.

What is an EEG?
This is a non-invasive device used to record electrical activity in the brain. It consists of several electrodes placed along the scalp for different regions of the brain.

Possible Risks:
Motion/simulator sickness

Location:
G435 LEEP 2



Requirements & Compensation:

- Participants must have a valid **U.S. driver's license** with at least three years of driving experience with an annual mileage no less than 5000 miles.
- Age of participants must be **18 - 65 years**
- Participants will receive a $50 gift card as compensation for their time and effort.
- Participants must complete a pre-screening questionnaire. This can be obtained via **this link**

Link to pre-screening:

Approximate time: 45 mins

[https://kusurvey.ca1.qualtrics.com/jfe/form/SV_6z2c9qBWFE9hrRH]

For More Information or To Participate:
Contact: Vishal Kummetha
Email: kummetha@ku.edu
Phone: (785) 312-0845
2160 Learned Hall
Department of Civil, Envir. & Arch. Engineering
Faculty Supervisor: Dr. Alexandra Kondyli

Appendix D: Informed Consent Document

INFORMED CONSENT DOCUMENT

Dr. Alexandra Kondyli, PhD
Principal Investigator
Department of Civil, Environmental, and Architectural Engineering
1530 W. 15th Street | 2159A Learned Hall
University of Kansas, Lawrence, KS 66045
(785) 864-6521

Modeling Driver Behavior and Driver Aggressiveness Using Biobehavioral Methods

INTRODUCTION

The Department of Civil, Environmental, and Architectural Engineering at the University of Kansas supports the practice of protection for human subjects participating in research. The following information is provided for you to decide whether you wish to participate in the present study. You may refuse to sign this form and not participate in this study. You should be aware that even if you agree to participate, you are free to withdraw at any time. If you do withdraw from this study, it will not affect your relationship with this unit, the services it may provide to you, or the University of Kansas.

PURPOSE OF THE STUDY

The research is part of a Mid-America transportation Center (MATC) project and will be used to analyze driver behavior and aggressiveness. The findings of this research will help us better understand how driver behaviour and aggressiveness are linked to changes in driving performance and workload. The research will help to improve existing traffic flow models by incorporating biobehavioral architecture.

PROCEDURES

This study is part of a MATC research project. The study will recruit 90 drivers to participate in the experiments, from 18 to 65 years old. During the experiment you will be asked to drive the driving simulator for approximately 70 minutes. The first 5 minutes will be for you to familiarize with the vehicle/simulator and also to see if you have any signs of motion sickness. After that, and provided you do not have motion sickness, we will start collecting data related to your driving along the simulated scenarios. A heart rate monitoring strap will be placed in the center of your chest to collect data on heart beats per second. An elastic cap, surface electrodes, and ear clip will also be used to record the electrical activity of your brain throughout the experiment, a procedure known as electroencephalogram or EEG. We will use a wireless system to record EEG. We will be recording EEG from the electrodes applied to your scalp during the entire duration of the experiment. All electrodes will be dry without the need for gel. You will have intermediate breaks every 5-15 minutes depending on the driving scenario. The principle investigator (PI) will be analyzing your drive and video recordings after the experiment is finished. Only people that are related to this research (Vishal Kummetha and Dr. Alexandra Kondyli and Dr. Christopher Ramey) will have access to these recordings, which will be securely stored in hard drives and kept in the Driving Simulator Lab.

Your responses will never be associated with your name and they will be stored electronically on a password-protected computer. Your behavioral test results may be made available to other researchers in our laboratory via an electronic database, which will be stored on a password-protected computer. Your behavioral test results and background demographics information will be maintained in this database. Researchers in our lab will be able to consult the database for later analysis. Your name and contact information will not be included within the database but will be maintained in a locked cabinet as well as electronically in a separate password-protected list.

The research team is committed to confidentiality. Your identity will not be revealed in the final report for this project, nor in any of the manuscripts produced. Instead, you will be assigned a participant ID number.

