Incorporating Biobehavioral Architecture into Car-Following Models: A Driving Simulator Study

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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-related 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), was the primary component of this research. The major objectives of this research were to investigate how psychophysiological constructs can be modeled to replicate car-following behavior, and to correlate subjective measures of behavior with actual car-following behavior.

This dissertation presents a thorough literature review into car-following models and existing driving and biobehavioral relationships that can be capitalized to improve the calibration and predicting capabilities of these models. A framework was theorized to utilize the task-capability interface to incorporate biobehavioral parameters such as cognitive workload, situation awareness, and level of activation in order to better predict changes in driving performance. Ninety drivers were recruited to validate the framework by participating in virtual scenarios within a driving simulator environment. The scenarios were created to capture all the necessary parameters by varying the situation complexity of individual tasks. A biobehavioral extension to the IDM was developed to easily calibrate predicted and observed values by grouping individual driver performance and behavioral traits. The model was validated and found to be an effective way of utilizing behavioral and performance variables to efficiently predict car-following behavior.

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List of Abbreviations

Biobehavioral-Intelligent Driver Model (b-IDM)

Cognitive Reflection Task (CRT)

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)

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)

Standard Deviation of Lateral Position (SDLP)

Standard Deviation of Steering Wheel Movement (SDSTW)

The University of Kansas (KU)

Task Load Index (TLX)

Task-Evoked Pupillary Response (TEPR)

Useful Field of View (UFOV)

Mental Workload (WL)

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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 introduce driver behavioral variability through various distributions and factors such as speed, spacing, acceleration, deceleration, reaction time, and standstill distance. 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 to replicate field conditions by considering elements such as driving complexity and distracted driving.

Biobehavioral aspects encompass the variability of cognitive workload and situation awareness with the driving pattern of individuals. In this study, driving variables such as preferred gap, speed, jerk, acceleration, and deceleration, are used together with biobehavioral variables such as level of activation/engagement (LA), mental workload (WL), changes in situation awareness (SA), and static driver properties (age, experience, and driving history), to classify drivers from the study pool into clusters of similar driving traits. This collection of variables and traits are used to identify the best-suited coefficients to improve car-following behavioral predictions, depending on the situation complexity experienced by a particular driver.

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 performance with actual car-following behavior. To achieve these goals, the following objectives were accomplished:

- Conduct a thorough literature review comprising of techniques and past studies aimed at incorporating behavioral aspects into traffic models, including parameters previously used to categorize drivers;
- Develop the methodological framework to incorporate behavioral aspects into an existing car-following model (i.e. the Intelligent-Driver-Model–IDM);
- Classify drivers by self-reported/subjective measures (NASA-TLX (Task load index), situation awareness rating technique (SART), and screening questionnaires), biobehavioral measures (level of activation, heart rate, pupil dilation, and gaze duration), and performance measures (speed, acceleration, gaps, and standard deviation of lateral position);
- Collect static and dynamic behavioral parameters of ninety drivers using a driving simulator;
- Establish a non-subjective technique to determine SA using driver comprehension derived from time spent gazing;
- Analyze data to establish driving performance and behavioral thresholds for the different driver categories; and

- Incorporate attained thresholds into the biobehavioral-Intelligent Driver Model (b-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 Dissertation

The dissertation 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, mental workload, and level of activation, experimental techniques, and existing biobehavioral methodologies. The methodology is described in Chapter 3, while the data collection procedure is presented in Chapter 4. Chapter 5 discusses the data analysis process which included the exact methods followed to select, filter, and combine all the available data. Chapter 6 shows the achieved results with respect to the general trend observed from the driving tasks. Chapter 7 discusses in detail the process of developing and validating the b-IDM. Finally, conclusions and possible future research are presented in chapter 8.

Chapter 2 Literature Review

This chapter 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 previously established relationships between them. Literature was 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 is 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 cognitive restraints.

A discussion consisting of existing psycho-physical models and a few other car-following models such as the Intelligent Driver Model (IDM) and human driver model (HDM), 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 driver dynamics 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 travelling 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).

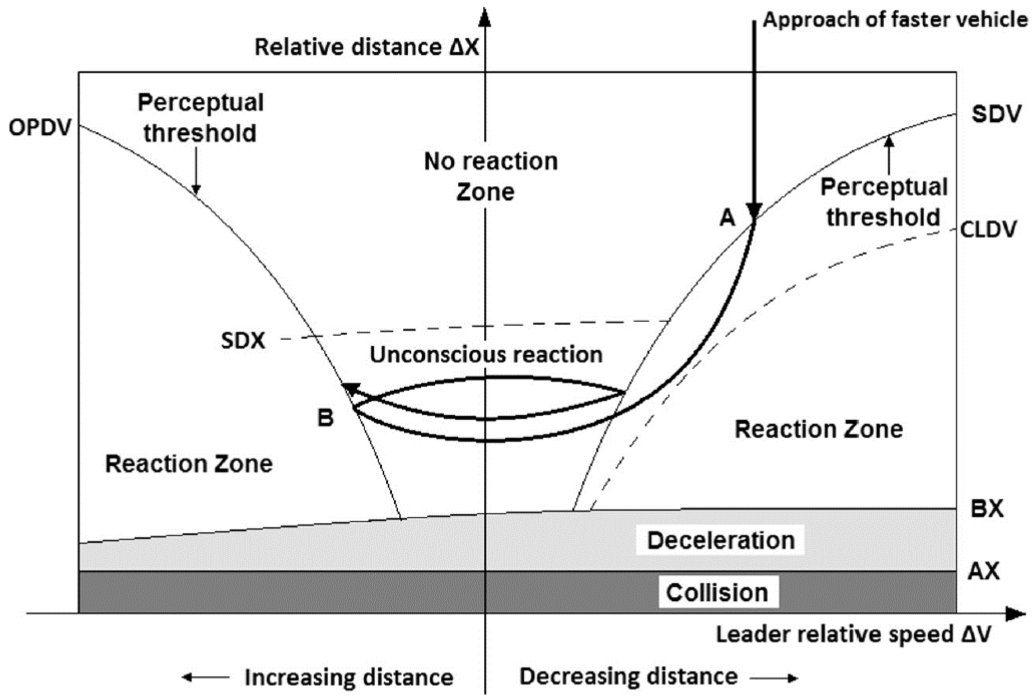


Figure 2.1 Wiedemann car-following model (Wiedemann, 1974)

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).

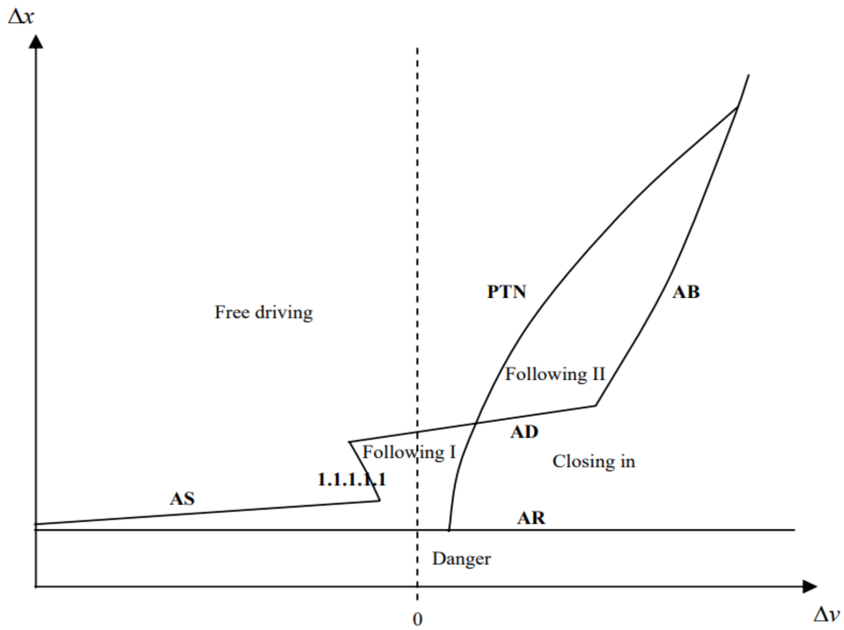


Figure 2.2 Fritzsche car-following model (Olstam, 2004)

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.

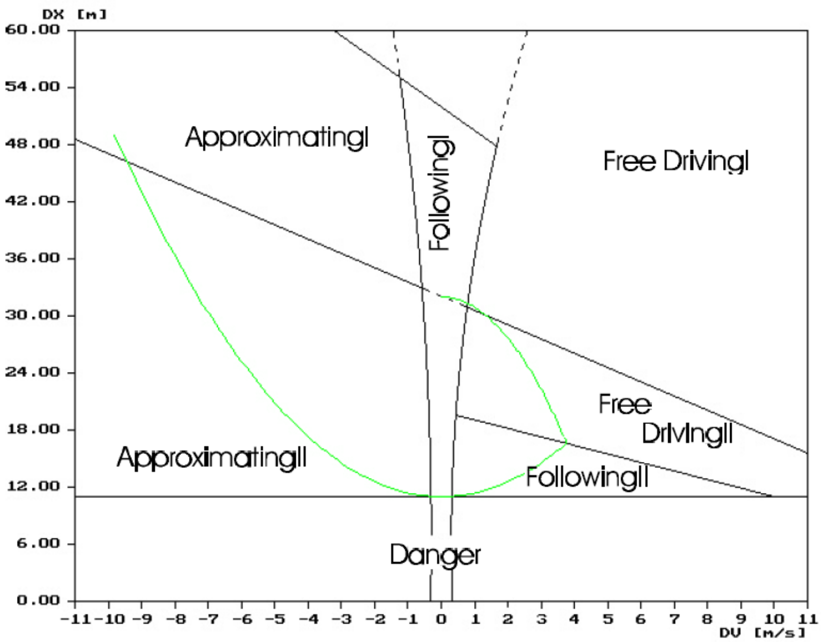


Figure 2.3 Urban traffic psycho-physical model (Schulze & Fliess, 1997)

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).

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

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

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).

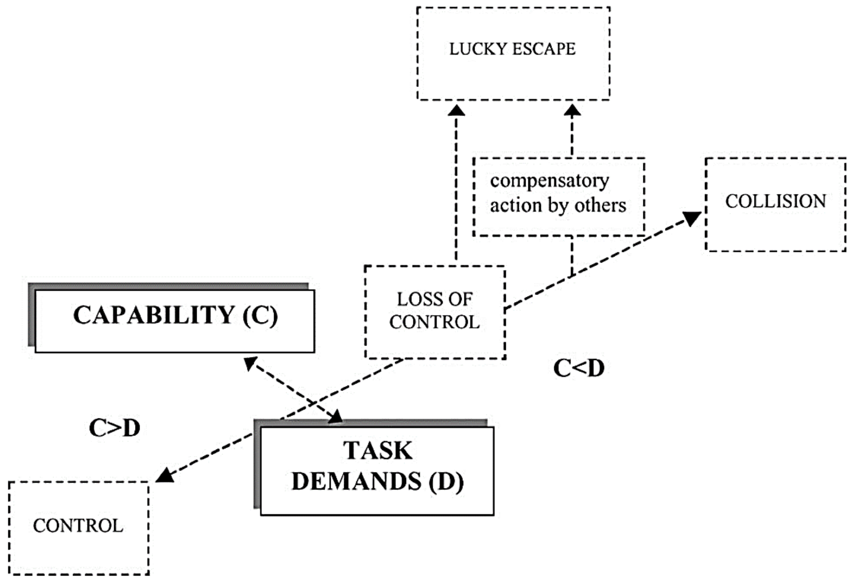


Figure 2.4 Task demand and capability interface (Fuller, 2005)

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:

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

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 mental workload and situation awareness) (De Waard & Brookhuis, 1991).

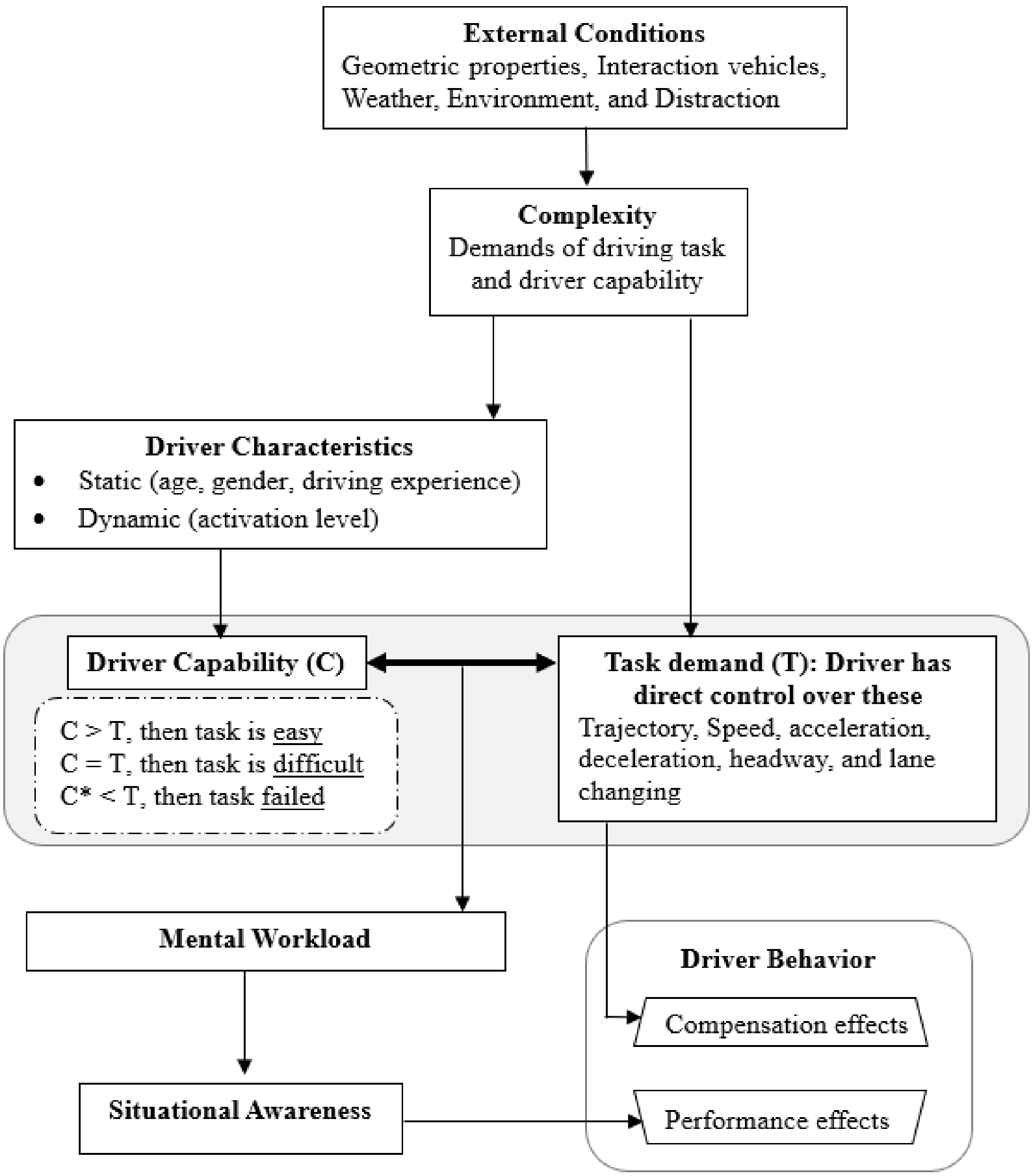


Figure 2.5 Framework developed by Hoogendoorn et al. (2012) to modify the IDM

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:

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

Saifuzzaman et al. in 2015 performed extensive literature reviews to incorporate task difficulty using the TCI, developed by Fuller (2005), into car following models such as Gipps' and the IDM, where task difficulty is the product of the interaction between driver capability and task demand (Saifuzzaman et al., 2015). In the research performed by Saifuzzaman et al. (2015), an assumption that desired time headway selection is inversely proportional to the driver capability is made. When a driver selects to follow smaller time headway than usually desired, the ability to perform an evasive maneuver in case of an emergency is reduced, thus making the task difficult and uncomfortable. So, in general, if a driver elects smaller desired time headway (assuming drivers are a good judge of their risk and discomfort), he/she can be categorized as more capable than someone with larger time headway (Saifuzzaman et al., 2015).

$$TD_n(t) = \left(\frac{V_n(t-\tau'_n)\tilde{T}_n}{(1-\delta_n)s_n(t-\tau'_n)}\right)^{\gamma} \qquad (2.11)$$

$\tau'_n = \tau_n + \varphi_n$

Where,

$TD_n(t)$ represents the task difficulty perceived by the driver *n* at time *t*;

s_n is the spacing between two vehicles (front of follower to rear of leader);

$\tilde{T}_n$ is the desired time headway;

V_n is the speed of the subject vehicle;

δ_n is a risk parameter;

γ is the driver sensitivity parameter towards task difficulty level;

τ_n is the reaction time of the driver;

φ_n is the increase in reaction time as a result of increased difficulty; and

$\tau'_n$is the modified reaction time.

The parameter δ_n captures the risk perceived by drivers (usually less than 1). A positive number indicates that the driver perceives the risk associated with reduced capability. However, a negative parameter indicates that the driver underestimated the risk. Also, the modified reaction time (τ'_n) captures the change in reaction time associated with varying task difficulty.

The result of incorporating equation 2.11 into the IDM is shown in equation 2.12

$$a_n(t+\tau'_n) = a_{max}\left[1-\left(\frac{v_n(t)}{v_0(t)}\right)^{\delta} - \left(\frac{s^*{}_n(t) * TD_n(t+\tau'_n)}{s_n(t)}\right)^2\right] \qquad (2.12)$$

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 mental workload, situation awareness, and level of activation. In this study, the focus was to modify Hoogendoorn's framework and establish a methodology to capture/incorporate the compensatory and performance effects resulting from an imbalance in task demand and driver capability.

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. Where, 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.

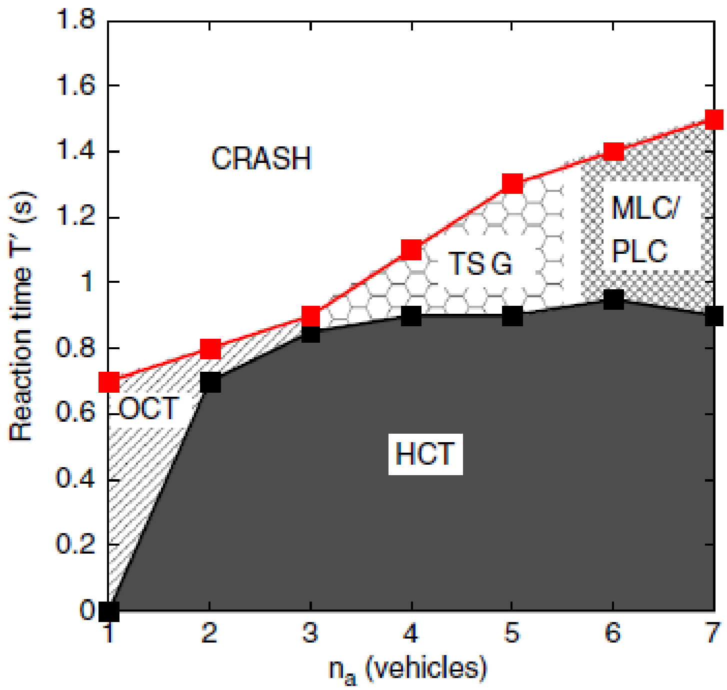


Figure 2.6 Regimes of the HDM

2.2 Driver Classification

Classification of drivers is a strategy used to easily group individuals based on common traits, style, and characteristics (Murphey et al., 2009; Feng et al., 2017). This makes establishing constraints to strategically categorize a sample/population easier and more efficient, especially when developing a model, than individual traits that have numerous unique variables. The number of classes can be pre-determined by the researcher or post-determined based on sample/population characteristics.

Several studies have been able to categorize participants/drivers based on their behavior and driving style. Lin et al. (2006) also carried out a study, using a virtual reality driving simulator, to classify ten drivers by analyzing physiological measures in response to an unexpected obstacle. Drivers were classified into two categories: aggressive and gentle, based in driving trajectory and steering deviation. Event-related potentials (ERP) were then extracted and compared to the driving measures (Lin et al., 2006). A noticeable power difference at 10Hz and 20Hz was observed between aggressive and gentle drivers.

Kondyli, in 2009, classified drivers using three behavioral types: aggressive, average, and conservative. Where, the aggressive driver tends to drive at high speeds (15 mph over speed limit), perform six discretionary lane changes, short merging, and no remorse when cutting individuals off. The average driver was categorized as one that drives at speeds not exceeding 10 mph over the speed limit and performs five discretionary lane changes. A conservative driver, on the other hand, would demonstrate more cautious maneuvers when lane changing, maintain longer headways, and not drive in excess of 5 mph over the speed limit (Kondyli & Elefteriadou, 2011). Participants were categorized using field observations and background surveys.

A study by Murphey et al. (2009) used jerk (defined as the rate of change of acceleration and deceleration) analysis to predict driver's style classification using the Powertrain System Analysis Toolkit simulation program. Four categories of driving style were established: calm-anticipates other road user's movements and avoids hard acceleration/deceleration, normal-drives with moderate acceleration/deceleration, aggressive-drives with abrupt changes in acceleration and braking, and no speed-vehicle not moving (Murphey et al., 2009). Also, the calm driver is classified to be the most fuel-efficient. An algorithm capable of predicting driver class based on fuel efficiency and jerk parameter was developed. A similar study was conducted by Feng et al. (2017) using longitudinal jerk to identify aggressive drivers. Driving data from a previously conducted study was randomly sampled to obtain profiles of 88 drivers. Drivers were classified using acceleration, jerk, and gas pedal travel parameters. Two classifications were used: aggressive and normal (Feng et al., 2017). The two groups were then further examined using driving behaviors such as speeding, tailgating, and risk of crash. The study concluded that the aggressive group consisted mostly of young male drivers and had a higher jerk (20-30 years old).

Manjunatha and Elefteriadou (2019) performed a study that involved classifying participants through a cluster analysis based on individual mental workload and situation awareness. The result was two distinct clusters A and B. The properties of the participants from the two clusters were then compared to the responses from the pre-screening questionnaire. Individual properties such as age, gender, driving frequency, take joy in driving, aggressiveness, accident history, and traffic violation tickets issued. The comparison showed that individuals in group B, with lower mean age, enjoyed driving but received more traffic violations (Manjunatha & Elefteriadou, 2019).

In this study, the number of categories will be dependent on what is observed from the drive (speed, headway, jerk) and survey questionnaires (age, experience, accident history, traffic violations), along with the mutual behavioral traits (mental workload, situation awareness, level of activation) of the selected participants.

2.3 Situation Awareness, Mental Workload, and Level of Activation

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

2.3.1 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 more significant factors 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.

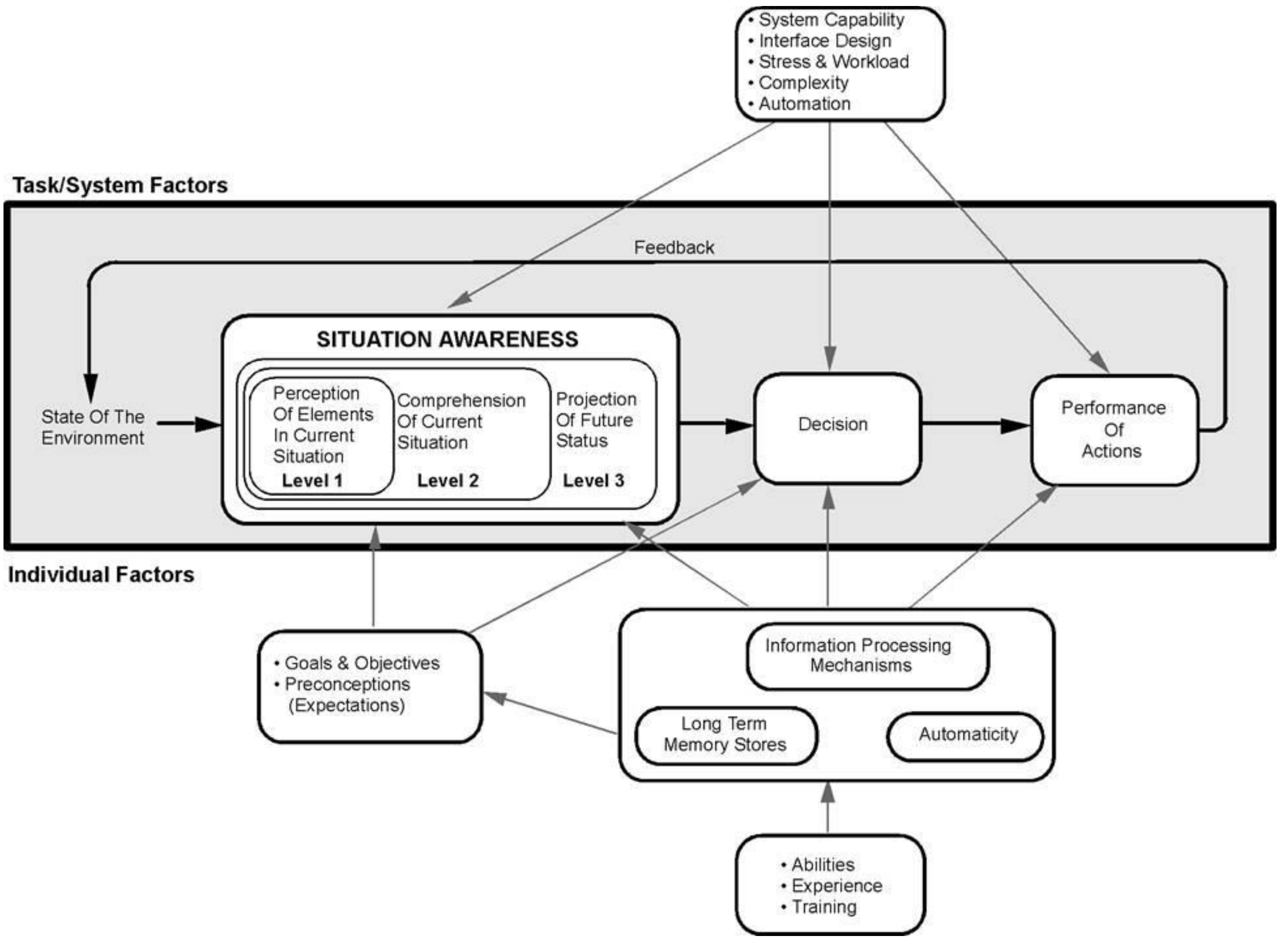


Figure 2.7 Levels of SA in relation to decision-making and performance (Endsley, 1995)

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.

2.3.1.1 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).

2.3.1.2 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).

2.3.1.3 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 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).

Although SART is a widely used measure of SA, comparisons of the efficiency of SAGAT (best known measure of SA) and SART exist. A study by Endsley, in 2000, reported significant correlation between overall SART scores and level 1 SAGAT. However, a study carried out by Salmon et al. (2009) showed no correlation between SART and SAGAT or performance measures. This raises concerns about self-rating techniques being susceptible/biased to the last performed task.

2.3.1.4 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 not intrusive. 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).

2.3.1.5 Physiological Technique

The typical physiological technique used to measure SA is 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 the 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 non-intrusive and do not affect the performance of the primary task (Salmon et al., 2006). However, devices and relevant software can be very expensive.

A study by Coyne and Sibley, in 2015, used eye-tracking to establish SA in an unmanned aerial vehicle study. Twenty participants were recruited to carry out military training missions at the Naval Research Laboratory involving identifying vehicles and carrying out target assignments through a map. The SmartEye Pro 6.1 was used to track eye movements and gaze at 60Hz along with the SA probe technique (Coyne & Sibley, 2015). The study concluded that as task demand increased, participants spent less time looking at their map targets, thus negatively impacting their target assignment. The study showed, in both instances (eye tracker and probe), that SA decreased with an increase in task demand (Coyne & Sibley, 2015).

2.3.2 Mental Workload (WL)

Mental workload, also known as cognitive 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.

2.3.2.1 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), driving activity load index (DALI), and the rating scale mental effort (RSME). Each technique is briefly discussed in the sections that follow.

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.

Driving 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, and 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).

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 and is thus not favored over the NASA-TLX.

2.3.2.2 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 mean headway and standard deviation of the headway, and lane keeping parameters such as standard deviation of lateral position (SDLP) and steering wheel movement (SDSWM). A couple of studies also found that an increase in WL significantly increased the time to traverse the same route (De Waard, 1996). 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). Studies summarized by de Waard (1996), have shown varying results with respect to SDLP and SDSWM. In some studies, as WL increased, the SDLP increased (more lateral variability) while in others it decreased. However, this could be because of the layout of the driving scenarios used. (Some regions were on a horizontal curve and required lane changing, thus introducing ambiguities in the data). Hence, extra caution must be observed during the planning and design of the experiment (scenarios). Ideally, performance measures should be coupled with other WL measures to provide a more holistic picture.

2.3.2.3 Physiological Measures

Physiological measures are used to assess WL 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.

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 WL 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.

Numerous researchers have utilized the ECG and HR monitors to study changes in WL. Kahneman et al. (1969) used ten volunteers to perform arithmetic tasks with three levels of difficulty. The study not only measured HR but also pupil diameter and skin resistance. The HR was recorded using a cardiotachometer with electrodes placed on the upper arms of participants (Kahneman et al., 1969). From the study, it was evident that there was an increase in the HR with an increase in question difficulty (with the most difficult question causing a change by up to 5 beats/min). However, the HR (beats/min) values were seen to peak much earlier than the pupil diameter (mm) and skin resistance (ohms).

Dahl and Spence in 1971 performed a similar study using thirteen categories of tasks (Initial resting, digit symbol, word list, recall, discrimination, color reading, color naming, strop color-word, white noise on, color word IR-RI, color work RI-IR with noise, Noise off, and final resting). The study consisted of 61 participants (three sample groups) and participants' task demand was measured using the Bergum's taxonomic analysis (9-point rating scale system to determine task demand) for each category. Not all groups performed all categories of tasks and HR was measured using a photocell transducer in two of the groups while the third used an ECG. The study showed that there was significant correlation between the subjective score and mean HR of the participants. It was also seen that the HR increased almost linearly, with an increase in task demand (Dahl & Spence, 1971). A summary of other studies listed by de Waard (1996) showed similar trends in mean HR. An increase in task demand is seen to cause an increase in HR.

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. Figure 2.8a and 2.8b show the different regions of the brain.

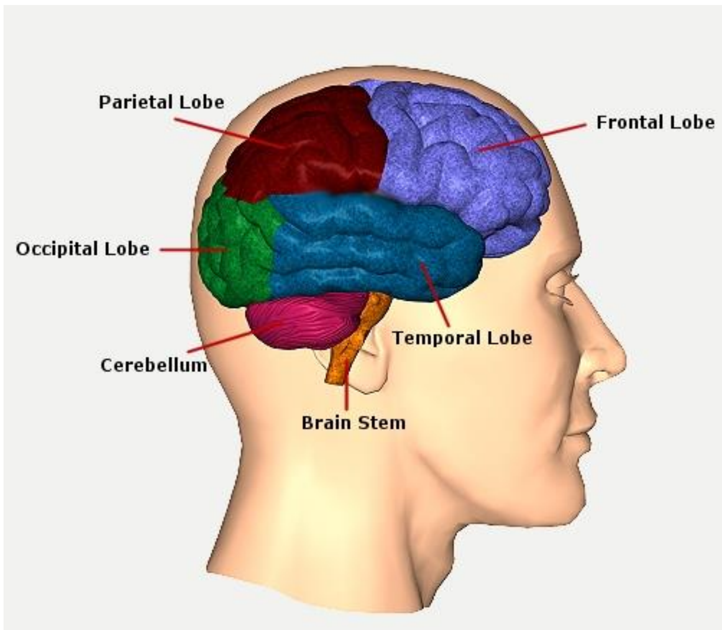


Figure 2.8a Regions of the brain (Lehr, 2015)

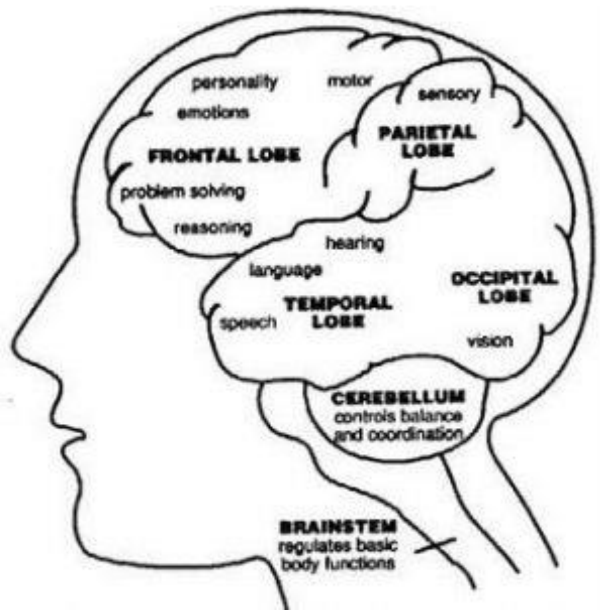


Figure 2.8b Regions of the brain (Lehr, 2015)

The EEG electrodes are placed in positions shown in figure 2.9 according to the 10-20 system. 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 but indicates the central position of the electrodes. Other letters such as “FP” represent the frontopolar and “A” represents the auricular (ear electrode). The number represents the hemisphere location of the brain, with even numbers located in the right and odd numbers in the left. The 10% and 20% refer to the distance between adjacent electrodes with respect to the front-back or right-left dimension of the skull.

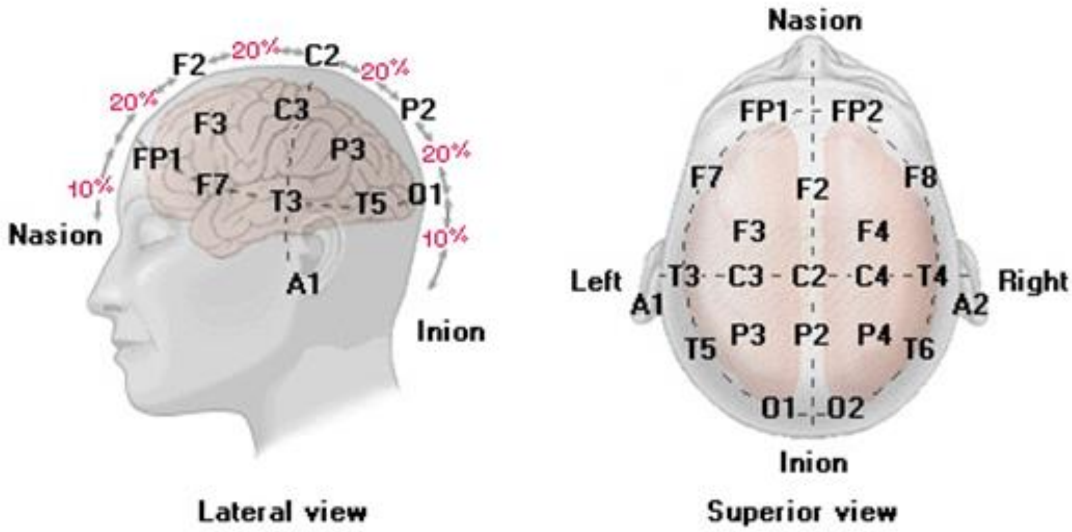


Figure 2.9 EEG electrode positions

The EEG provides two main ways of determining WL: extracting raw EEG data by synchronizing the timeline of the drive and using event related potentials (ERPs) (Kincses et al., 2008). Analyzing the raw EEG signal can be complex and requires filtering noise from AC power lines (60Hz filter in the United States), blinking, and other muscle movements. The raw EEG signal can be typically separated into the following frequency bands using fast Fourier transformation: delta (0.5-4Hz), theta (4-8Hz), alpha (8-13Hz), beta (13-40Hz), gamma (>40Hz). Power spectrum analysis is the most common method to detect changes in WL through raw EEG signal (Walter, 2015). Data is usually divided into epochs consisting of critical task moments. The power spectrum analysis provides insight into the signal power of the different frequencies with respect to the various regions of the brain (electrode positions). Studies have shown that the power of alpha band increases in the drowsy or more relaxed driver state while an increase in the power of beta band is associated with tension and cognition (Kim et al., 2014). A decrease in alpha band activity and an increase in theta band activity is usually associated with increased WL (De Waard, 1996; Kramer, 1991).

ERPs related to cognitive load are mainly associated with the P300 amplitude (usually peaks around 300ms or more), as several studies have used this as a reference to identifying changes in WL (Prinzel III et al., 2001). The P300 amplitude is sensitive to the participants expectancy disrupted by WL (Prinzel III et al., 2001). A summary of studies carried out by de Waard (1996) shows a decrease in P300 amplitude and an increase in latency, with increased task load.

The P300 amplitude can be further split into P3a (latency 250-280ms) and P3b (latency 280-500ms). Where, the P3a (novelty P300) is associated with re-orienting and attention shifting and the P3b is associated with cognitive processing (Light et al., 2010). A study by Causse et al. (2015) showed a decrease in P3b amplitude with an increase in WL as the high WL task requires more processing power/working memory than the low WL task. The drop in P3b amplitude at the PZ (P2) electrode of a participant is shown in figure 2.10.

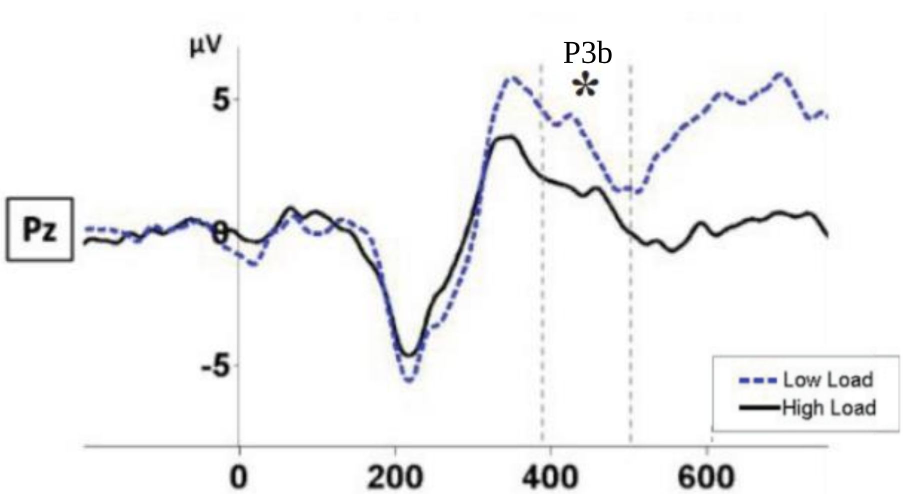
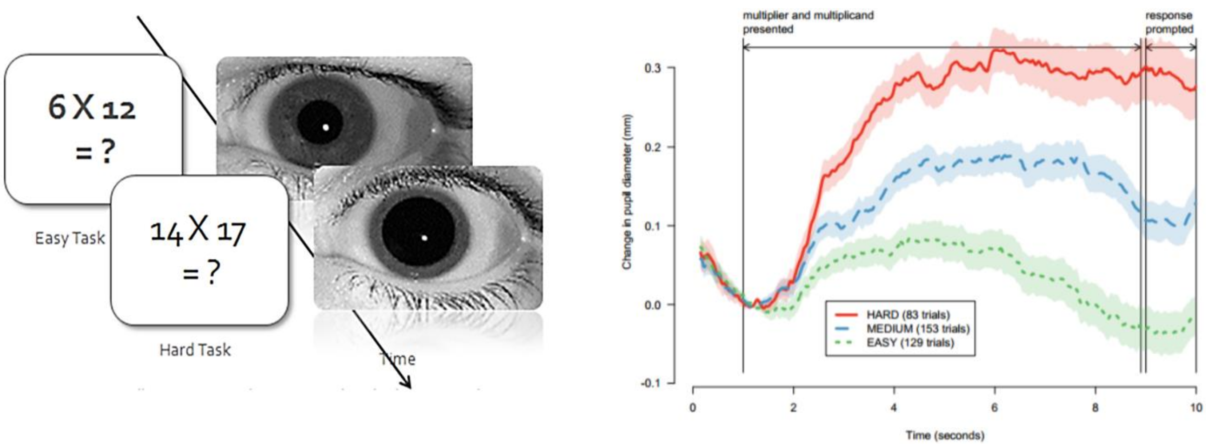


Figure 2.10 Effect of WL on ERP (Causse et al., 2015)

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) (Strayer et al., 2013; Gangeddula et al., 2017). Several studies have shown that as cognitive workload increases, the diameter of the pupil increases (Hess & Polt, 1964; Kahneman et al., 1969; Klingner, 2010; Szulewski et al., 2014). Hess and Polt, using five test subjects ranging in age and educational qualification, carried one of the first studies out in 1964. Since advanced eye tracking devices did not exist at the time of the study, the researchers used an animation motion camera (essentially an older version of a video camera) to take multiple pictures of the test subject's face at equal time intervals, concentrating on the eyes (Hess & Polt, 1964). Four mathematical questions ranging in difficulty were asked (vocally) and the pupil diameter recorded. The pupils were observed to reach a larger peak diameter, with increase in difficulty of the mathematical problem. It was also seen that the pupil diameter increase ranged from 4% up to 29.5% when compared to the non-stimulated pupil diameter, depending on the participant and question difficulty (Hess & Polt, 1964).

Klingner, in 2010, carried out extensive studies on changes to pupil diameter using the Tobii 1750 eye tracker and the Neuroptics VIP-200 ophthalmology pupillometer as a reference instrument. The study first concluded that the Tobii eye tracker was not as precise as the Neuroptics ophthalmology pupillometer. However, the results from the Tobii eye tracker were still adequate to show variations in pupil diameter. The study also presented a visual take on the auditory stimuli presented by Hess and Polt. Mathematical problems varying in difficulty (easy, medium, and hard) were presented on a screen for a duration of eight seconds, before prompting a response (Klingner, 2010). The participants were asked to attempt the questions to the best of their ability, without requiring the final answer to be correct. The results obtained are shown in figure 2.11 (b), pupils are seen to get to a larger peak diameter with increased question difficulty. Also, the pupil diameter increases more steeply with an increase in question difficulty (a reflection of cognitive workload). In this experiment, Klingner ensured to control the brightness and contrast of the visual cues as changes to these could cause pupil dilation and contraction. This aspect was carefully enforced in the scenario design of this research.

Figure 2.11 (a) shows the visual response of the human eye to an increase in cognitive workload.



Change in Pupil Diameter (mm), Time (Seconds)

(a) (b)

Figure 2.11 WL on pupil diameter ((a)-Hossain & Yeasin, 2014, (b)-Klingner, 2010)

A study performed by Szulewski et al. in 2014, validated the results obtained by Klingner. Similar experimental setup and arithmetic problems were used. However, only two levels of difficulty (easy and hard) were tested. The results showed an added dimension to those obtained by Klingner, with easy questions causing a peak pupil dilation three seconds quicker than hard questions. However, maximum pupil diameter attained was still larger for hard questions than for easy questions (Szulewski et al., 2014). A study by Marquart and De Winter in 2015, consisting of thirty participants, validated the measurement of workload using pupillometry by comparing the data to that obtained using the well-established NASA-TLX questionnaire. However, the authors suggested using caution when tackling tasks that cause pupil reflexes due to light sensitivity. They also recommend using multiple measures (HR, EEG) to eliminate instances of extreme variability (Marquart & De Winter, 2015).

This property of the pupils can be used to assess cognitive workload continuously throughout a drive. Advanced software tools have been developed by device manufacturers to analyze the observed changes and patterns in pupil dilation/contraction and compare it to baseline conditions, identifying any changes resulting from the task. This can be used in simulation environment, to track changes in cognitive load experienced by the driver.

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 and are thus not very effective in establishing actual WL.

The ISO 17488 (2016) presents several coordinated studies on WL and resource allocation. The studies show that an increase in hit rate and reduction in stimuli response time can be associated with lower mental demand, as performance with respect to the task is improved. Strayer et al. (2013 & 2014) compared the results of the DRT to other subjective (NASA-TLX) and physiological measures such as the EEG and HR, using both driving simulators and instrumented vehicles. The results showed that the DRT data is equally capable in tracking WL when compared to the other measures.

2.3.2.4 Sensitivity of the Various Measures

De Waard observed that some WL measures were sensitive at a particular difficulty of the task demand than others. This can be clearly observed in figure 2.12. 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.

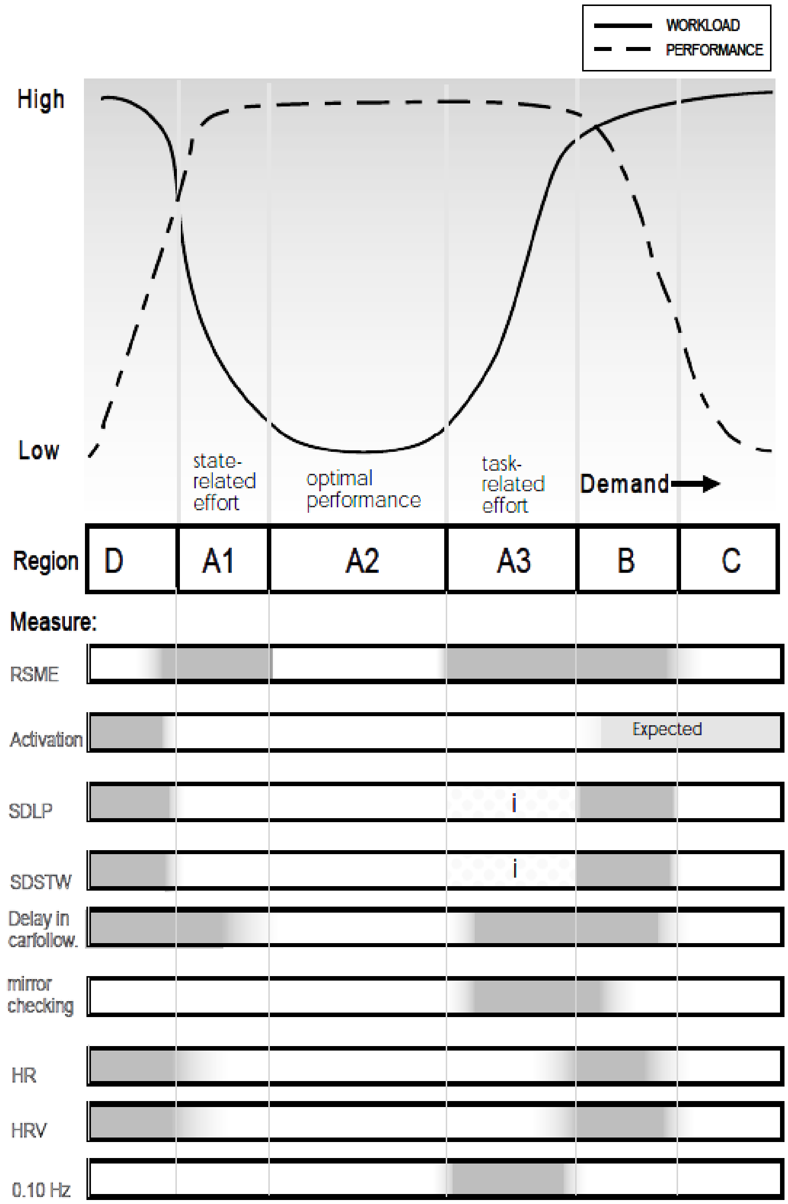


Figure 2.12 Sensitivity of workload measures (De Waard, 1996)

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

2.3.3 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 20-beta, representing the frequency ranges 4-7Hz, 8-13Hz, and 14-22Hz, 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). Pope et al. in 1995, identified the electrode positions P3, PZ (P2), P4, and CZ(C2), to capture the "engagement index" of a driver, also known as the LA. The results of this study were validated by Prinzel III et al. (2001). However, both Pope et al. (1995) and Prinzel III et al. (2001) used the inverse of the formula suggested by de Waard and Brookhuis (1991).

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 (56 miles) on a highway while being monitored by researchers. The study showed that LA increased more 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.

2.4 Relationship Between WL, SA, LA and Performance

Endsley in 1995, theorized four constructs that link SA and WL. These include:

- **Low SA with low WL**: Operator had little idea of what is happening due to inattentiveness or lack of motivation;

- **Low SA with high WL**: Tasks that require more processing capabilities from the operator might lead to missing/overlooking of some elements in a given task (only a subset of information is processed along with incomplete perception);
- **High SA with low WL**: This state is what is ideally preferred by an operator, with information that can be easily comprehended without requiring high mental processing; and
- **High SA with high WL**: In this state, the operator is using more mental resources but is also successful at comprehending/adjusting to the situation.

Following these constructs, it is clear that SA and WL depend on the task, experiment design, and individual traits/behavior. A determent in SA is only expected when the operator is making an effort to attain SA and the demand of the task exceeds capability (Endsley, 1995).

The relationship between WL and task demand is well established by several studies. De Waard suggests a U-function as shown in figure 2.12, where WL initially starts off 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 2.13, it can be seen that as WL increases, the LA also increases. However, the relationship is not entirely linear.