SELECTION CRITERIA

Participants are required to be between the ages of 18 and 65 years. Participants are selected based on possession of a valid US driver's license with at least 3 years of driving experience and no less than 5000 miles of annual driving. Participants with any significant heart conditions or at any stage of pregnancy will not be approved for the study. Also, participants with medical conditions such as severe motion sickness or a history of seizures will not be approved for participation in the study.

RISKS

Driving Simulator
The risks for this experiment are primarily related to motion sickness that you might experience as you are driving in the simulator. Motion sickness does not happen to everyone, but typical motion sickness symptoms include: general discomfort, fatigue, headache, eye strain, difficulty focusing, increased salivation, sweating, nausea, difficulty concentrating, fullness of head, blurred vision, dizzy eyes, vertigo, stomach awareness, and burping.

We will be monitoring you during the entire duration of the experiment for signs of motion sickness. During the frequent breaks, we will also ask you several questions on how you feel, so we determine whether you start to experience motion sickness or not.

Additionally, you might experience mild stress during decision-making during the driving portion of the study, but this stressor is no more than most people experience on a daily basis. You might also experience mild anxiety about being video recorded while you are driving.

Behavioral Testing
The testing, as with any testing, may be an inconvenience and cause fatigue, but the tests are not known to cause undue distress or emotional stress. You may be asked to perform a task that you find very difficult or irritating. If you find the task too annoying or frustrating the experiment will be discontinued. Although there is a possible risk of loss of confidentiality with the maintenance of databases, every effort will be made to minimize this risk through the use of password-protection and the separation of name and contact information from behavioral testing results as discussed above.

Electroencephalogram
There are no risks associated with EEG recordings. There might be slight itchiness or tightness around the head due to the application of the head cap and electrodes.

Heart Rate Chest Strap
There are no risks associated with the Polar HR10 monitor.

BENEFITS

There are no direct personal benefits from participating in this research.

PAYMENT TO PARTICIPANTS

You will be given $50 compensation (in the form of a gift card) for participating in this driving simulator data collection experiment. You will be receiving cash at the end of the experiment. Investigators may ask for your social security number in order to comply with federal and state tax and accounting regulations.

PARTICIPANT CONFIDENTIALITY

Your name will not be associated in any publication or presentation with the information collected about you or with the research findings from this study. Instead, the researchers will use a study number or a pseudonym rather than your name. Your identifiable information will not be shared unless (a) it is required by law or university policy, or (b) you give written permission.

Permission granted on this date to use and disclose your information remains in effect indefinitely. By signing this form you give permission for the use and disclosure of your information for purposes of this study at any time in the future.

INSTITUTIONAL DISCLAIMER STATEMENT

In the event of injury, the Kansas Tort Claims Act provides for compensation if it can be demonstrated that the injury was caused by the negligent or wrongful act or omission of a state employee acting within the scope of his/her employment.

REFUSAL TO SIGN CONSENT AND AUTHORIZATION

You are not required to sign this Consent and Authorization form and you may refuse to do so without affecting your right to any services you are receiving or may receive from the University of Kansas or to participate in any programs or events of the University of Kansas. However, if you refuse to sign, you cannot participate in this study.

CANCELLING THIS CONSENT AND AUTHORIZATION

You may withdraw your consent to participate in this study at any time, without consequence, and receive part of the compensation of $10 in gift card. If participants do not show up at appointment time or withdraw before the start of the study, no compensation will be provided.

QUESTIONS ABOUT PARTICIPATION

If you have any questions or concerns about the research study, please contact Vishal Kummetha or Dr. Alexandra Kondyli. They will be glad to answer any of your concerns (Contact information is provided below).

PARTICIPANT CERTIFICATION

I have read this Consent and Authorization form. I have had the opportunity to ask, and I have received answers to, any questions I had regarding the study. I understand that if I have any additional questions about my rights as a research participant, I may call (785) 864-7429 or (785) 864-7385, write the Human Research Protection Program (HRPP), University of Kansas, 2385 Irving Hill Road, Lawrence, Kansas 66045-7568, or email irb@ku.edu.

I agree to take part in this study as a research participant. By my signature I affirm that I am at least 18 years old and that I have received a copy of this Consent and Authorization form.

_________________________________ ______________________

Type/Print Participant's Name Date

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Participant's Signature

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