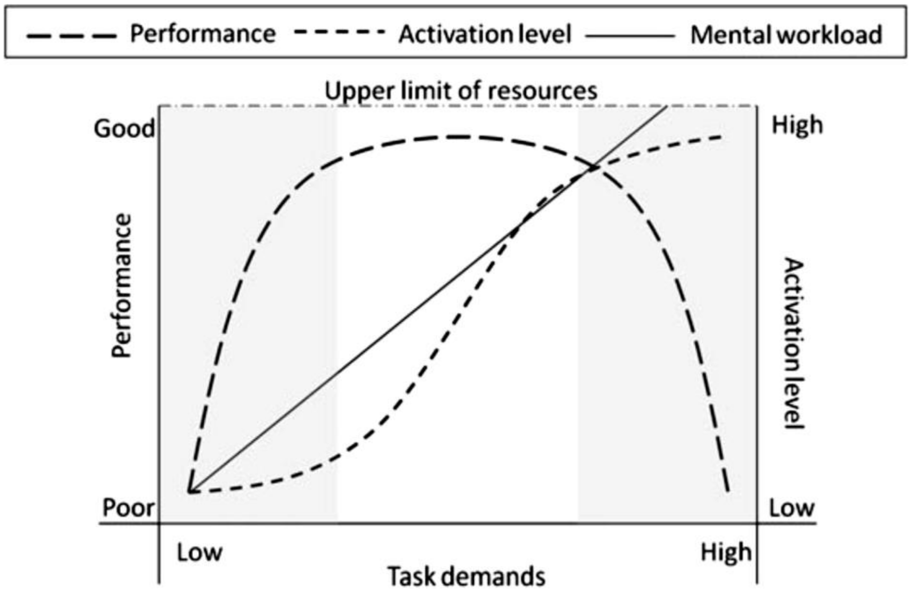


Figure 2.13 Relationship of WL, LA, and performance (Young et al., 2015)

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 SDLP and SDSTW. No significant relationship was seen between the performance measures and WL.

From figure 2.14, 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.

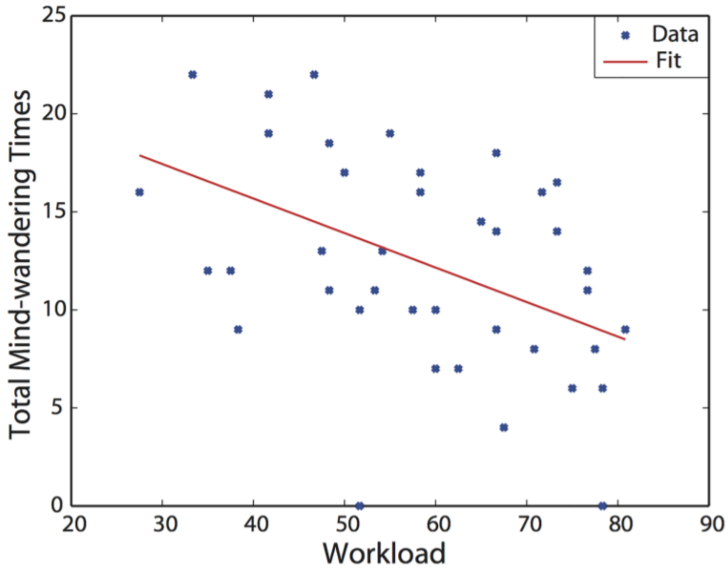


Figure 2.14 Mind wandering and WL (Zhang & Kumada, 2017)

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.

2.5 Summary of Literature Review

In summary, the literature review provided an understanding of the existing relationships between behavioral parameters, subjective measures, and driving performance. Driver performance under high WL and low SA becomes significantly impaired. Measures such as pupillometry, EEG, survey questionnaires, and HR, coupled with driving performance can be used to track these relationships. However, a model that captures these key variables that are affected by changing situation complexity to better predict car-following behavior is lacking. Also, using bulk calibration techniques by considering group traits rather than individual-specific parameters could further ease traffic modeling.

Chapter 3 Methodology

The methodology was divided into two main phases. The first phase involved a simulator study to establish different driver categories through performance parameters and biobehavioral trends. The second phase incorporated the established driver categories with their subsequent biobehavioral parameters into the IDM. A validation of the developed model was also performed. The framework for the proposed methodology is provided in figure 3.1.

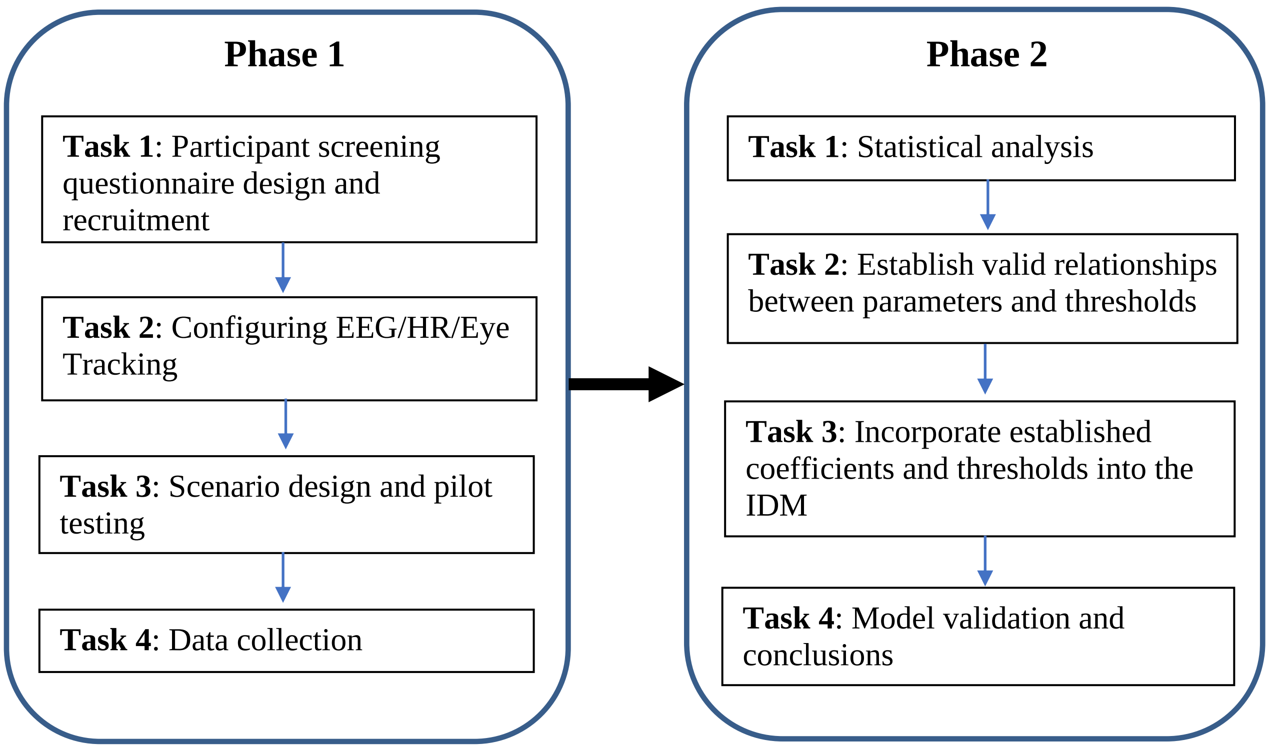


Figure 3.1 Methodological plan

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.

When describing the theory behind the proposed framework, terms such as task demand, driver capability, task difficulty, mental workload, and situation awareness, are used. The definitions of these terms with respect to this dissertation are shown in table 3.1.

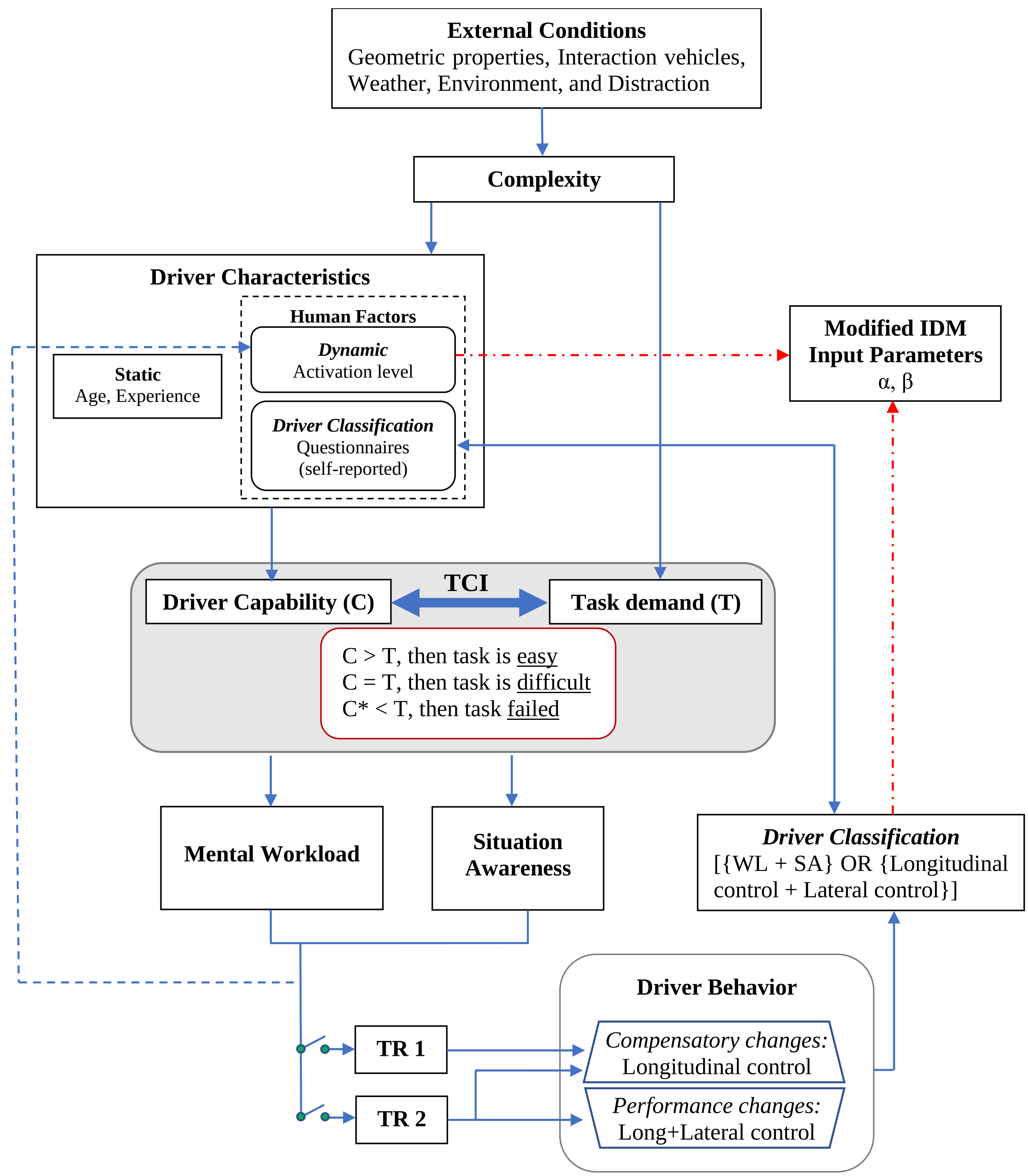
Table 3.1 Important definitions

Term	**Definition**
Task demand	The amount of effort required to successfully meet the set requirements of a task, independent of the individual (Kahneman, 1973).
Driver capability	The individual traits/biological characteristics of a driver that affect his/her ability to complete a task. Some traits include: speed, reaction time, information processing ability, experience, knowledge of driving, and motor coordination (Fuller, 2005).
Task difficulty	The strategies or behavior followed to cope with changes to task demand during a task (Mosaly et al., 2017). Fuller (2005) quotes task difficulty to be inversely proportional to the difference between task demand and driver capability.
WL	The proportion of mental capacity required by an individual to perform a task (Brookhuis et al., 1991).
SA	The ability to perceive, comprehend, and project future status of elements in an environment (Endsley, 1995).
LA	The level of engagement/arousal experienced with a particular task (Pope et al., 1995)

The external conditions in a specific situation 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 certain level of 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 closely 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 LA can affect driving performance. LA 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 a mentally aroused 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 drivers can complete this task at a lower LA 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.



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

Figure 3.2 Theoretical framework for incorporating biobehavioral parameters

This leads to a trigger (TR) 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 i.e. the 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). Where compensatory changes are theorized to only affect longitudinal driving variables while performance changes are theorized to affect longitudinal and lateral (SDLP) driving variables. Essentially, this implies that task difficulty is split into TR1 and TR2, depending on the extent of the imbalance between task demand and driver capability.

Speed and headway (longitudinal parameters) have been previously established to represent compensation behavior of drivers (Alm & Nilsson, 1995 and Hoogendoorn et al., 2012). Measures such as SDLP and route time, have been established to represent driver performance (Brookhuis et al., 1985; Brookhuis et al., 1991; Brookhuis & de Waard, 1994; De Waard, 1996). Route time indicates the time taken by the driver to complete a set route, depending on the speed and the preferred headway (longitudinal control).

Drivers were also categorized by behavioral (LA, WL, SA) and static characteristics (age, experience, number of speeding tickets, number of accidents), into two/three groups (depending on the sample population). The resulting effect of the driver from a particular group trying to match his/her capability to the task demand was used to establish how drivers in different classes react to the same task. Would the driver experience lower mental workload, implying lower compensation and performance changes, while completing a difficult task? Or would the driver increase the speed and follow shorter headways during an easy task, to increase the level of difficulty to match his/her optimal capability? The established classifications were also compared to the driving variables such as average speed, average headway, and maximum acceleration, to measure the accuracy of self-perception in driver classification.

3.1 The Proposed 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 was made because the desired variables capture what the driver wants to do at that moment but is unable due to a higher than usual task demand. The compensation and performance coefficients are theorized to be functions of performance, WL, SA, and LA. Equations 3.1 and 3.2 show how the overall acceleration of the IDM was modified when TR1 or TR2 are activated.

Compensation only (TR 1):

$$a_n(t) = a_{max}\left[1 - \left(\frac{v_n(t)}{(\alpha)v_0(t)}\right)^{\delta} - \left(\frac{s^*{}_n(t)}{s_n(t)}\right)^2\right]; \quad x < \alpha \leq 1 \;\; and \; 0 < x \leq 1 \tag{3.1}$$

$$s^*{}_n(t) = s_0 + \left(\frac{1}{\alpha}\right)T_n v_n(t) + \frac{v_n(t)\Delta v_n(t)}{2\sqrt{a_{max}b_{comf}}}$$

Where,

α = Compensation coefficient

Compensation and Performance (TR 2):

$$a_n(t) = a_{max}\left[1 - \left(\frac{v_n(t)}{(\beta)v_0(t)}\right)^{\delta} - \left(\frac{s^*{}_n(t)}{s_n(t)}\right)^2\right]; \quad 0 < \beta \leq x \;\; and \; 0 < x \leq 1 \tag{3.2}$$

$$s^*{}_n(t) = s_0 + \left(\frac{1}{\beta}\right)T_n v_n(t) + \frac{v_n(t)\Delta v_n(t)}{2\sqrt{a_{max}b_{comf}}}$$

Where,

β = Compensation and 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 was theorized as an add-on to the model, essentially depicting a reaction time threshold. Upon activation of brake lights by the leader, the time-gap ($T(t)$) between the leader and follower at time (t) was determined to be lower than the desired time-gap (T_n). In this case, the modified IDM model was triggered to recalculate the car-following trajectory using the acceleration/deceleration ($a(t)$) at that instance. However, if $T(t)$ was greater than T_n, it was assumed that the driver does not apply brakes or accelerate, resulting in a uniform deceleration of -0.5m/s^2 (Kesting & Treiber, 2013). $T(t)$ and T_n were used to establish constraints because it was theorized that drivers more readily perceive time-gap than the acceleration of the leader. Equation 3.3 shows the implementation of brake light parameter along with the resulting acceleration/deceleration.

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

$$\text{If } bl = 1 \text{ then, } a_n(t)^* = \begin{cases} a(t) & 0 < T(t) \le T_n \\ -0.5\, m/s^2 & T_n < T(t) < 5 \end{cases} \tag{3.3}$$

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 Measuring Techniques

A list of the techniques that were used during data collection to determine correlations between the compensation and performance coefficients and driving performance are listed in table 3.2.

Table 3.2 Measuring techniques

Variable	Measuring technique
Mental workload	• Changes in heart rate • TEPR • Index of cognitive activity • NASA-TLX
Situation awareness	• Changes in time to comprehension • SART
Level of activation	• EEG power spectral density

Chapter 4 Data Collection

This section discusses the design of the scenarios and the strategies that were followed during data collection. The simulation study was carried out from May 08, 2019 to June 17, 2019. Data were obtained in three formats: subjective, driving variables, and physiological. The subjective data were collected using electronically administered questionnaires such as the screening questionnaire, NASA-TLX, and SART. Driving variables were derived from the simulation tasks and they include: speed, headway, acceleration, jerk, SDLP, number of collisions, and braking force. Physiological variables were collected using the EEG, HR monitor, and eye tracker.

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 advertised in several public places (libraries, universities/colleges, grocery stores, and community centers) around towns in Kansas and Missouri including Lawrence, Overland Park, Shawnee, and Kansas City, using flyers, emails, and targeted advertising within Facebook. Ninety participants were recruited to participate in this research, equally split between males and females. The descriptive statistics of the participants are shown in table 4.1 and figure 4.1. The participants' recruitment was carried out in three age groups 18–24, 25–49, and 50–65 years, depending on availability and willingness to participate. Participants were screened using a questionnaire and selected if they were between the age of 18 and 65 years, with at least one year of driving experience, procession of a valid U.S. driver's license, annual mileage no less than 1000 miles, satisfactory completion of pre-screening and behavioral questionnaires, and good health (free from seizures, eye conditions, ear problems, heart conditions, arthritis, excessive motion sickness, and possibility of pregnancy).

Table 4.1 Descriptive statistics of participants

Age Group	Group ID	Males	Females	Mean and SD by age group
18-24 years	1	25	20	20.3 ± 1.4 years
25-49 years	2	14	15	35.0 ± 8.0 years
50-65 years	3	6	10	56.3 ± 3.7 years
	Sum	45	45	**31.4 ± 14.2 years**

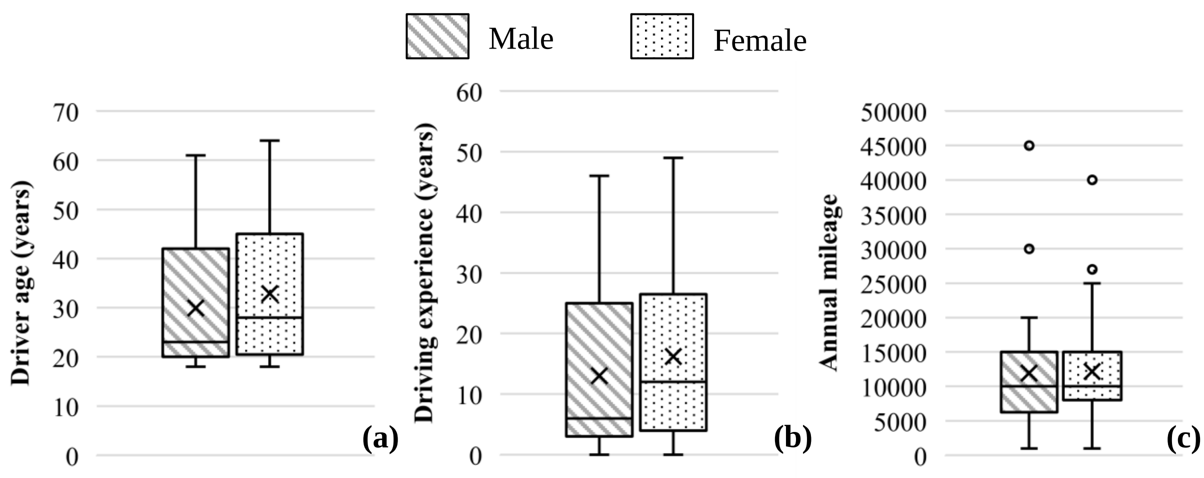


Figure 4.1 Participant demographics (a) driver age, (b) driving experience, and (c) annual mileage

A $50 gift card was issued to the participants after the completion of the study as compensation for their time. Participants were required to complete a 45-minute screening questionnaire prior to their driving appointment, attached in Appendix D, 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. A summary of the participants' demographic data is shown in Appendix F.

The next subsections comprise of behavioral/personality information gathered during the screening process. This dissertation included a series of behavioral self-report measures aimed to capture cognitive effort, personality, and social decision-making variables that could account for aspects of driving performance that have not been considered before in car-following behavior. The objective with the inclusion of these measures was to investigate whether current mood and generally stable descriptors of individual differences among drivers can improve the IDM by incorporating predictors of driver behavior based on cognitive and socio-affective (i.e. emotion, motivation, personality, attitude) variables. The measures incorporated well-established tests of (a) mood and personality; (b) cognitive engagement; and (c) empathy and social decision-making. The specific self-report measures employed are briefly summarized below:

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).

4.1.2 Cognitive Engagement Measures

- Cognitive Reflection Task (CRT): This questionnaire assesses individuals' ability to suppress an intuitive and spontaneous wrong answer in favor of a reflective and deliberative right answer (Frederick, 2005). Three common CRT questions include:

Qn 1: “A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost? _____ cents.” (Correct answer: 5 cents)

Qn 2: “If it takes five machines 5 minutes to make five widgets, how long would it take 100 machines to make 100 widgets? _____ minutes.” (Correct answer: 5 minutes)

Qn 3: “In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? _____ days.” (Correct answer: 47 days)

- 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).

4.1.3 Empathy and Moral Decision-Making Measures

- Interpersonal Reactivity Index (IRI) (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 (PES) (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.

4.2 Equipment

The data were collected using the KU driving simulator, a fixed-based simulator in an Acura MDX chassis (half cab). The simulator provides a 170^{o} 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.

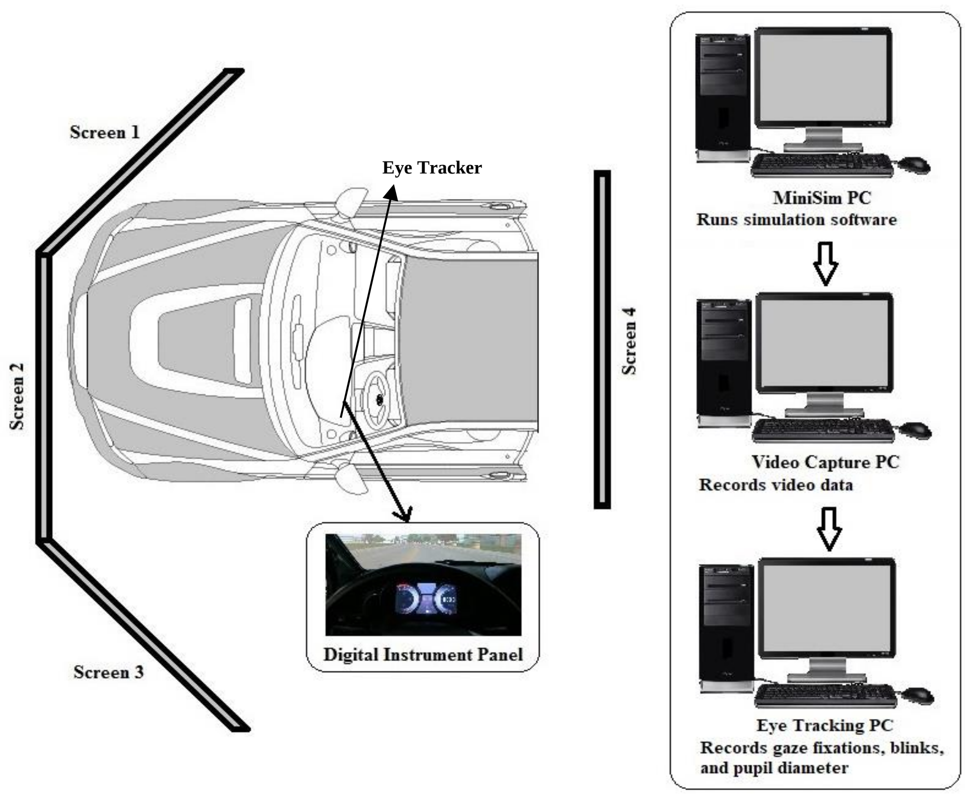


Figure 4.2 Layout of the KU driving simulator

The simulation run and respective data are recorded on the MiniSim (MiniSim User's Guide, 2015) computer while the video of the participant's drive is captured on the video capture computer. Separate systems were used for the eye-tracking and EEG recordings. All the data were later synchronized using the available system times.

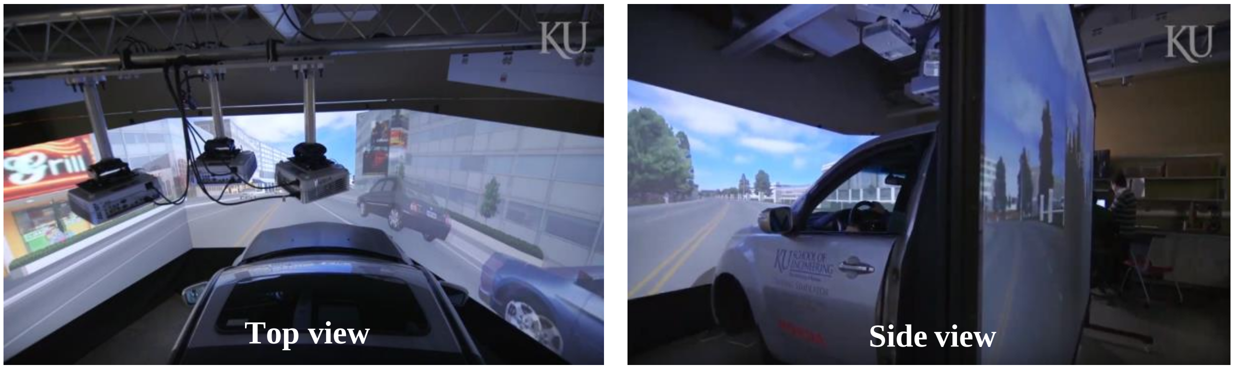


Figure 4.3 KU driving simulator in action

4.3 Configuring the EEG, HR Monitor, and Eye Tracker

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

During the drive, participants' attentional trajectory was captured using the EEG at a sampling frequency of 500Hz (Neuroelectrics User Manual: Enobio 8, 2019). A portable, lightweight, wireless, and rechargeable system for EEG recording was available for this project. The system (Enobio 8) allowed for the reliable reproduction of EEG and EMG signals with a rapid setup that took less than 20 minutes and was optimal for multi-component, multi-method studies. The accompanying software allowed 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 provided continuous online EEG signal quality with an option to filter out noise due to AC power lines (60Hz frequency in the United States). Eight EEG electrode positions were used, and they include: P3, PZ, P4, CZ, T7, T8, O1, and FZ (Pope et al., 1995; Prinzel III et al., 2001). Two additional mandatory reference electrodes were also included to achieve a high-quality electrical signal, i.e., common mode sense (CMS) and driven right leg (DRL). The selected electrode positions, shown in figure 4.4, allowed for the capturing of the functions shown in table 4.2.

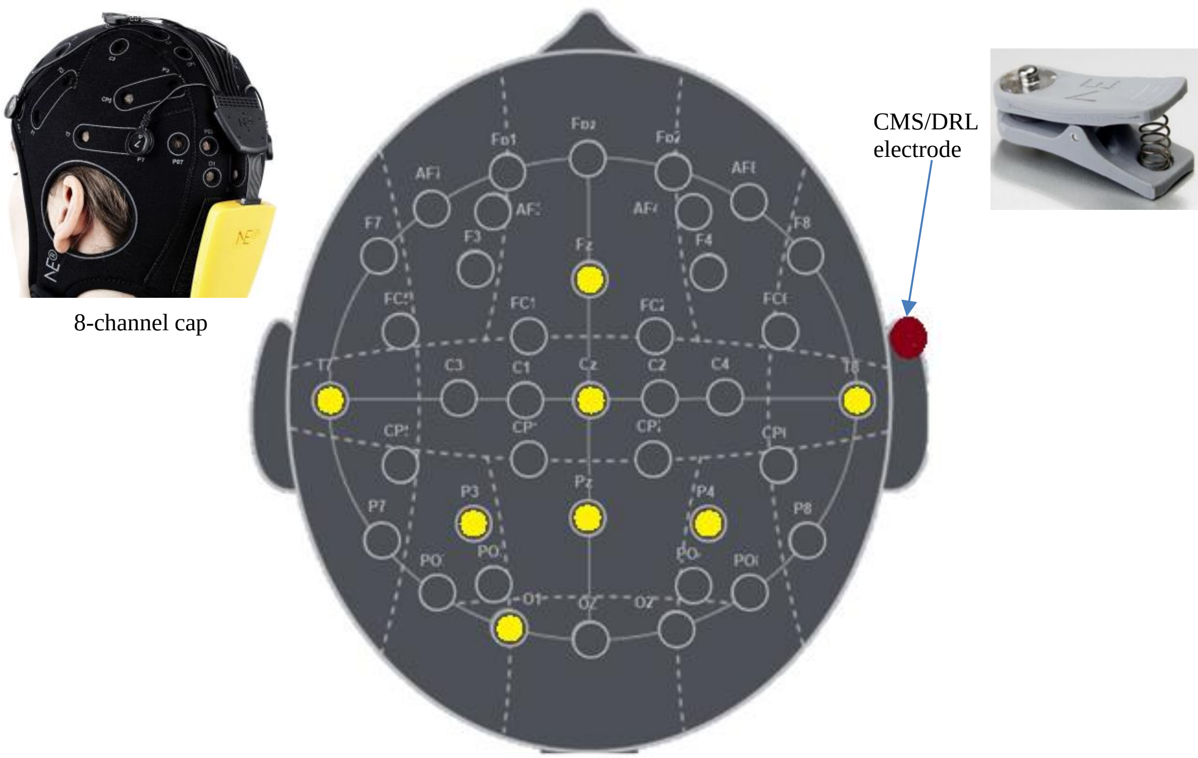


Figure 4.4 Electrode position scalp map

Table 4.2 Selected electrode positions

Electrode Position	**Brain Region**	**Captured Function**
P3, PZ, P4	Parietal	Sensory and Object recognition
CZ	Central	Motor
T7, T8	Temporal	Memory
O1	Occipital	Vision
FZ	Frontal	Concentration, Planning, Judgement
CMS/DRL ear clip	None (right earlobe)	Reference electrodes

The Polar H10 chest strap, shown in figure 4.5, was used to monitor the HR at 1Hz. The obtained data needed to be manually synchronized with the frames of miniSim. Participants were shown how to correctly place the device against their chest to ensure accurate data collection.

Figure 4.5 Polar H10 sensor and chest strap

A Fovio-FX3 eye tracker was installed directly over the instrument cluster of the simulator chassis (EyeWorks 3 User Manual, 2019). The eye tracker collects WL through TEPR at 1Hz and gaze points at approximately 60Hz. Other eye-related measures such as pupil diameter, blink rate, gaze point vector coordinates, ICA, and gaze fixations, were also collected. NASA-TLX was also administered after every task as a surrogate measure of WL.

Due to the restriction of not being able to pause a scenario (in miniSim) to perform the SAGAT by Endsley (1995), another measure was devised. SAGAT was mostly verified by studies on airplane pilots and military professional (combat SA). However, driving might not require the same level of skills to project the status of future events, especially if the task is routine/instinctive (following, braking, lane changing). Also, studies suggest that SAGAT might interfere and make the primary driving task feel discontinuous, therefore not accurately representing the car-following behavior.

The devised method made use of probe questions (similar to Endsley (1995)), visual cues, and time spent gazing, to estimate the SA of the driver, without pausing the scenario. Five SA probe locations were present in every task and require participants to answer questions related to the last five seconds of activity. The questions are tailored to cover all three components of SA (perception, comprehension, and projection). An example of how the SA probe was administered is as follows: a deer crossing sign (cue) was shown five seconds before the probe question is asked. The probe question asked was “Do you expect a crossing deer?”. Participants were required to say their answer out loud, either yes/no or I do not know. In post-processing, participants gaze was monitored to compute the percentage spent looking at the cue from its appearance on screen (approximately 1000 feet). Time required by the drivers to achieve full comprehension of the cue was recorded and used to develop probabilistic models shown in section 5.3.3. The probe questions were designed to consider all three components of SA, i.e., ability to perceive the sign, comprehend to what the sign is saying, and project any upcoming events (status of the crossing deer). A complete list of the probe questions is shown in table 4.3.

Table 4.3 Probe questions for SA

Qn	Probe Question	Possible Answers
1	Do you expect crossing deer?	Yes: Deer crossing sign shown No: Deer crossing sign not present
2	Did the sign say 'speeding kills'?	Yes: Sign said speeding kills No: Sign says something else or no sign present
3	Did you avoid a roadkill?	Yes: Roadkill present No: Roadkill not present
4	Did you see a green color car on the shoulder?	Yes: Car present was green No: Car present was black
5	Does the left shoulder close ahead?	Yes: Left shoulder closed sign shown No: No sign shown
6	Did you see or avoid a worn-out tire?	Yes: Tire present No: Tire not present
7	Is the current speed limit 70 mph?	Yes: Speed limit is 70 mph No: Speed limit is not 70 mph

Three questions with outcome 'yes' and two with outcome 'no' were randomly placed in each task to counterbalance the answers and avoid guessing. SART questionnaires were also administered at the end of the tasks to observe how the devised method compared to existing subjective measures.

4.4 Scenario Design

After recording baseline thresholds for the EEG and HR, participants received an extensive tutorial of the driving simulator. Before the tutorial, the eye-tracker was calibrated to the driver's viewpoint. The tutorial comprised of driving at low and high speeds, lane changing activity, familiarizing participants with distances and headways in a simulator setting, gas and brake pedal responsiveness, and steering wheel sensitivity. During the tutorial, participants were also screened for simulator sickness. Any participants who showed severe signs of simulator sickness (i.e., vertigo, nausea, sweating, dizziness, fatigue, stomach awareness, vomiting, and general discomfort) were advised to forfeit the study and received a compensation of $10.

A preliminary driving scenario, shown in figure 4.6, was designed with two phases: free driving and car-following. The free driving phase was used to capture the participant's desired speed and maximum acceleration components on an empty four-lane divided rural highway, while the car-following phase captured the participant's desired time-gap and preferred standstill distance. Participants were instructed to only focus on maintaining comfortable gap to the lead vehicle during the car-following phase. Each phase was configured to be driven at both 55 mph (88.5 km/h) and 70 mph (112.7 km/h) speed limits, to capture the variability in performance. Eight probe questions were also presented to obtain an estimate of the baseline SA. A breakdown of the full appointment schedule for each participant is shown in table 4.4.

Figure 4.6 Preliminary scenario

Table 4.4 Time breakdown by activity

<table>
<tr><th colspan="4">Description</th><th>Approximate Time</th></tr>
<tr><td colspan="4">Consent form explanation.</td><td>5 minutes</td></tr>
<tr><td colspan="4">Equipping participants with EEG & HR monitor.</td><td>10 minutes</td></tr>
<tr><td colspan="4">Baseline EEG and HR data: Watching short video.</td><td>5 minutes</td></tr>
<tr><td colspan="4">Introduction to simulator driving, calibrating the eye tracker, and tutorial.</td><td>10-15 minutes</td></tr>
<tr><td colspan="5"><u>Preliminary scenario:</u></td></tr>
<tr><td colspan="4">Free driving (no other roadway traffic) with 88.5 km/h and 112.5 km/h speed limits.</td><td>3 minutes</td></tr>
<tr><td colspan="4">Following (one lead vehicle): lead speed changes first from 70 mph to 55 mph, then speeds up to 65 mph.</td><td>4 minutes</td></tr>
<tr><td colspan="4">Total time</td><td>7 minutes</td></tr>
<tr><td colspan="5"><u>Actual scenario:</u></td></tr>
<tr><th rowspan="2">Traffic density</th><th colspan="4">Task</th></tr>
<tr><th>1, 2</th><th>3</th><th>4, 5</th><th>6</th></tr>
<tr><td>Medium</td><td>8 minutes</td><td>–</td><td>5 minutes</td><td>–</td></tr>
<tr><td>High</td><td>5 minutes</td><td>5 minutes</td><td>5 minutes</td><td>5 minutes</td></tr>
<tr><td>Total time</td><td colspan="4">35 minutes</td></tr>
<tr><td colspan="4">NASA-TLX + SART Questionnaires</td><td>20 minutes</td></tr>
<tr><td colspan="5">Average duration per participant = 95 minutes</td></tr>
</table>

Before finalizing the configuration of the tasks, pilot testing was carried out on three participants to establish any design flaws in the scenario and assess the quality of data output. The identified flaws were corrected to ensure that all required data variables were being properly captured.

The actual scenario incorporates six tasks with varying levels of difficulty arising from varying traffic density, lane changing/deviation activity, heavy vehicle density, number of open lanes, and secondary tasks replicating visual distraction. Task 6 was designed to be the most complex while task 1 was the least. Each task was five miles long on a straight roadway with no horizontal curves and had a posted speed limit of 70 mph (112.7 km/h). Simulation traffic was configured to be free flowing, without any form of congestion or speed drop. The gaps between successive lead vehicles were set based on the traffic density of the task. Participants were asked to drive as they would normally, with similar car-following and lane changing behavior. The tasks were assigned and performed in a random sequence to eliminate any order-related bias. At the end of each task (including preliminary), drivers were required to fill out the NASA-TLX and SART questionnaires. A comprehensive description of all tasks is presented in the following sections.

4.4.1 Task 1

The first task, also considered as the baseline, was designed to capture car-following behavior during regular non-intensive highway driving. Participants were required to exhibit naturalistic behavior. The vehicles on the right lane were programmed to travel at 70 ± 2 mph (112.7 ± 2 km/h), while vehicles on the left lane were programmed to travel a bit faster at 74 ± 2 mph (119.1 ± 2 km/h). This provides an opportunity for the driver to exhibit a more naturalistic speed profile.

Figure 4.7 Task 1 design layout and driver view

The left and right lane speed configuration was consistent in all the driving tasks. The task contained no heavy vehicles and had a medium traffic density (16-18 pc/km/ln), shown in figure 4.7.

4.4.2 Task 2

The second task was very similar to the first task. However, the roadway had a higher density of vehicles (22-24 pc/km/ln). Also, lane changing and lane deviations were introduced to the behavior of leading traffic (one passenger car per mile) to further increase complexity. Figure 4.8 shows a snapshot from the task.

Figure 4.8 Task 2 design layout and driver view

4.4.3 Task 3

This task incorporated an inactive work zone that consisted of a closed left shoulder as shown in figure 4.9. The speed limit was maintained at 70 mph (112.7 km/h) to facilitate speed correlations with other tasks. The presence of barriers and channelizers were theorized to increase the situation complexity. Also, the traffic composition for this task consisted of 10% heavy vehicles along with two to three lane deviations/changes per mile. All work zone configurations were created by following KDOT (Kansas Department of Transportation) work zone guidelines.

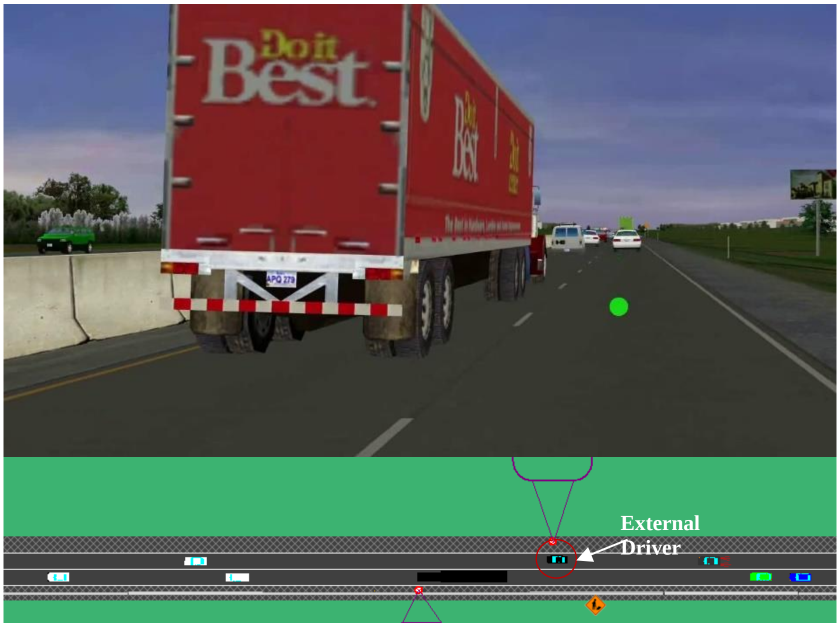


Figure 4.9 Task 3 design layout and driver view

4.4.4 Task 4

Task 4 consisted of a five-lane highway with three lanes closed in one direction. The two open lane edges were delineated using concrete barriers and traffic channelizers. The speed limit was still set at 70 mph (112.7 km/h) for easy comparisons and in order to prevent loss of speed perception in a fixed-base driving simulator (Hurwitz et al., 2005). An active work zone with moving construction workers and equipment was present along both sides of the roadway. The task also consisted of 20% heavy vehicles, medium traffic density (16-18 pc/km/ln), and 3-5 lane changes/deviations per mile. This setup was designed to further increase the complexity of the drive. Changes to the driver's mental workload and situation awareness were expected as a result of the increased complexity. Figure 4.10 shows the configuration of task 4.

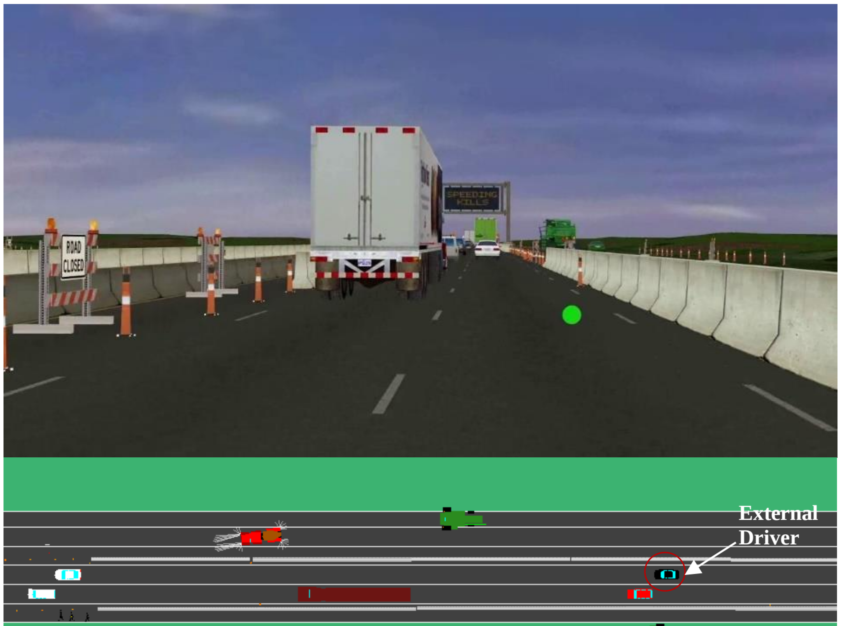


Figure 4.10 Task 4 design layout and driver view

4.4.5 Task 5

Task 5 was created very similar to task 4. However, a higher traffic density was used (i.e. 22-24 pc/km/ln). Figure 4.11 shows the layout of task 5.

Figure 4.11 Task 5 design layout and driver view

4.4.6 Task 6

Task 6 and task 5 were essentially the same apart from the presence of a secondary task. The secondary task used an application developed using Visual Basic Studio (VBA.NET), shown in figure 4.12. The application required participants to match the shown number correctly from the presented tiles during the drive. A computer-generated voice was used to alert the participants on when to start and stop attempting the secondary task. Four short distraction events lasting a distance of 610 meters (approximately 15 seconds depending on speed) each were configured into the task. Participants were advised to attempt tasks only when they felt comfortable during the events as their primary task was still driving.

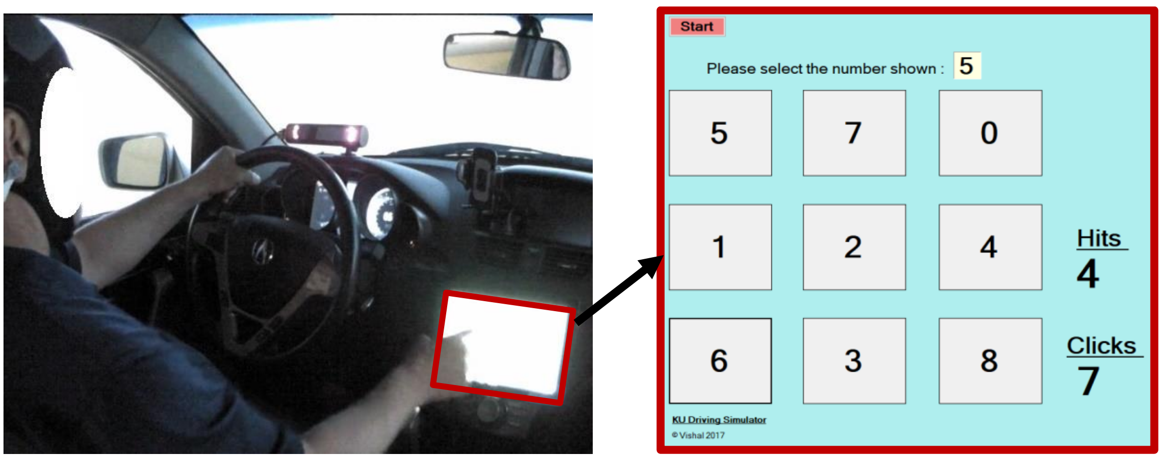


Figure 4.12 Secondary task used to simulate visual distraction

Participants' reaction to having additional tasks competing with the primary task of driving was critically assessed. The distraction provides data with respect to mental workload, situation awareness, level of activation, and driving performance on car-following behavior when engaged in an activity other than driving. A summary of all tasks and their composition is provided in table 4.5.

Table 4.5 Task configuration and composition summary

Name	**Composition**	**Work zone**	**Traffic density**	**Lane deviations**	**Distraction**
Pre	4-lane divided highway at varying speeds. 0% heavy vehicles.	None	0-2 pc/km/ln (LOS A)	None	None
Task 1	4-lane divided highway at 70 mph. 0% heavy vehicles.	None	16-18 pc/km/ln (LOS B/C)	Low (1 pc/km)	None
Task 2	4-lane divided highway at 70 mph. 0% heavy vehicles.	None	22-24 pc/km/ln (LOS D/E)	Low (1 pc/km)	None
Task 3	4-lane divided highway at 70 mph. 10% heavy vehicles.	Inactive: left shoulder closed	22-24 pc/km/ln (LOS D/E)	Medium (1-2 pc/km)	None
Task 4	10-lane divided freeway at 70 mph. 20% heavy vehicles.	Active: far right two and far left lanes closed	16-18 pc/km/ln (LOS B/C)	High (2-3 pc/km)	None
Task 5	10-lane divided freeway at 70 mph. 20% heavy vehicles.	Active on both sides: 3 lanes closed	22-24 pc/km/ln (LOS D/E)	High (2-3 pc/km)	None
Task 6	10-lane divided freeway at 70 mph. 20% heavy vehicles.	Active on both sides: 3 lanes closed	22-24 pc/km/ln (LOS D/E)	High (2-3 pc/km)	Yes (secondary task)

* passenger cars per kilometer per lane (pc/km/ln); level of service (LOS)

Chapter 5 Data Analysis

This chapter discusses, in detail, the techniques and assumptions made to synchronize, filter, sort, resample, and analyze the collected datasets from various equipment. It was essential to synchronize all data as multiple workstations and electronic devices were used to capture and store the data. All start/stop events for the various devices were recorded using the webcam to ensure secondary synchronization in case of system time/network failure. Figure 5.1 shows the device setup used during the data collection.

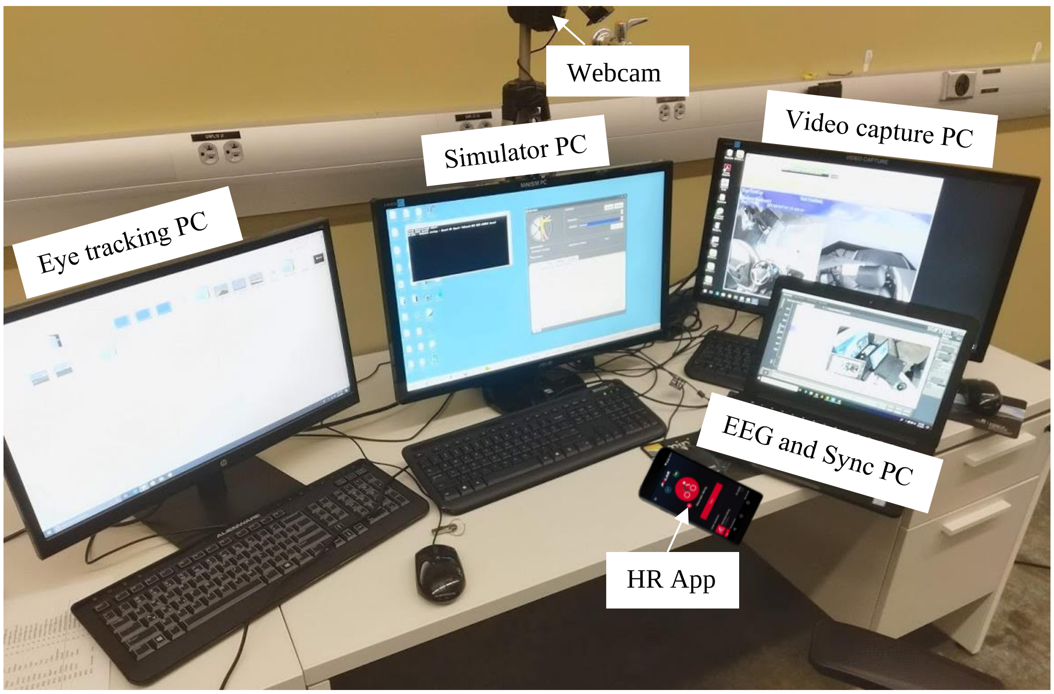


Figure 5.1 Device setup

5.1 Driving Simulator Data

The simulator data were collected at 60Hz and consisted of several variables (converted to metric units) such as time frame, vehicle speed (m/s), brake pedal force (Newtons), vehicle trajectory x, y, z (m), SDLP (m), collision count, lead vehicle velocity (m/s), lead vehicle trajectory x, y, z (m), time gap (s), headway (m), acceleration (m/s^2), and jerk (m/s^3). Although all tasks were five miles long, only the middle four miles were used during the analysis. Event triggers were set at the beginning and end of these analysis zones during the design phase to permit easy identification. The data collection zones for all the tasks performed by the participants are shown in figures 5.2-5.4.

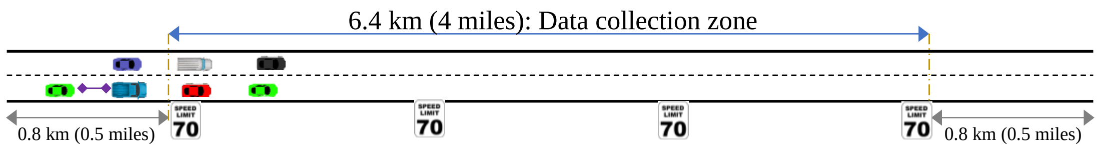


Figure 5.2 Task 1 and 2 analysis zones

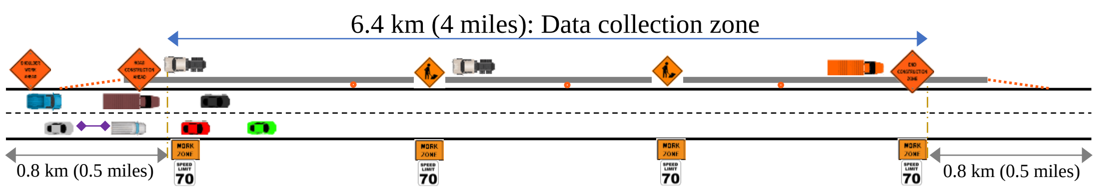


Figure 5.3 Task 3 analysis zone

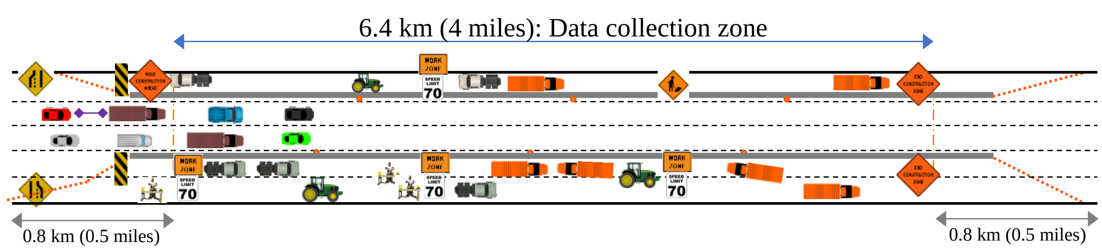


Figure 5.4 Task 4, 5, and 6 analysis zones

5.2 Subjective Data

Although the objective was to capture continuous data that could be used for modeling, it was important to validate the experimental setup by using extensively reviewed techniques for measuring WL (i.e. NASA-TLX) and SA (i.e. SART). The full NASA-TLX and 10-D SART questionnaires were administered at the end of each of the six tasks. The questionnaires were administered electronically using a windows tablet. A visual basic (VBA) version of the SART questionnaire was developed to ensure data were collected and saved securely. A total of 1208 questionnaires were administered during the data collection. The trends observed from these questionnaires are discussed further in Chapter 6.

5.3 Eye-Tracking Data

The data from the eye-tracker were split between continuous, multi-point, and task averages. Task averages were used as a surrogate to NASA-TLX in computing WL. The next few sections describe the significance and terminology of the collected variables.

5.3.1 Gaze Position

The concentration of gaze position (i.e. a phenomenon that causes drivers to direct attention towards a specific point of the roadway) has been linked to increased WL by several researchers (Cooper et al., 2013; He et al., 2014; Li et al., 2018; Kountouriotis et al., 2015; Wang et al., 2014). In order to facilitate the use of this variable, some assumptions had to be made. From the distribution patterns and heat maps obtained from the data, the gaze concentration area was approximated to represent the area (pixels^2) enclosed by the ellipse formed by one standard deviation in the horizontal and vertical positions of the gaze center (i.e. mean gaze position) shown in figure 5.5.

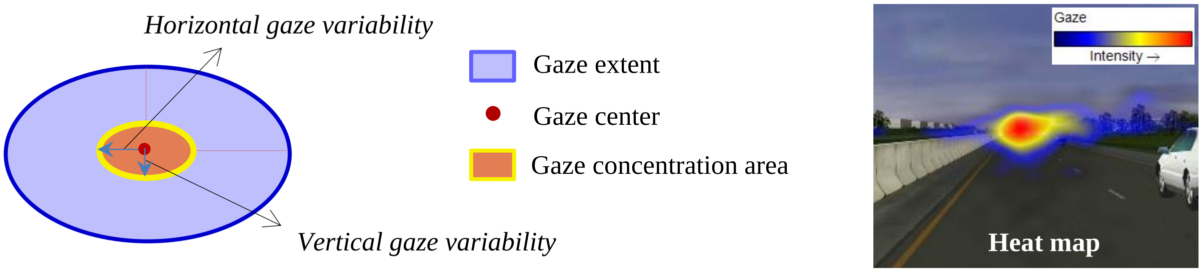


Figure 5.5 Gaze positions and concentration

The horizontal and vertical gaze variabilities were used to identify the role of gaze concentration in determining the WL of the driving tasks.

5.3.2 Index of Cognitive Activity (ICA)

The ICA is a patented pupillometric technique that measures frequency of rapid pupil dilations (Vogels et al., 2018). The ICA is a relatively new technique and is constantly being reviewed. However, its ability to disentangle pupil response due to changes in lighting conditions makes it an attractive method for use in a driving simulator setting. Bright environments cause the pupil to constrict while dark environments cause them to dilate. As the driving simulator consists of several screens of varying brightness and environments ranging in color schemes, measures taken to systematically control the lighting conditions may not fully work. EyeTracking Inc. (2019), manufacturer of the Fovio FX3 eye tracker used in the KU driving simulator, patented the technique and uses custom algorithms along with scaled ICA to predict WL of an individual in increments of one second.

5.3.3 Time to Comprehension

Driver comprehension is one of the more substantial components of SA that involves the ability of an individual to understand the significance of an object, traffic sign, or hazard while driving. The time to a comprehension metric was specifically developed to quantify the SA of a driver without being fully subjective in nature. This metric measures the percentage of time taken looking at a cue from the moment it is visible until it has been comprehended. The probe questions listed in table 4.3 were used together with gaze path overlays and regions of interest (shown in figure 5.6) to determine if a cue was comprehended.

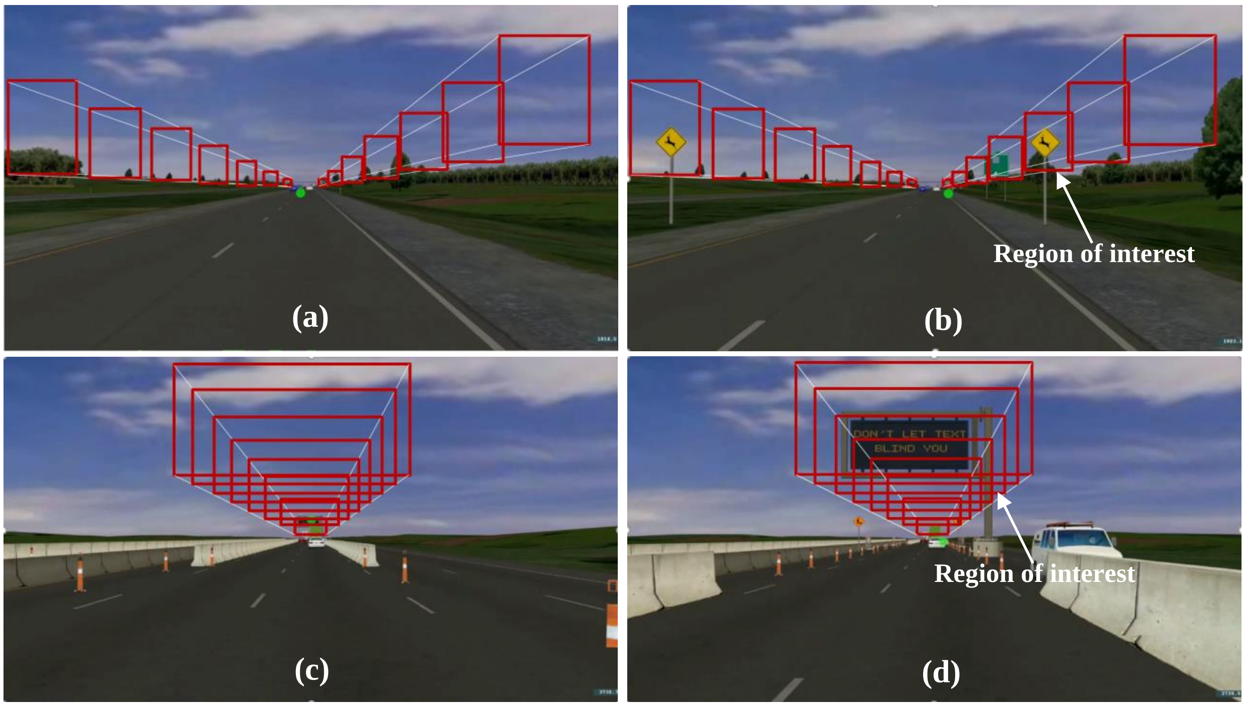


Figure 5.6 Setting up regions of interest

The regions of interest were created in the EyeWorks software after data collection was completed. A progressive mesh of rectangular regions of varying size and shape depending on the type of visual cue and the lane position of the driver were created. Multiple events were created before the onset of a cue for each driver and they varied in duration between 8 and 12 seconds depending on the size of the cue (i.e. visibility) and vehicle speed.

The total gaze duration in each of the regions of interest was computed and recorded together with the participant's verbal confirmation of the cue. Correct responses together with the percent spent gazing from cue onset were combined to form probabilistic distributions for each task as shown in figure 5.7. The key assumption made was that a driver would stop gazing at a cue after perceiving and achieving full comprehension. If gazing continued, full comprehension was not achieved. The best-fit distributions from the data were obtained by running the distribution analysis in Minitab 19 (Minitab, LLC., 2019). Weibull distributions were deemed as the best-fit for the cumulative distributive functions (CDFs) of the six tasks, resulting in the highest R-squared values. The parameters for the Weibull plots are shown in table 5.1.

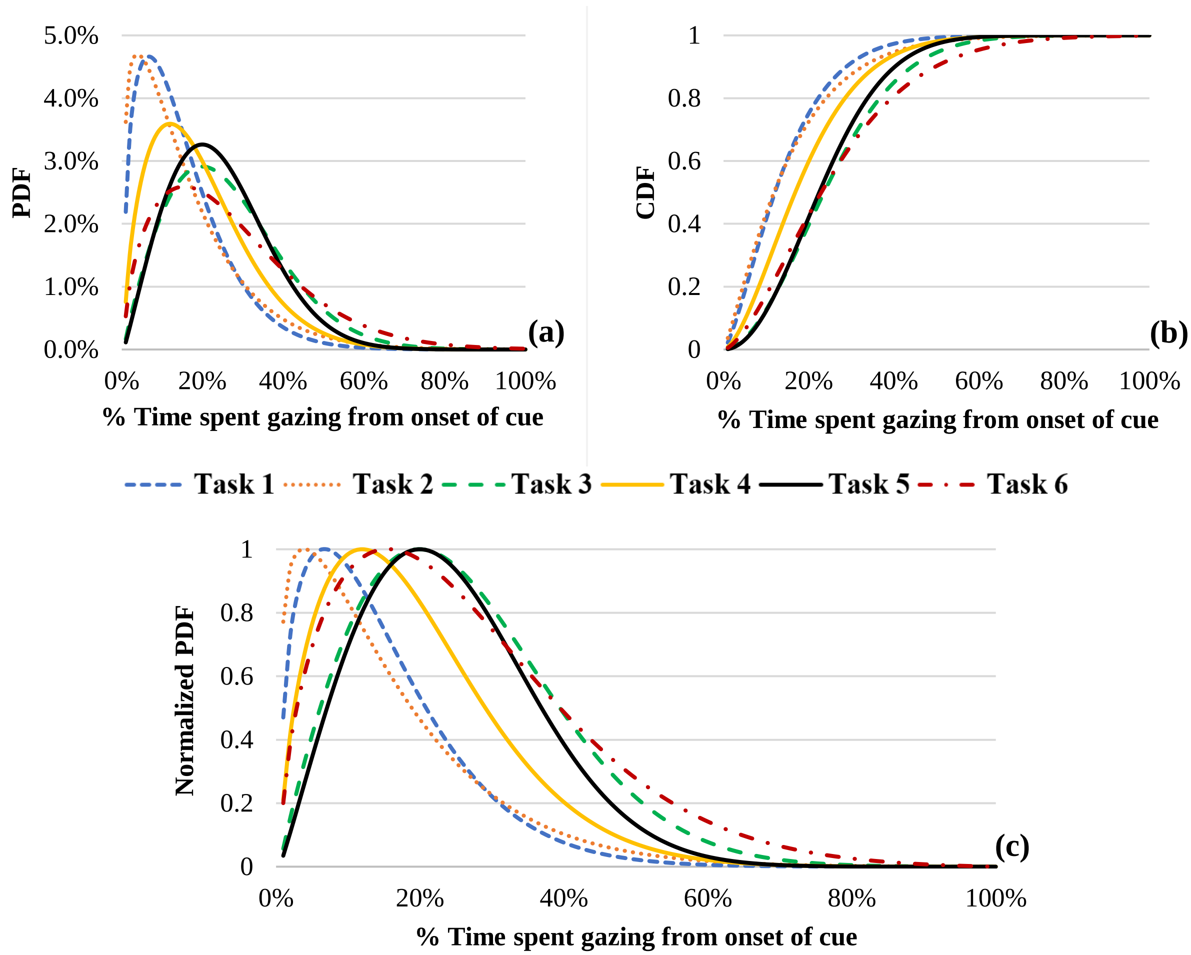


Figure 5.7 Weibull plots for driver comprehension showing (a) PDFs, (b) CDFs, and (c) Normalized PDFs

Table 5.1 Weibull plots parameters

Parameter	**Task 1**	**Task 2**	**Task 3**	**Task 4**	**Task 5**	**Task 6**
Shape	1.3821	1.1866	1.9093	1.5990	2.0631	1.5552
Scale	0.1575	0.1614	0.2859	0.2118	0.2683	0.2906
R-squared	0.9900	0.9821	0.9841	0.9940	0.9821	0.9683

After obtaining the CDFs, the probability density functions (PDFs) were then established. Tasks 1 and 2 showed similar trends of attaining comprehension. Drivers spent between 6 to 7% of the time from the onset of the cue to comprehend it. As the tasks increased in complexity, the optimal time for comprehension increased. This is shown in figure 5.7. However, in task 6, the optimum time spent to comprehend decreased, indicating the onset of competition for attentional resources with the visual distraction. False positives where participants obtained the correct verbal answer without any gaze match were excluded from the CDF curves. Gaze paths were also manually checked to make sure data were not missed or poorly interpreted from the regions of interest. The regions of interest could not capture gaze matches in 10.4 % of the dataset. However, this could be attributed to the deviations in eye-point calibration during the drive.

The obtained PDF curves were then normalized between 0 and 1 to generate the normalized PDFs. These normalized PDF plots were used to interpolate a single value of SA as a probability of achieving comprehension to a given cue in a particular task.

5.4 Heart Rate Data

HR was captured throughout all the tasks. The resting HR was captured during a short (5 minutes) informative video played before the start of the driving experiments. During the analysis, most participants were observed to have reached a lower HR while driving than during the baseline calibration video. This issue was not previously accounted for in the methodology or preliminary testing, thus leading to assumptions during the analysis such as using the absolute minimum HR as a surrogate for the baseline value.

The HR data were normalized between 0 and 1 for each participant with respect to their lowest and highest values. This also acted as an indicator for increased WL, with zero implying low WL and one implying high WL.

5.5 EEG Data

Several steps had to be followed in order to obtain LA from the EEG datasets. The obtained data had to be synchronized with the respective driving simulator data to identify analysis zones (described in Section 5.1). The EEGLAB v14.1.1 toolbox, shown in figure 5.8, in MATLAB was exclusively used for postprocessing (Delorme & Makeig, 2004). A description of the steps is provided below.

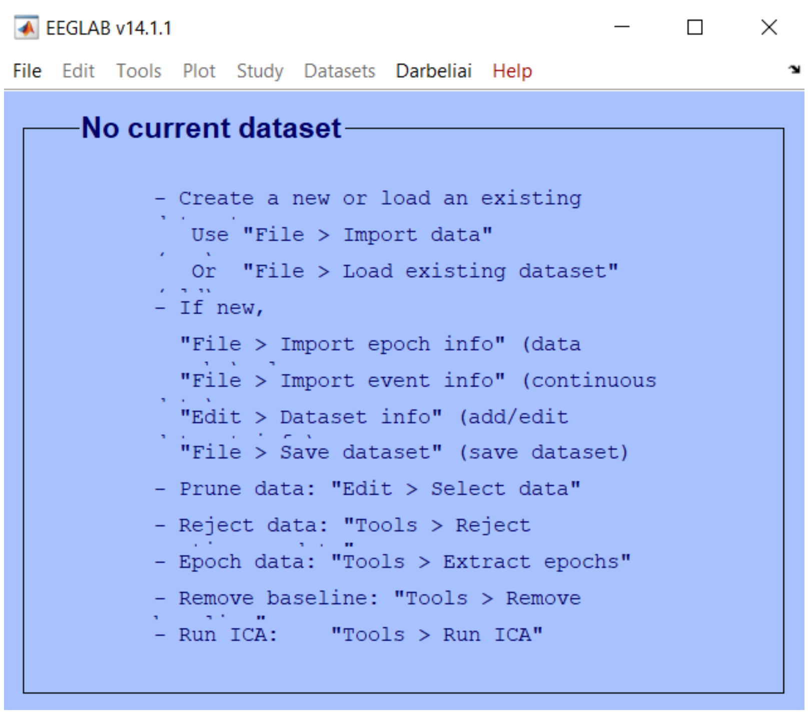


Figure 5.8 EEGLAB interface

Step 1: Set unique identifiers for 10-second events in the EEG dataset. This was done because LA has to be computed in time intervals typically between 10 and 30 seconds. Each driving task resulted in approximately twenty 10-second events.

Step 2: Load and convert data from Neuroelectrics (.easy) format to EEGLAB (.set) compatible format. This was done by utilizing the Neuroelectrics plugin in EEGLAB. The raw data collected had to be downsampled from 500Hz to 240Hz in order to eliminate some of the artifacts and ease system processing. The following MATLAB code that was used to load, convert, assign 3D scalp locations, and resample (from 500Hz to 240Hz).

```
myDir = 'C:\\Users\\path';     % gets directory
myFiles = dir(fullfile(myDir,'*easy')); %    Added    closing
parenthese!
for k = 1:length(myFiles)
     baseFileName = myFiles(k).name;
     fullFileName = fullfile(myDir, baseFileName);  % Changed
myFolder to myDir
     fprintf(1, 'Now reading %s\n', fullFileName);

[ALLEEG EEG CURRENTSET ALLCOM] = eeglab;
EEG = pop_easy(fullFileName,0,0,'');
[ALLEEG   EEG   CURRENTSET]   =   pop_newset(ALLEEG,   EEG,
0,'gui','off');
EEG = eeg_checkset( EEG );
EEG = pop_resample( EEG, 240);
[ALLEEG   EEG   CURRENTSET]   =   pop_newset(ALLEEG,   EEG,
1,'gui','off');
EEG=pop_chanedit(EEG,  'load',{'C:\\Users\\path'  'filetype'
'autodetect'});
[ALLEEG EEG] = eeg_store(ALLEEG, EEG, CURRENTSET);
EEG = eeg_checkset( EEG );
EEG = pop_saveset( EEG, 'filename',baseFileName,'filepath',
'path');
[ALLEEG EEG] = eeg_store(ALLEEG, EEG, CURRENTSET);
eeglab redraw;
end
```

Step 3: The resulting datasets were then filtered. A high-pass filter was applied at 1.6Hz, followed by a notch filter at 60Hz to eliminate noise resulting from the 120V powerlines within close proximity to the EEG device. An independent component analysis was then performed to improve signal quality by identifying and pruning any significant artifacts (i.e. blinks, muscle movements). A low-pass filter was then applied to the signal at 40Hz, essentially rejecting any waveforms above 40Hz as they are not required in the analysis.

Step 4: The filtered signal was then split into 2-second epochs with 5% overlap. The overlap ensured signal continuity when the fast Fourier transform (FFT) window was applied. The 2-second epochs essentially provided four to five individual time-series analysis zones (shown by blue dotted lines in figure 5.9) for the 10-second event due to artifact rejection. Each 10-second event resulted in one absolute power value.

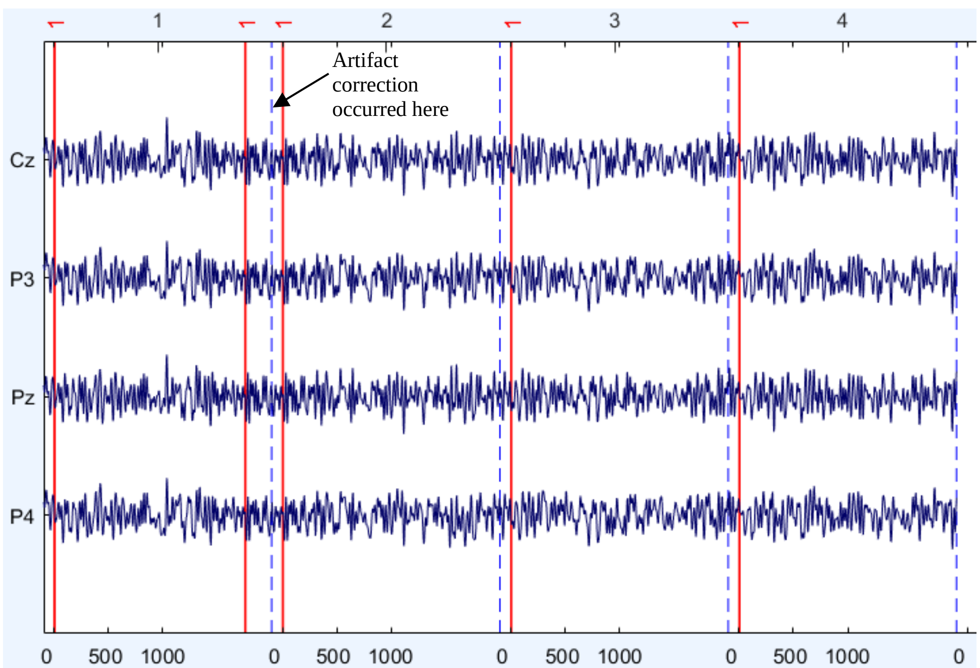


Figure 5.9 2-second epochs

Step 5: The EEG signal was divided into three waveforms for the analysis. Theta waves (4–8Hz), alpha waves (8–13Hz), and beta waves (13–22Hz) as defined by Pope et al. (1995). A 2-second FFT window was applied using the Darbeliai plugin in EEGLAB. The power spectral density

(PSD) was calculated by finding the combined PSD for each waveform at the PZ, CZ, P3, and P4 electrode locations (10-20 system) and applying $\beta/(\alpha+\theta)$ (Pope et al., 1995; Prinzel III et al., 2001). The value obtained provided a quantitative measure of LA for the 10-second period.

5.6 Synchronizing and Resampling

All the collected variables from the multiple equipment were synchronized using the system time and webcam recordings. This ensured that the lag between the data sets was not offset by more than half of a second across all equipment. Since the data were collected at multiple frequencies i.e. driving simulator variables at 60Hz, eye-tracking at 60Hz, LA at 0.1Hz, HR at 1Hz, SA at 1Hz, and ICA at 1Hz, multiple resampling algorithms were used to convert all data to 10Hz. Lower frequency datasets were upsampled while larger frequency datasets were downsampled in MATLAB. Variables that were continuous and showed high deviations were resampled using block averages, while less-volatile variables were resampled by elimination of data points.

Time points with data losses were marked and ignored during model development and validation. The next chapter discusses the task-averaged results to establish a clear biobehavioral distinction between the six driving tasks.

Chapter 6 Results

This chapter provides the obtained results and discusses their relevance with respect to the six driving tasks. The null hypothesis was that changes in environment complexity do not result in changes to WL and SA and cannot be directly correlated to driving measures (compensation and performance), thus providing no basis for incorporating these into the IDM. A significance level of 95% was used to substantiate any evidence. The results are presented in four categories: driving variables, physiological measures, subjective measures, and behavioral questionnaires. Multiple repeated measures analysis of variance (ANOVA) were carried out to identify any significant differences between the various tasks and variables. Task 1 was used as the baseline condition because of its low level of complexity.

6.1 Subjective Measures

The average NASA-TLX scores showed no significant differences between the mean scores of task 2 and task 1 (baseline) with α set to 0.05. However, significant differences in scores were observed for task 3 ($F(1, 83) = 4.087$, $p = 0.046$, $\eta_P^2 = 0.047$, $1-\beta = 0.515$), task 4 ($F(1, 83) = 16.298$, $p < 0.001$, $\eta_P^2 = 0.164$, $1-\beta = 0.979$), task 5 ($F(1, 83) = 35.230$, $p < 0.001$, $\eta_P^2 = 0.298$, $1-\beta = 1.000$), and task 6 ($F(1, 83) = 201.257$, $p < 0.001$, $\eta_P^2 = 0.708$, $1-\beta = 1.000$) with the baseline (shown in fig. 6.1). The significant increases in NASA-TLX scores suggest that the developed tasks captured a variability in mental workload due to increased complexity.

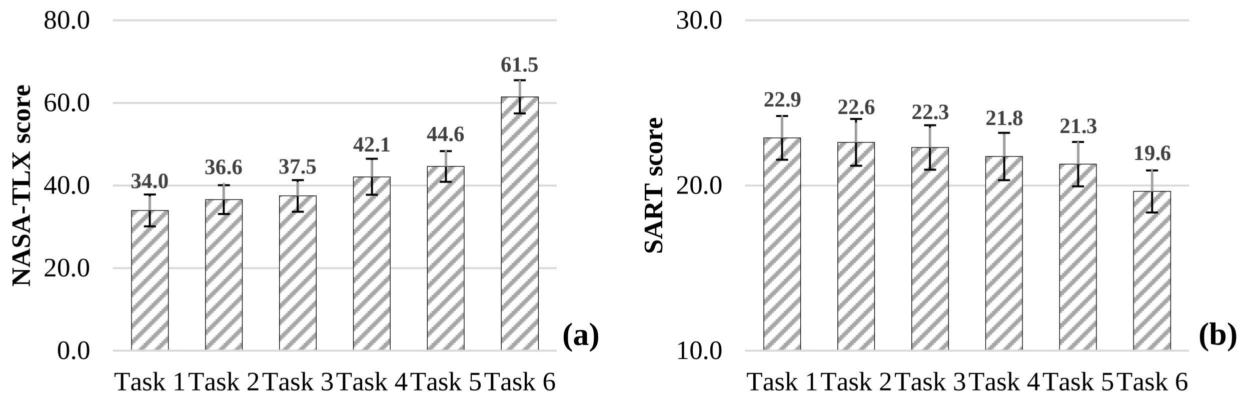


Figure 6.1 Average (a) NASA-TLX and (b) SART scores

Individual NASA-TLX subscales (i.e. mental demand, physical demand, temporal demand, performance, effort, and frustration) were also analyzed for an in-depth understanding of the scores as shown in figure 6.2.

Mean mental demand was found to be significantly different for all tasks when compared to the baseline (task 2 *($F(1, 83) = 5.138$, $p = 0.026$, $\eta_P^2 = 0.058$, $1\text{-}\beta = 0.610$)*; task 3 *($F(1, 83) = 4.939$, $p = 0.029$, $\eta_P^2 = 0.056$, $1\text{-}\beta = 0.594$);* task 4 *($F(1, 83) = 13.448$, $p < 0.001$, $\eta_P^2 = 0.139$, $1\text{-}\beta = 1$)*; task 5 *($F(1, 83) = 30.716$, $p < 0.001$, $\eta_P^2 = 0.270$, $1\text{-}\beta = 1$);* task 6 *($F(1, 83) = 190.880$, $p < 0.001$, $\eta_P^2 = 0.697$, $1\text{-}\beta = 1$))*. Physical demand was also found to be significantly different but only for task 4 *($F(1, 83) = 4.687$, $p = 0.033$, $\eta_P^2 = 0.053$, $1\text{-}\beta = 0.571$)*, task 5 *($F(1, 83) = 9.050$, $p = 0.003$, $\eta_P^2 = 0.098$, $1\text{-}\beta = 0.845$)*, and task 6 *($F(1, 83) = 80.344$, $p < 0.001$, $\eta_P^2 = 0.492$, $1\text{-}\beta = 1$)*. Similar results were also found for the mean of the temporal demand scores, with only task 4 *($F(1, 83) = 14.501$, $p < 0.001$, $\eta_P^2 = 0.149$, $1\text{-}\beta = 0.964$)*, task 5 *($F(1, 83) = 30.301$, $p < 0.001$, $\eta_P^2 = 0.267$, $1\text{-}\beta = 1.000$)*, and task 6 *($F(1, 83) = 156.538$, $p < 0.001$, $\eta_P^2 = 0.653$, $1\text{-}\beta = 1.000$)* configurations showing significant differences to the baseline. Mean performance scores were significantly different for task 5 *(F(1, 83) = 4.624, p = 0.034,* η_P^2 *= 0.053, 1-β = 0.566)* and task 6 *(F(1, 83) = 17.367, p < 0.001,* η_P^2 *= 0.173, 1-β = 0.985)* only.

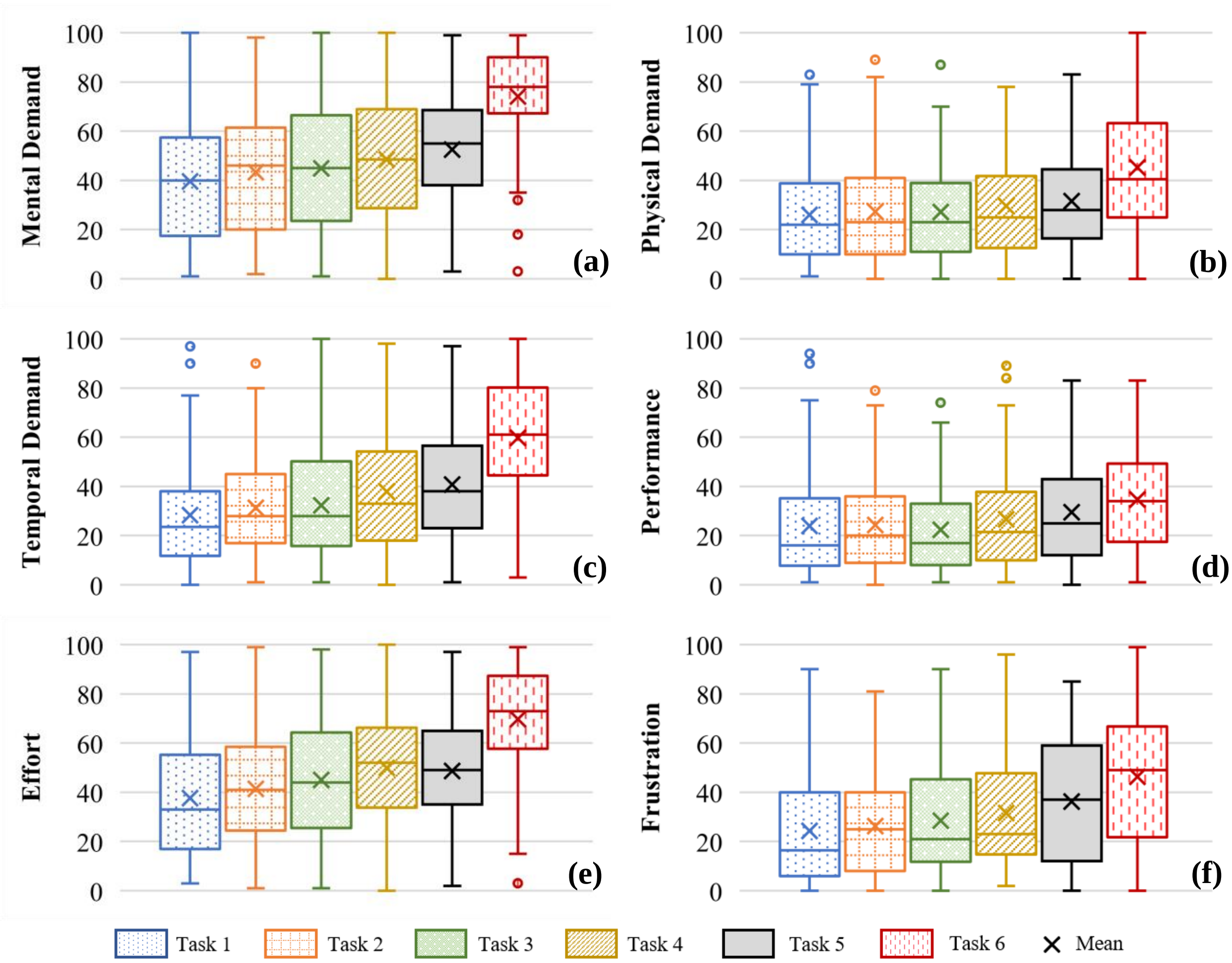


Figure 6.2 NASA-TLX subscale scores by task (a) Mental demand, (b) Physical demand, (c) Temporal demand, (d) Performance, (e) Effort, and (f) Frustration

Mean effort scores were significantly different for task 3 *(F(1, 83) = 10.531, p = 0.002,* η_P^2 *= 0.113, 1-β = 0.894)*, task 4 *(F(1, 83) = 19.722, p < 0.001,* η_P^2 *= 0.192, 1-β = 0.992)*, task 5 *(F(1, 83) = 22.109, p < 0.001,* η_P^2 *= 0.210, 1-β = 0.996)*, task 6 *(F(1, 83) = 145.655, p < 0.001,* η_P^2 *= 0.637, 1-β = 1)*. Finally, mean frustration scores were significantly different for task 4 *(F(1, 83) = 6.473, p = 0.013,* η_P^2 *= 0.072, 1-β = 0.710)*, task 5 *(F(1, 83) = 24.648, p < 0.001,* η_P^2 *= 0.229, 1-β = 0.998)*, and task 6 *(F(1, 83) = 50.755, p < 0.001,* η_P^2 *= 0.379, 1-β = 1)*. Overall, individual subscale scores showed similar results to the weighted NASA-TLX score. Increases in mental demand, physical demand, temporal demand, effort, and frustration were observed with complexity. However, an increase in performance scores with an increase in task demand indicated a reduction in driving performance.

Similar trends were observed with the SART scores. No significant differences were observed between the mean scores of the task 2 and task 3 configurations with respect to the baseline, but task 4 ($F(1, 83) = 7.448$, $p = 0.008$, $\eta_P^2 = 0.082$, $1\text{-}\beta = 0.770$), task 5 ($F(1, 83) = 7.840$, $p = 0.006$, $\eta_P^2 = 0.086$, $1\text{-}\beta = 0.790$), and task 6 ($F(1, 83) = 26.794$, $p < 0.001$, $\eta_P^2 = 0.244$, $1\text{-}\beta = 0.999$) showed significant differences. With the complexity and demand of the tasks increasing, an increase in subjective workload scores was observed along with a decrease in SART scores. This trend seems consistent with the framework theorized and the TCI. Table 6.1 provides a summary of the descriptive statistics for key variables.

Table 6.1 Descriptive statistics of key variables (mean ± SD)

Variable	N	Task 1	Task 2	Task 3	Task 4	Task 5	Task 6
Avg NASA-TLX Score	84	34.2 ± 18.0	36.5 ± 16.2	37.1 ± 17.8	41.5 ± 20.0	44.5 ± 17.2	61.1 ± 18.6
Avg SART Score	84	22.8 ± 6.1	22.6 ± 6.6	22.1 ± 6.1	21.4 ± 6.4	21.2 ± 6.1	19.5 ± 5.9
Avg Speed (km/h)	84	117.6 ± 3.1	115.1 ± 3.4	114.6 ± 6.4	113.6 ± 3.5	112.8 ± 5.0	109.4 ± 8.7
Avg Headway (m)	83	108.1 ± 81.1	98.4 ± 62.2	86.4 ± 55.0	95.6 ± 75.3	84.5 ± 50.9	111.8 ± 60.8
Avg SDLP (m)	84	0.324 ± 0.084	0.306 ± 0.086	0.309 ± 0.076	0.274 ± 0.066	0.261 ± 0.062	0.286 ± 0.085
Avg Lap Time (s)	85	197.5 ± 5.0	203.8 ± 14.9	203.9 ± 15.0	204.9 ± 9.3	207.9 ± 17.4	213.6 ± 26.4
Avg HR (beats per minute)	83	75.7 ± 11.7	75.6 ± 11.4	75.0 ± 11.5	75.2 ± 11.9	75.5 ± 11.8	75.4 ± 12.0

Table 6.1 (Continued) Descriptive statistics of key variables (mean ± SD)

Variable	N	Task 1	Task 2	Task 3	Task 4	Task 5	Task 6
Avg Blink Rate (blinks per minute)	85	17.0 ± 5.6	16.5 ± 5.9	16.2 ± 6.0	15.9 ± 6.5	15.5 ± 6.3	14.4 ± 4.7
Avg SD of Horizontal Gaze Position (pixels)	85	128.4 ± 42.9	126.6 ± 44.5	130.6 ± 41.4	99.7 ± 31.2	99.6 ± 33.7	93.0 ± 34.3
Avg SA as a function of comprehension	82	0.704 ± 0.279	0.633 ± 0.292	0.734 ± 0.272	0.733 ± 0.268	0.714 ± 0.279	0.732 ± 0.257
Avg LA	82	1.235 ± 0.355	1.253 ± 0.361	1.240 ± 0.362	1.262 ± 0.382	1.219 ± 0.333	1.236 ± 0.343

6.2 Driving Variables

Driving variables can also be used to detect imbalance between mental workload and situation awareness. The correlation of these variables to subjective measures discussed in section 5.1 is key to this research. Average headway was one of the key variables in detecting changes to longitudinal control. Significant differences were obtained for tasks 3 *($F(1, 82) = 7.168$, $p = 0.009$, $\eta_P^2 = 0.080$, $1\text{-}\beta = 0.754$)* and 6 *($F(1, 82) = 8.186$, $p = 0.005$, $\eta_P^2 = 0.091$, $1\text{-}\beta = 0.807$)*, where participants were observed to maintain closer headways than the baseline. The pairwise tests revealed significant differences between task 5 and task 6 *(Mean difference = -89.510, $p < 0.001$)* with participants observed maintaining larger headways when engaged in the visual distraction.

Average speed was a more sensitive measure in this study as a decreasing trend was observed across all tasks (from 2 to 6) as shown in figure 6.3. All tasks were significantly different to the baseline condition: task 2 *($F(1, 83) = 46.897$, $p < 0.001$, $\eta_P^2 = 0.361$, $1\text{-}\beta = 1.000$)*; task 3 *($F(1, 83) = 21.748$, $p < 0.001$, $\eta_P^2 = 0.208$, $1\text{-}\beta = 0.996$)*; task 4 *($F(1, 83) = 133.949$, $p < 0.001$, $\eta_P^2 = 0.617$, $1\text{-}\beta = 1.000$)*; task 5 *($F(1, 83) = 97.801$, $p < 0.001$, $\eta_P^2 = 0.541$, $1\text{-}\beta = 1.000$)*; and task

6 *(F(1, 83) = 98.844, p < 0.001,* η_P^2 *= 0.544, 1-β = 1.000)*. However, tasks 2 and 3 alongside tasks 3, 4 and 5, showed no pairwise differences amongst each other. This could indicate no significant imbalance in the TCI for these tasks. A high inverse correlation can also be observed to the average NASA-TLX scores.

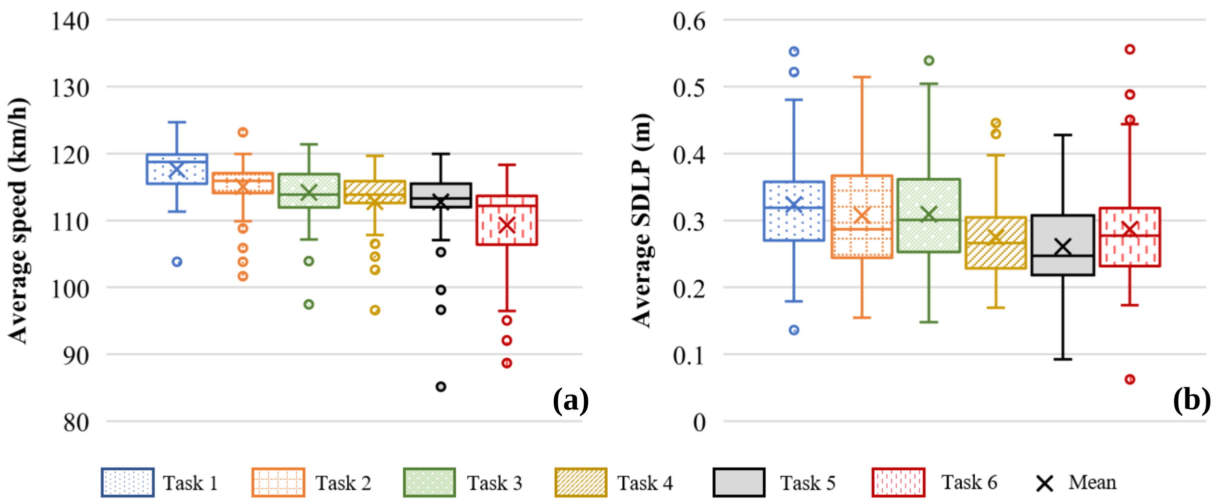


Figure 6.3 (a) Average speed and (b) average SDLP by task

Average SDLP was also found to change along with task complexity. Significant differences were observed between the baseline and tasks 4 *(F(1, 83) = 29.791, p < 0.001,* η_P^2 *= 0.264, 1-β = 1.000)*, 5 *(F(1, 83) = 42.691, p < 0.001,* η_P^2 *= 0.340, 1-β = 1.000)*, and 6 *(F(1, 83) = 10.622, p = 0.002,* η_P^2 *= 0.113, 1-β = 0.896)*. The average SDLP was observed to decrease (improved lane keeping ability) with a substantial increase in task complexity. This was similar to what was observed in past research where a decrease in SDLP was theorized to occur due to lateral position being inherently performed at a level below optimal unless being subjected to higher cognitive load (Cooper et al. 2013, He et al. 2014, Li et al. 2018, Kountouriotis et al. 2015, Wang et al. 2014).

The average lap time was also used as a driving variable, indicating the time taken to complete a stretch of four miles of roadway across the six tasks. Significant differences were observed across all tasks and the baseline: task 2 *($F(1, 84) = 13.742$, $p < 0.001$, $\eta_P^2 = 0.141$, $1\text{-}\beta = 0.956$)*; task 3 *($F(1, 84) = 17.031$, $p < 0.001$, $\eta_P^2 = 0.169$, $1\text{-}\beta = 0.983$)*; task 4 *($F(1, 84) = 61.899$, $p < 0.001$, $\eta_P^2 = 0.424$, $1\text{-}\beta = 1.000$)*; task 5 *($F(1, 84) = 33.030$, $p < 0.001$, $\eta_P^2 = 0.282$, $1\text{-}\beta = 1.000$)*; and task 6 *($F(1, 84) = 38.614$, $p < 0.001$, $\eta_P^2 = 0.315$, $1\text{-}\beta = 1.000$).* This was expected as average speed was observed to decrease with increase in task complexity and demand.

Overall, on a holistic level, some substantial differences were observed across the various tasks, suggesting positive progress towards the theorized framework. Time-series data analysis was performed as described in section 6.5 to study the interaction of these variables and car-following behavior.

6.3 Physiological Measures

As stated in the literature, physiological measures are also observed to change with respect to an imbalance in WL and SA. The average HR was found to not be significant between most of the tasks except for task 3 *($F(1, 82) = 5.712$, $p = 0.019$, $\eta_P^2 = 0.065$, $1\text{-}\beta = 0.656$)*, which was significantly less than the baseline. However, physiological measures might not be good predictors as an average value by task, rather using time-series analysis would provide more sensitive results.

SD of horizontal gaze position was also used as a key variable (shown in fig. 6.4). Research has shown a decrease in horizontal gaze variability with increasing cognitive workload. Significant gaze position differences were observed in tasks 4 *($F(1, 84) = 66.023$, $p < 0.001$, $\eta_P^2 = 0.440$, $1\text{-}\beta = 1.000$)*, 5 *($F(1, 84) = 49.379$, $p < 0.001$, $\eta_P^2 = 0.370$, $1\text{-}\beta = 1.000$)*, and 6 *($F(1, 84) = 81.746$, $p < 0.001$, $\eta_P^2 = 0.493$, $1\text{-}\beta = 1.000$)*. A decreasing trend as observed in past research was observed, indicating changes to mental workload across the tasks (Cooper et al. 2013).

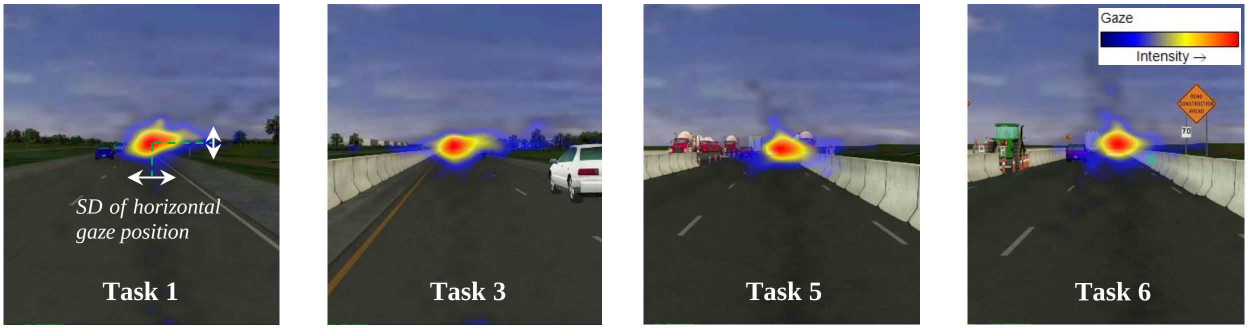


Figure 6.4 Gaze position variability (Driver ID 79)

The average blink rate was also used to determine changes in WL. Significant differences were observed for tasks 3 *($F(1, 84) = 4.262$, $p = 0.042$, $\eta_P^2 = 0.048$, $1\text{-}\beta = 0.532$),* 4 *($F(1, 84) = 6.680$, $p = 0.011$, $\eta_P^2 = 0.074$, $1\text{-}\beta = 0.724$),* 5 *($F(1, 84) = 17.765$, $p < 0.001$, $\eta_P^2 = 0.175$, $1\text{-}\beta = 0.986$),* and 6 *($F(1, 84) = 35.679$, $p < 0.001$, $\eta_P^2 = 0.298$, $1\text{-}\beta = 1.000$).* A decreasing blink rate with increasing WL was noted from the results.

No significant differences were observed across the six tasks with the average SA score obtained by using driver comprehension. Average LA scores were found to be consistent across all tasks. Also, no correlation was observed between the SART and driver comprehension-based SA scores.

6.4 Behavioral Questionnaires

The relationships between driving performance and the behavioral assessments was measured using a series of Pearson correlations with a statistical significance value set at $p = 0.05$ (two-tailed). The dependent measures included the following: self-reported estimated miles driven annually; love of driving; self-reported number of traffic violations or tickets/year; average driving speed during simulated drive in m/s; SD of lateral position in meters; average headway in meters; average heart-rate in beats per minute; average pupil diameter in mm; and the ICA from the right pupil, for the six driving tasks. Possible relationships between the self-reported behavioral measures and the NASA-TLX as well as the SART were also examined. Behavioral questionnaire total scores are shown in Appendix G of this dissertation. The main results across these analyses are summarized in the following paragraphs.

Participants who scored higher on the PANAS (indicating positive mood) reported significantly higher preference and love of driving *($r = 0.32$, $p = 0.003$)* but also deviated significantly from their driving lanes during task 1 *($r = .33$, $p = 0.002$)* and task 3 *($r = 0.325$, $p = 0.002$)*. Participants who scored higher on this scale further showed lower scores on the NASA-TLX index *($r = -0.29$, $p = 0.007$)* indicating lower perceived WL during the simulated drive. Given that the PANAS measured the current mood of an individual and was performed during the pre-screening phase (which could have occurred up to two months before the drive), the correlation to the simulated drive and the WL measures for most participants were affected by a time lag. Future studies should implement the administration of the PANAS immediately preceding the simulated drive for the valid examination of the impact of current mood. Nevertheless, these findings point to a relationship between mood and affective disposition and driving performance and could be incorporated into car-following models.

Significant relationships were observed between the CRT and driving behavior and performance measures. Performance on the CRT was negatively correlated with SART scores for tasks 4 *($r = -0.28$, $p = 0.009$)* and 6 *($r = -0.27$, $p = 0.01$)* of the simulated drive suggesting that participants with higher cognitive reflection evaluated the driving simulation as less cognitively demanding relative to participants who scored lower on the CRT. Given that the CRT is a relatively stable measure of cognitive engagement, this is an aspect of participants' disposition that can add value to understanding driver behavior.

The five-factor model of personality generates scores for each participant on five main aspects of personality that are considered situationally stable: neuroticism, extraversion, openness to experience, agreeableness, and conscientiousness. Participants scoring high in neuroticism tended to drive significantly faster during the simulated drive for the higher difficulty tasks 5 *($r = 0.25$, $p = 0.02$)* and 6 *($r = 0.22$, $p = 0.04$)*. They also not only showed lower SDLP *($r = -0.28$, $p = .01$)* but lower average headway *($r = -0.21$, $p = 0.047$)* for the first task. Neuroticism scores were negatively correlated with extraversion *($r = -0.31$, $p = 0.003$)*, agreeableness *($r = -0.28$, $p = 0.008$)*, and conscientiousness *($r = -.34$, $p = .001$)* scores. Participants higher in extraversion reported significantly higher preference for driving *($r = 0.36$, $p = 0.001$)*, but also higher self-reported annual traffic violations *($r = 0.21$, $p = 0.04$)*. In line with these findings, participants higher in extraversion deviated significantly from their lanes during task 1 *($r = 0.30$, $p = 0.005$)* and task 5 *($r = 0.28$, $p = 0.01$)*. They also showed significantly higher pupil dilation for tasks 1 through 4 *(all $ps < .05$)* indicating higher WL. Participants scoring higher in openness to experience, also self-reported more annual traffic violations *($r = 0.28$, $p = 0.009$)*. Participants scoring higher in agreeableness tended to report that they follow vehicles very closely at 30 mph zones *($r = 0.24$, $p = 0.03$)*. Lastly, participants higher in conscientiousness tended to report that they follow vehicles very closely at 30 mph zones *($r = 0.22$, $p = 0.04$)*, but also drove slower during task 2 of the simulated drive *($r = 0.22$, $p = 0.04$)*.

To capture different but complimentary aspects of empathy, two measures of empathy were used—the Interpersonal Reactivity Index (IRI) and the Empathy Assessment Index (EAI). The IRI (Davis, 1983) is the earliest and most widely used multidimensional measure of empathy, which includes four factors: perspective taking (i.e. the tendency to spontaneously adopt others' psychological point of view), fantasy (i.e. respondents' tendencies to transpose themselves imaginatively into the feelings and actions of fictitious characters in books, movies, and plays), empathic concern (i.e. the tendency to have sympathy for others' concerns and problems), and personal distress (i.e. feelings of personal anxiety and unease in tense interpersonal settings). This measure was used due to its prevalence in the literature; however, it has been recently re-evaluated to potentially have lower validity and less accuracy of empathy assessments (Chrysikou & Thompson, 2016). The results showed that participants who scored high on the perspective taking subscale of the IRI, reported higher number of traffic violations *($r = 0.21$, $p = 0.047$)*, as well as tendency to follow others closely at 70 mph *($r = -0.24$, $p = 0.02$)* and 50 mph *($r = -0.25$, $p = 0.02$)* zones. Participants who scored higher on the fantasy scale also tended to report significantly more traffic violations *($r = 0.24$, $p = 0.025$)* and lower scores on the SART in tasks 4 *($r = -0.28$, $p = 0.008$)* and 5 *($r = -0.25$, $p = 0.02$)*. Higher scores on the personal concern subscale were significantly associated with higher NASA-TLX scores for tasks 1 through 5 *(all $ps < 0.05$)*. Higher scores on the personal distress subscale were significantly associated with self-reported tendency to allow for a farther following distance at 30 mph zones *($r = 0.22$, $p = 0.035$)*. On the other hand, during the simulated drive, higher scores on this scale were associated significantly with increased average speeds during tasks 5 *($r = 0.26$, $p = 0.016$)* and 6 *($r = 0.31$, $p = 0.004$)*, as well as reduced average headway on tasks 1 *($r = -0.21$, $p = 0.049$)*, 2 *($r = -0.26$, $p = 0.016$)*, and 5 *($r = -0.36$, $p = 0.001$)*. These results on the personal distress scale mirror those of the personality trait of neuroticism, suggesting that general self-oriented anxiety may be associated with higher speeds and smaller headway distances—both evidence of a more aggressive driver profile.

The EAI is a more recent measure of empathy that is designed to capture a multidimensional model of empathy that is based on social cognitive neuroscience principles (Gerdes et al., 2011). The scale includes 5 sub-scales intended to tap on: participants' affective responses, their ability for emotion regulation, their ability for perspective taking, their awareness of self and others, and their empathic attitudes. Higher scores on the emotion regulation subscale were consistently associated with higher average pupil diameter for all tasks *(rs range from 0.22 to 0.30 and all ps <.05)* and marginally for task 2 *($r = 0.21$, $p = 0.07$)*. Participants scoring higher on perspective taking reported closely following vehicles at 70 mph *($r = -0.27$, $p = 0.01$)*, 50 mph *($r = -0.23$, $p = 0.03$)*, and 30 mph *($r = -0.26$, $p = 0.01$)* zones. Increased scores on self-other awareness were also consistently associated with higher average pupil diameter across all tasks *(all ps < .05)*, whereas increased empathic attitudes were associated with decreased liking of driving overall *($r = -0.31$, $p = 0.004$)* and increased headway in feet but for task 1 only *($r = 0.23$, $p = 0.03$)*. Overall, this measure of empathy did not provide as many insights on driving behavior as the IRI.

Consistent with the nature of the scale, increased scores on this scale were associated with decreased likelihood to self-report traffic violations *($r = -0.25$, $p = 0.016$)*. Also, there were no significant relationships between performance on these measures and any self-reported measures or driving performance variables.

In summary, despite the relatively high temporal time between the administration of the behavioral assessments and the driving simulation session, the above results indicate that self-reported assessments of mood, personality, and empathy are useful indicators of driving behavior. Specifically, a general tendency for positive mood and extraversion may be linked to more traffic violations, higher speeds, and increased lateral position deviations, possibly due to increased distractibility. On the other hand, neuroticism and empathic distress that can serve as indicators of self-oriented anxiety were consistently associated with increased speeds and lane deviations during the simulated drive.

6.5 Time-Series Data

As seen in previous sections, the average values of variables do not always provide the ideal comparisons. Comparing variables at individual time points show their probable relationships and correlations. Multiple Pearson correlation tests were carried out with respect to the variables with the greatest potential of being utilized in the car-following model. As speed was one of the most important factors in the model, several other driving and physiological measures were compared to it. Data from all drivers was compiled for all six tasks in one series and analyzed.

A high negative correlation was obtained between speed and SDLP *($r = -0.124$, $p < 0.001$)* indicating lower variability in lane position at high speeds. HR and speed were found to be positively correlated with higher speeds resulting in elevated heart rates *($r = 0.019$, $p < 0.001$).* This can be clearly observed in figure 6.5. No significant correlation was obtained between true LA (not normalized) scores and speed *($r = -0.001$, $p = 0.372$).* A significant correlation was observed between Speed and WL established from ICA of the left eye *($r = 0.022$, $p < 0.001$).* The data shows some valid relationships that might be useful to predict speeds during car-following. Figure 6.5 shows a sample time-series plot during the sixth task and the blue arrows indicate the duration of the distraction events. SDLP, HR, and WL_ICA can be observed to increase during the distractions.

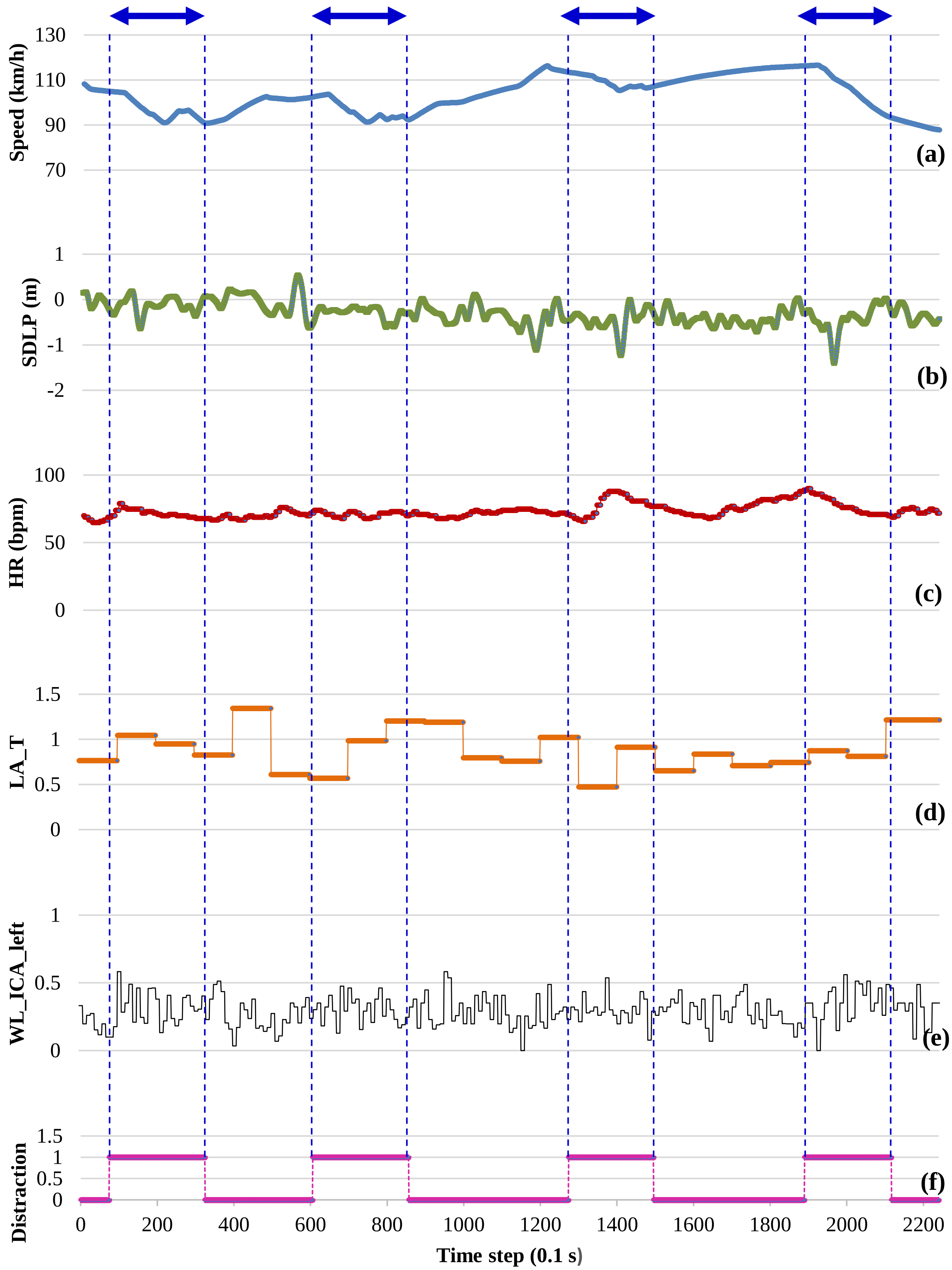


Figure 6.5 Time-series profile for driver ID 3 (a) Speed, (b) SDLP, (c) HR, (d) true LA score, (e) WL as a function of the left eye, and (f) Distraction – Task 6

6.6 Summary

In summary, the average scores of driving variables (i.e. speed, headway, and SDLP) and the subjective measures (i.e. NASA-TLX and SART) were effective in establishing the demand of the tasks. However, physiological measures were not sensitive due to the high variance between individuals. Variability in physiological measures was more apparent in time-series analysis.

Behavioral questionnaire data showed some promising results such as the tendency for positive mood and extraversion to be linked to more traffic violations, higher speeds, and increased lateral position deviations. This information was used while grouping individuals during the model development.

Chapter 7 Model Development and Validation

The proposed biobehavioral IDM (b-IDM) was theorized to optimize calibrating multiple car-following trajectories by grouping drivers with similar performance traits (i.e. supervised learning). As discussed in the literature, several methods exist to categorize drivers. In this research, participants were categorized based on their driving performance across all six tasks by evaluating their maximum speed (m/s), absolute maximum jerk (m/s^3), and minimum time gap (s). Only 80 participants were used in the clustering as four datasets showed bad/noisy data especially from the EEG device and eye tracker while data from six participants were excluded due to simulator sickness. A 75/25 data split was used for development and validation, respectively.

Multiple clustering algorithms (Two-Step, K-Means, and Hierarchical) were used to obtain distinct groups of drivers. The K-Means clustering algorithm resulted in the most distinct clusters (i.e. p < 0.001) and was selected. Figure 7.1 shows the obtained driver groups.

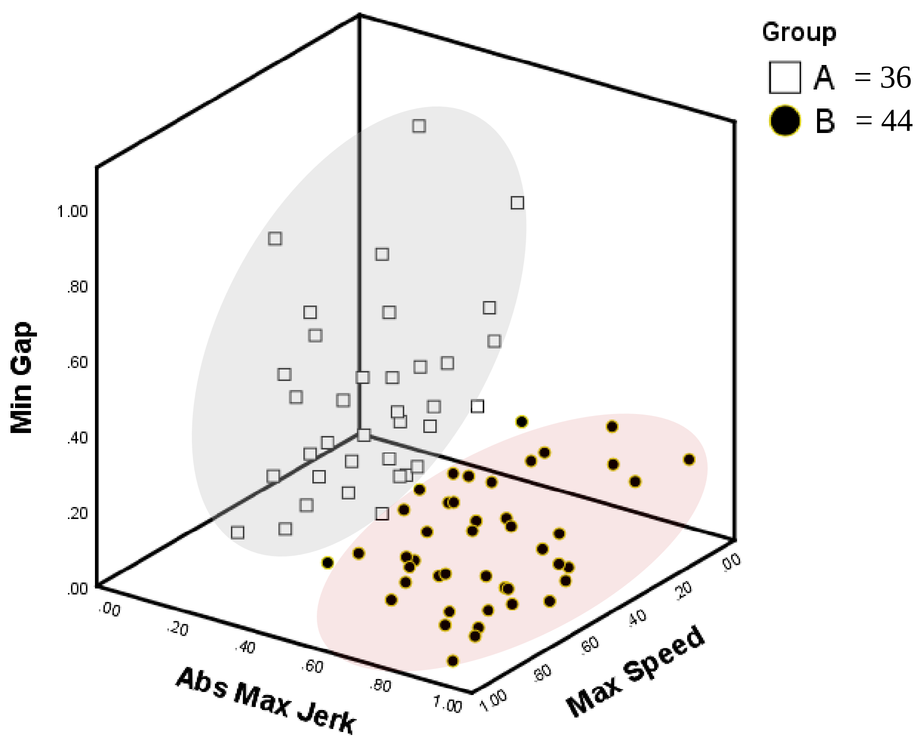


Figure 7.1 Established driver clusters

An optimal solution was reached with two distinctive clusters of similar size, i.e., group A consisted of 36 drivers and group B consisted of 44 drivers (*Minimum gap*: $F(1, 78) = 27.187, p < 0.001$; *Absolute maximum jerk*: $F(1, 78) = 164.415, p < 0.001$; *Maximum speed*: $F(1, 78) = 17.456, p < 0.001$).

Table 7.1 Cluster properties

Variables	Normalized cluster centers			Mean ± SD	
	A	B	Sig.	A	B
Minimum Gap (s)	0.36	0.16	< 0.001	1.12 ± 0.51	0.67 ± 0.23
Absolute Maximum Jerk (m/s^3)	0.31	0.78	< 0.001	4.29 ± 1.40	8.16 ± 1.30
Maximum Speed (m/s)	0.42	0.60	< 0.001	35.69 ± 1.27	37.05 ± 1.55
Age (years)				27.06 ± 11.65	34.25 ± 14.17
Driving Experience (years)				10.42 ± 12.20	17.82 ± 14.85
Annual Mileage				10740 ± 7450	13890 ± 9390
Maximum SDLP (m)				0.37 ± 0.21	0.39 ± 0.08
Maximum Acceleration (m/s^2)				0.828 ± 0.269	1.647 ± 0.816
Maximum Deceleration (m/s^2)				-2.644 ± 1.404	-4.541 ± 1.481
Maximum NASA-TLX score				64.05 ± 14.90	60.29 ± 19.17
Minimum SART score				17.31 ± 5.73	17.41 ± 5.85

Table 7.1 shows the properties of the obtained driver groups. Both groups consisted of a similar amount of male and female drivers. Group A consisted of drivers that followed larger gaps,

lower maximum jerk, and lower maximum speeds. Drivers in group A also had a lower average age and driving experience. Group B consisted of more aggressive drivers who exhibited greater overall speeds, shorter following gaps, and larger maximum jerk. Cluster properties also indicated that group B drivers had more driving experience, annually drove more miles, and experienced a lower maximum NASA-TLX score (i.e. experienced less WL in the most complex driving task).

In order to correlate self-reported questionnaire data (i.e. driving experience, traffic violations, following gap, accident history, take pleasure in driving, braking behavior, cell phone usage, CRT score, PANAS, IRI, PES, EAI, moral dilemmas, and neuroticism) and subjective behavioral traits (i.e. NASA-TLX and SART) with performance variables, additional clustering was carried out to establish similar groups. This could not be accomplished perfectly; however, it was noted that participants were able to accurately gauge their desired speeds. A significant correlation was obtained between the self-reported speeds and the maximum speeds recorded from the driving study. A Pearson correlation coefficient of 0.362 was attained $(N = 80, p < 0.001)$. Figure 7.2 compares the self-reported and simulation speeds. The observed offset could be a result of using the maximum achieved speed in a simulator setting versus a generalized self-reported question.

No significant correlation $(r = 0.211)$ was observed between the self-reported and simulator-recorded gaps $(N = 80, p = 0.06)$. Since gaps are not usually displayed in the instrument cluster of a vehicle, they are largely estimated by drivers and thus the result seems intuitive.

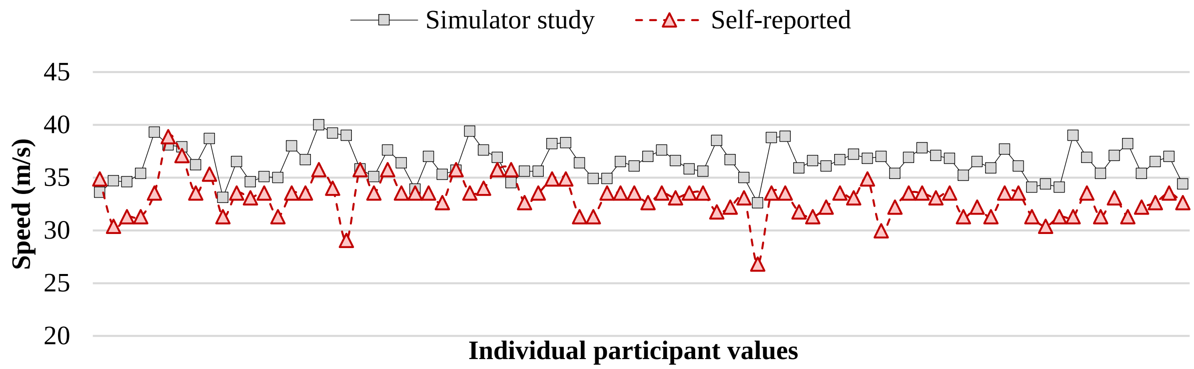


Figure 7.2 Comparison of self-reported and simulator-recorded speeds

It was concluded that overall driving performance cannot be predicted solely based on demographic and subjective data. Driving metrics are a crucial part of the puzzle and cannot be entirely substituted for subjective data.

Three variations of the IDM were compared, i.e., calibrated IDM, group IDM, and b-IDM. The calibrated IDM utilized individual-specific parameters rather than the identified group traits. Basic calibration was carried out by using the naturalistic driving parameters provided in table 2.1. Individual driver values based on their driving trajectories are shown in tables 7.2 and 7.3.

Table 7.2 Calibrated IDM parameters for validation group A

Group A				
ID	$\boldsymbol{v_o(t)}$ **(m/s)**	$\boldsymbol{T_n}$ **(s)**	$\boldsymbol{a_{max}}$ **(m/s²)**	$\boldsymbol{b_{max}}$ **(m/s²)**
5	35.4	1.41	0.611	1.895
13	36.5	0.91	1.143	2.309
28	33.9	0.75	0.567	4.340
37	35.6	1.66	1.193	1.380
43	34.9	1.10	0.418	3.275
51	35.6	1.40	0.464	2.387
64	36.8	1.31	0.422	1.965
88	36.5	2.00	1.212	4.837
89	37.0	1.10	0.792	1.455

Table 7.3 Calibrated IDM parameters for validation group B

Group B				
ID	$v_o(t)$ **(m/s)**	T_n **(s)**	a_{max} **(m/s^2)**	b_{max} **(m/s^2)**
11	38.7	0.42	1.314	1.562
18	38.0	0.44	0.473	4.634
23	39.0	0.73	1.316	5.095
32	35.7	0.51	2.078	5.966
46	36.1	0.88	1.148	2.864
53	36.7	0.99	1.821	4.743
56	32.6	0.78	3.765	5.444
63	37.2	0.37	1.327	5.338
70	37.1	0.84	0.982	4.235
73	36.5	0.31	1.414	5.930
80	39.0	0.48	3.074	5.710

The group IDM and b-IDM are modeled by using the group maximum speeds, group minimum gaps, group maximum accelerations, and group minimum decelerations. The unchanged group parameters for the group IDM and b-IDM are shown in Table 7.4.

Table 7.4 Group IDM and b-IDM parameters

IDM Variables	**Group A**	**Group B**
$v_0(t)$ – maximum speed	37.0 m/s	38.6 m/s
a_{max} – maximum acceleration	1.097 m/s^2	2.464 m/s^2
b_{max} – maximum deceleration	4.048 m/s^2	6.022 m/s^2
T_n – minimum gap	0.610 s	0.440 s
δ – unchanged parameter	4	4
s_0 – standstill distance	2 m	2 m

The top four variables (i.e. $v_0(t)$, a_{max}, b_{max}, and T_n) for the groups are obtained by taking one upper standard deviation of the relevant cluster properties obtained in table 7.1. This made sure that at least two-thirds of the group population were accounted for by the chosen interval.

The goal seek function in excel was used to attain values of α shown in equation 7.1. Any value of alpha that exceeded the constraint $0 < \alpha \leq 1$ was set to 1. Equation 7.1. revisits the theorized additions to the IDM.

$$a_n(t) = a_{max}\left[1 - \left(\frac{v_n(t)}{(\alpha)v_0(t)}\right)^{\delta} - \left(\frac{s^*{}_n(t)}{s_n(t)}\right)^2\right]; \quad 0 < \alpha \leq 1 \tag{7.1}$$

$$s^*{}_n(t) = s_0 + \left(\frac{1}{\alpha}\right)T_n v_n(t) + \frac{v_n(t)\Delta v_n(t)}{2\sqrt{a_{max}b_{max}}}$$

Several variables were used as inputs to the model and they include: WL from ICA, WL from normalizing HR (WL_HR), raw pupil diameter, raw HR, raw LA, normalized LA, normalized SA, leader brake light activation, presence of distraction (1 = distracted, 0 = not distracted), leader acceleration, and leader velocity. Each driver could exhibit multiple trajectories. This was a result of considering car-following with a constraint gap of 5 seconds, as past research indicates that any car-following gap that exceeds 5 seconds cannot be considered as a following trajectory.

Three levels of interaction terms were used when building the model and the terms were dropped if found to be insignificant ($\alpha > 0.05$). Several linear transformations (natural log, exponential, square root, and inverse) and univariate ANCOVAs (analysis of covariance) were performed on the datasets and the natural log transformation resulted in the most appropriate fit as confirmed by the box-cox results in RStudio (RStudio, 2020).

7.1 Group A Model

Out of the 36 drivers, datasets from 27 drivers were randomly selected to build the model while the datasets from the remaining 9 drivers were preserved for the validation set.

The residual plots for the group A participants are shown in figure 7.3. The residual plots satisfied the normality and equal variance assumptions. Although some of the interaction terms were significant, their contribution towards the R-squared value of the model were negligible and were dropped in order to prevent overfitting that could potentially hinder the validation process of the dataset.

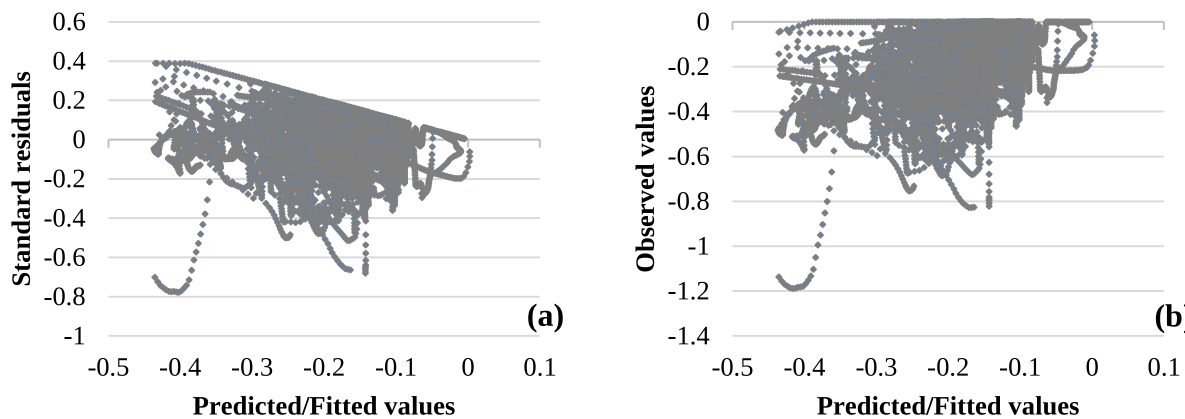


Figure 7.3 Residual plots for group A showing (a) Residuals vs predicted values and (b) Observed vs predicted values

The finalized non-linear model resulted in an R-squared value of 0.17. Although this is low, most behavioral models tend to have similar values of R-squared (i.e. between 0.15 and 0.40) as having the exact same variability in physical and cognitive properties is uncommon among individuals. Also, the relatively conservative sample size used for the study restricts the predictability. Table 7.5 shows the properties of the model selected for group A drivers.

Table 7.5 Group A regression model statistics

Regression Statistics	
Multiple R	0.412
R Square	0.170
Adjusted R Square	0.170
Standard Error	0.0757
Observations	206674

ANCOVA

	df	*SS*	*MS*	*F*	*Sig*
Regression	5	241.68	48.3368	8439.464	< 0.001
Residual	206668	1183.68	0.0057		
Total	206673	1425.37			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	η_P^2	*1-β*
Intercept	-2.9615	0.01441	-205.540	< 0.001	0.170	1.000
ln (LA)	-0.0005	0.00026	-1.9756	0.0482	0	0.506
ln (SA)	-0.0011	0.00026	-4.1811	< 0.001	0	0.987
ln (WL_HR)	-0.0014	0.00029	-4.7149	< 0.001	0	0.997
Distraction	-0.0324	0.00072	-44.903	< 0.001	0.010	1.000
ln (Lead v(t))	0.81614	0.00417	195.677	< 0.001	0.156	1.000

*ln denotes natural log

Achieved Model:

ln (***α***) = –2.9615 – 0.0005*ln (LA) – 0.0011*ln (SA) – 0.0014*ln (WL_HR) – 0.0324*Distraction – 0.81614*ln (Lead v(t))

Final model:

$$\alpha = e^{-2.9615-0.0324*Distraction} LA^{-0.0005} SA^{-0.0011} WL\_HR^{-0.0014} Lead\ v(t)^{0.81614} \quad (7.2)$$

7.2 Group B Model

Group B consisted of 44 drivers out of which 33 were used to build the model and 11 were used to validate the model. The same methods described in the previous section were used to build the model. The residual plots for the observed and predicted set are shown in figure 7.4. The residual plots were observed to satisfy the normality and equal variance assumptions.

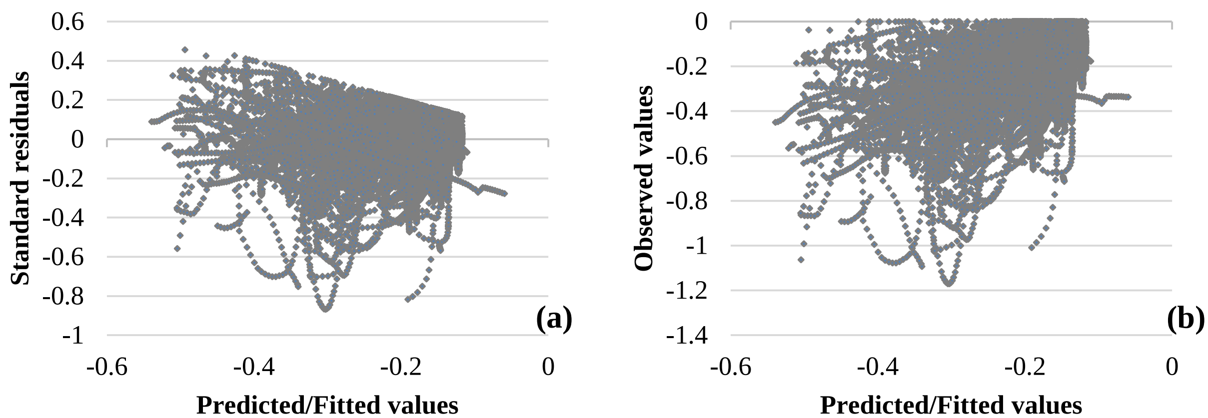


Figure 7.4 Residual plots for group B showing (a) Residuals vs predicted values and (b) Observed vs predicted values

The finalized model was also non-linear and resulted in an R-squared value of 0.205. Table 7.6 shows the properties of the model selected for group B drivers. Group B drivers also resulted in the same significant model parameters as group A, i.e., WL from normalizing HR (*WL_HR*), normalized LA (*LA*), normalized SA (*SA*), presence of distraction (*Distraction*), and leader velocity (*Lead v(t)*).

Table 7.6 Group B regression model statistics

Regression Statistics	
Multiple R	0.452
R Square	0.205
Adjusted R Square	0.205
Standard Error	0.073
Observations	293532

ANCOVA

	df	*SS*	*MS*	*F*	*Sig*
Regression	5	403.65	80.7310	15094.810	< 0.001
Residual	293526	1569.85	0.0053		
Total	293531	1973.51			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	η_P^2	*1-β*
Intercept	-3.2796	0.01182	-277.493	< 0.001	0.208	1.000
ln (LA)	0.00104	0.00022	4.6554	< 0.001	0	0.996
ln (SA)	0.00082	0.00024	3.3808	< 0.001	0	0.922
ln (WL_HR)	-0.00051	0.00025	-2.0469	0.0407	0	0.535
Distraction	-0.0344	0.00058	-59.548	< 0.001	0.012	1.000
ln (Lead v(t))	0.89750	0.00341	263.216	< 0.001	0.191	1.000

*ln denotes natural log

Achieved Model:

ln ($\boldsymbol{\alpha}$) = –3.2769 + 0.00104*ln (LA) + 0.00082*ln (SA) – 0.00051*ln (WL_HR) – 0.0344*Distraction – 0.89750*ln (Lead v(t))

Final model:

$$\alpha = e^{-3.2769-0.0344*Distraction} LA^{0.00104} SA^{0.00082} WL\_HR^{-0.00051} Lead\ v(t)^{0.89750} \quad (7.3)$$

7.3 Group A Validation

Validation charts for one driver from group A for all tasks are shown in figures 7.5 to 7.7. Graphs for the remaining participants are shown in Appendix H.

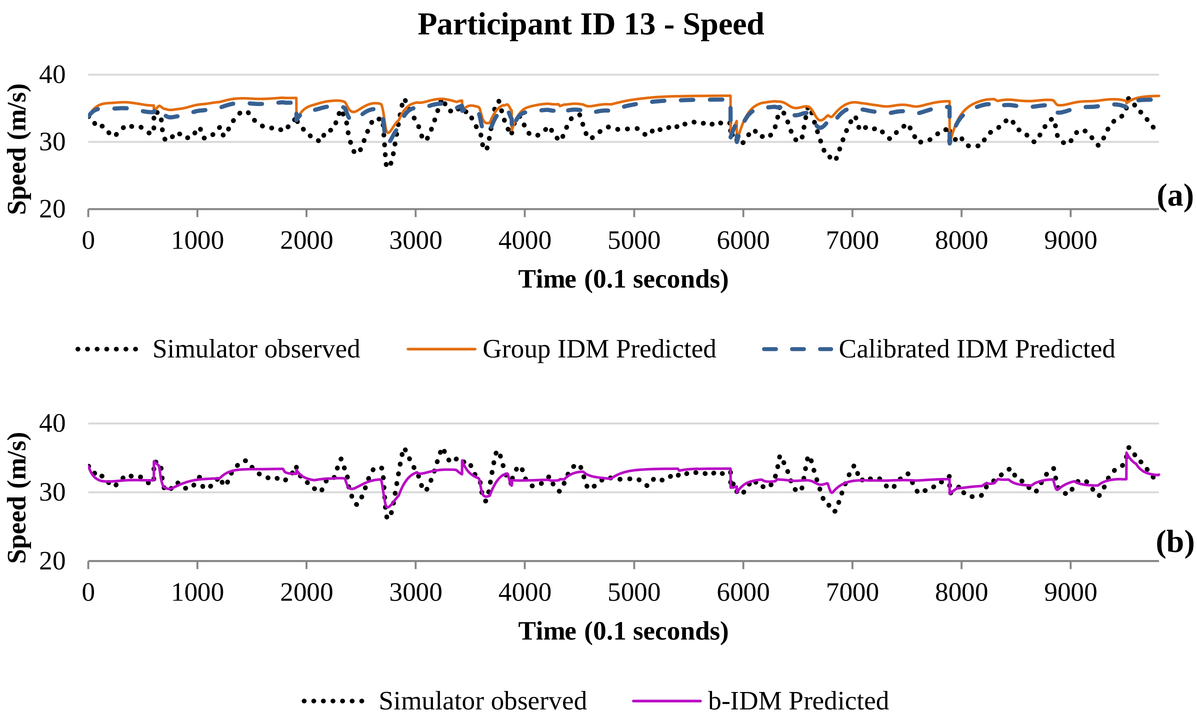


Figure 7.5 Speed validation plots for participant ID 13 showing (a) Calibrated and group IDM predicted and (b) b-IDM predicted

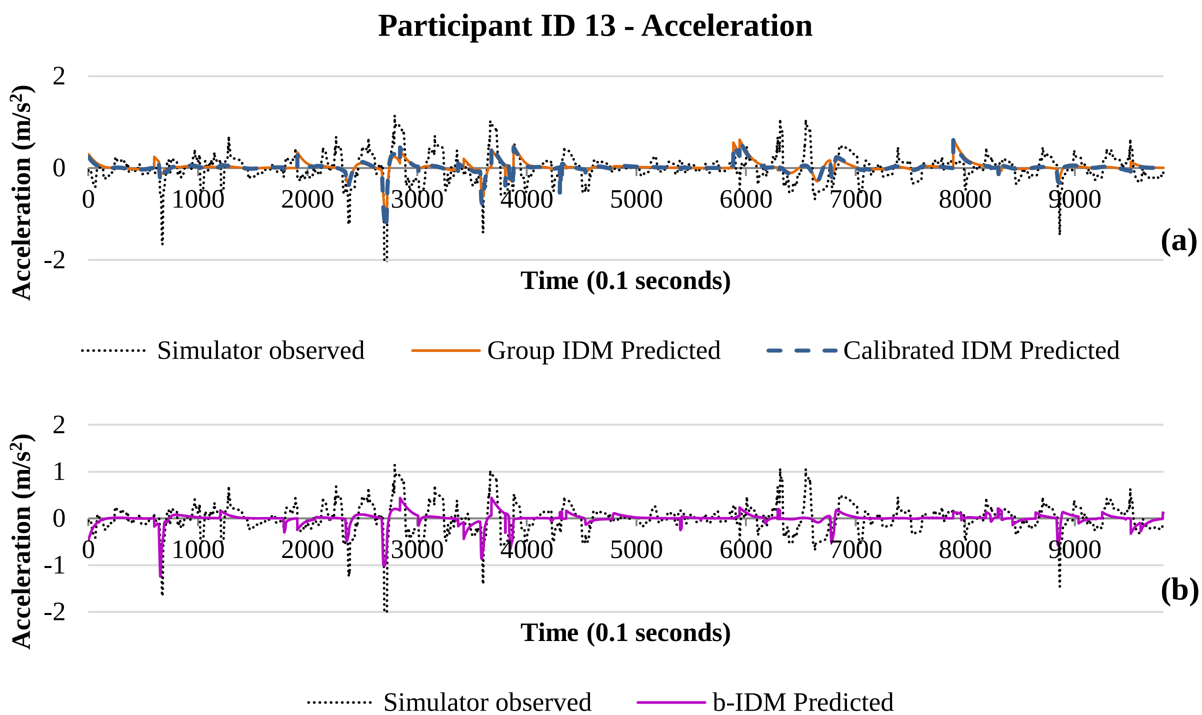


Figure 7.6 Acceleration validation plots for participant ID 13 showing (a) Calibrated and group IDM predicted and (b) b-IDM predicted

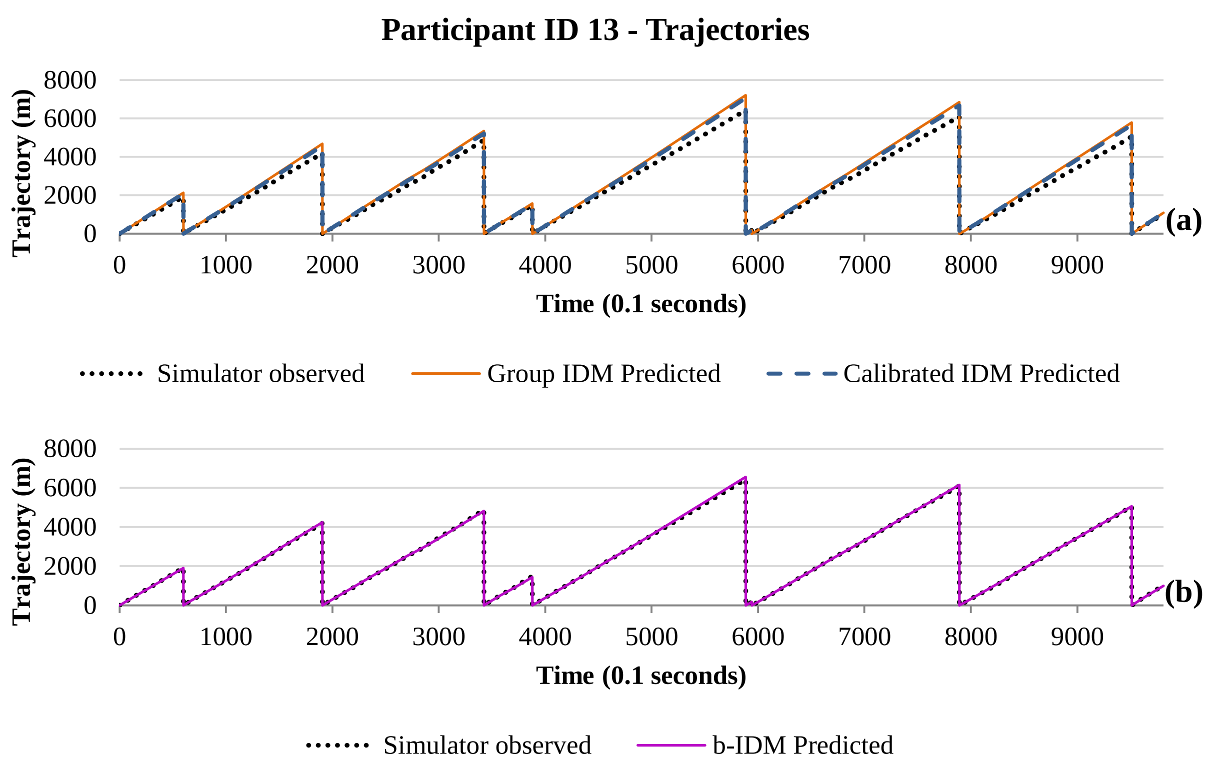


Figure 7.7 Trajectory validation plots for participant ID 13 showing (a) Calibrated and group IDM predicted and (b) b-IDM predicted

From the figures the b-IDM better predicts all three validation variables. Goodness of fit calculations are shown in section 7.5. Figures 7.8 to 7.10 show the combined speed, acceleration, and trajectory charts for all participants in the group A validation set. Similar trends are observed with the b-IDM resulting in a better fit.

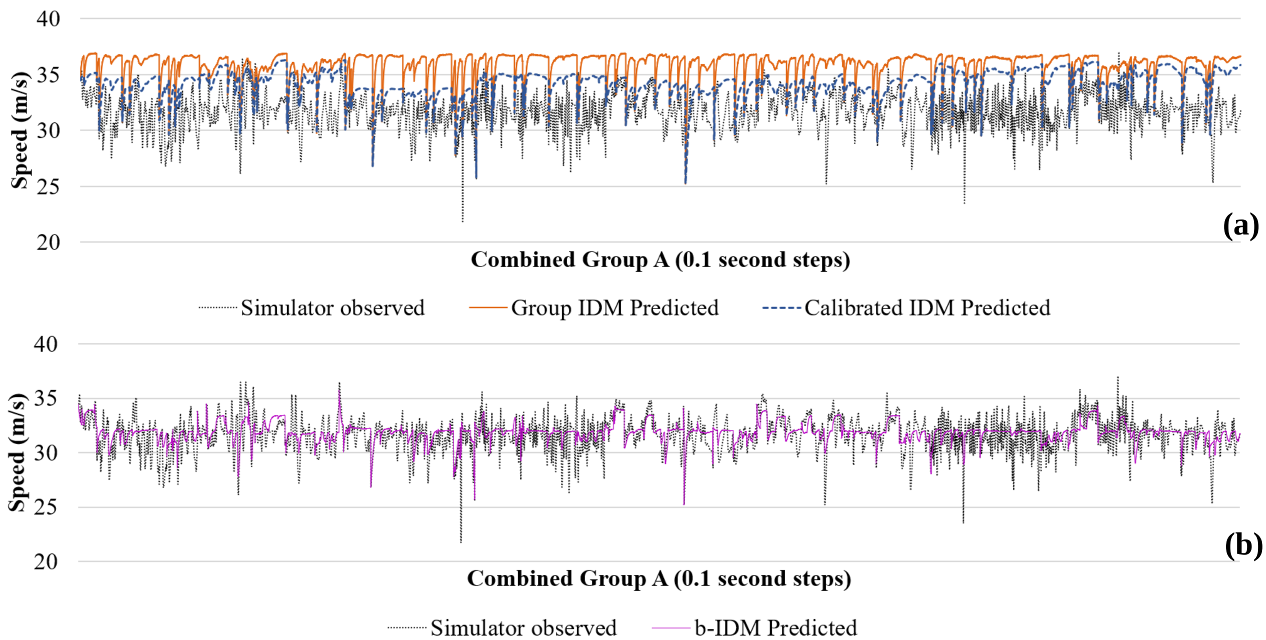


Figure 7.8 Speed plots for the entire group A validation set showing (a) Calibrated and group IDM predicted and (b) b-IDM predicted

The b-IDM also resulted in better predictions for decelerations, as seen in figure 7.9. For in-depth results, individual participant validation charts are presented in Appendix H of this dissertation.

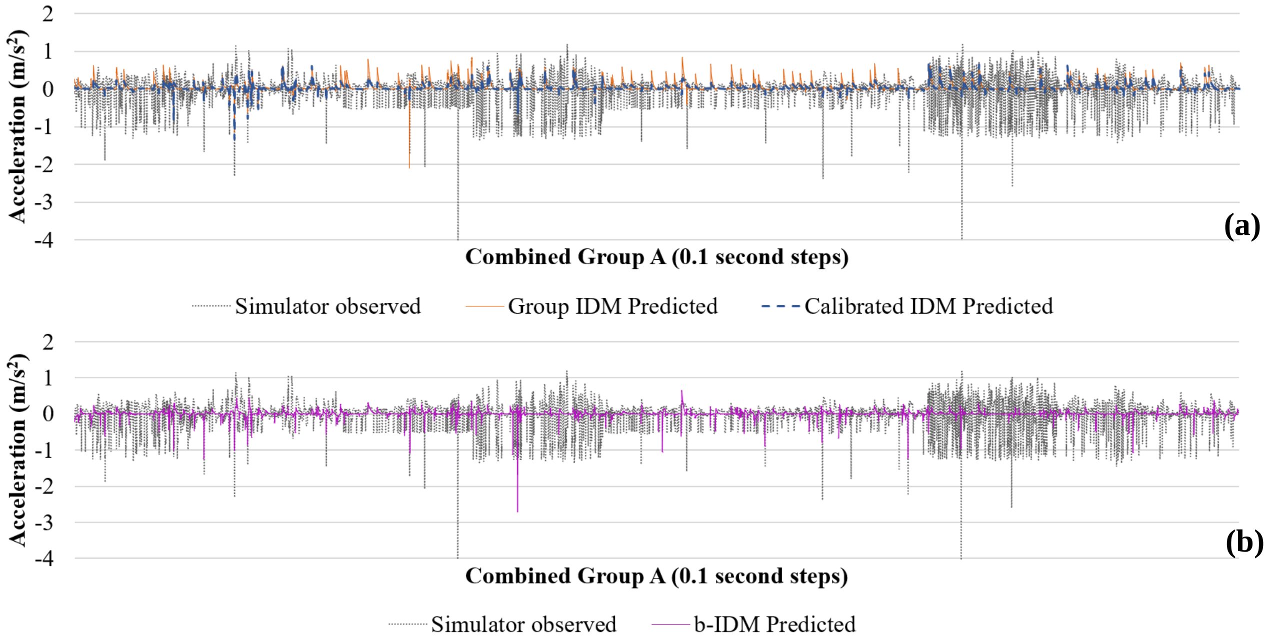


Figure 7.9 Acceleration plots for the entire group A validation set showing (a) Calibrated and group IDM predicted and (b) b-IDM predicted

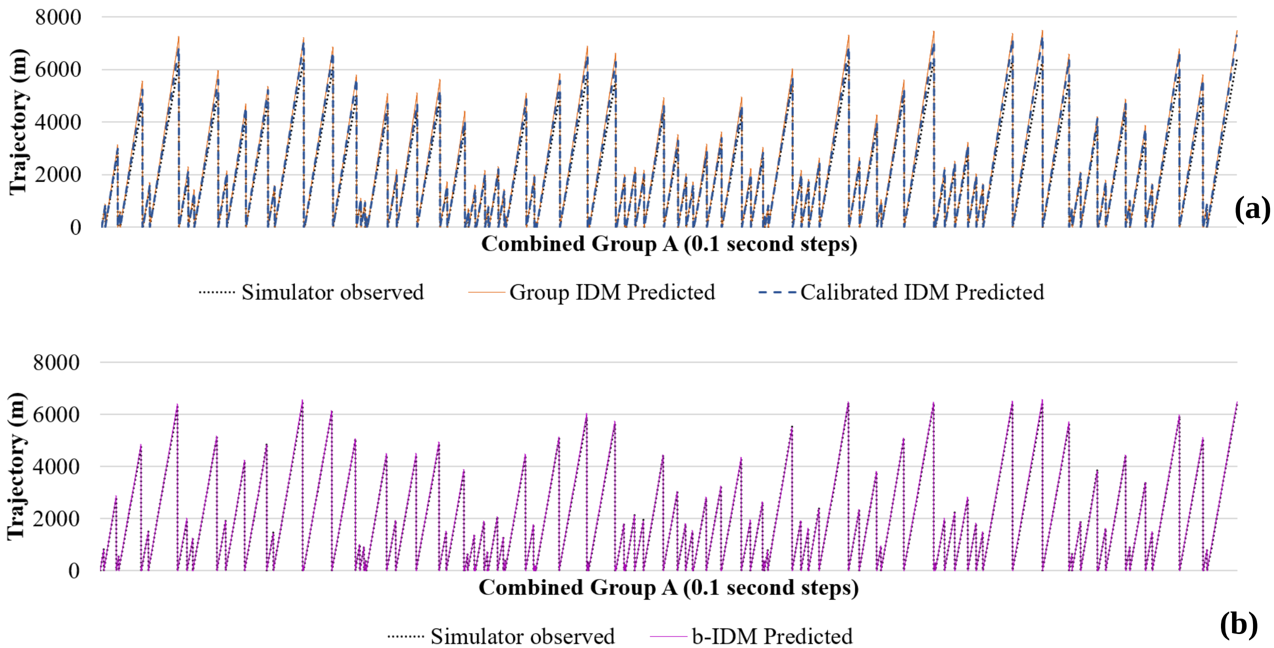


Figure 7.10 Trajectory plots for the entire group A validation set showing (a) Calibrated and group IDM predicted and (b) b-IDM predicted

7.4 Group B Validation

Similar trends seen in group A were observed in the group B validation dataset.

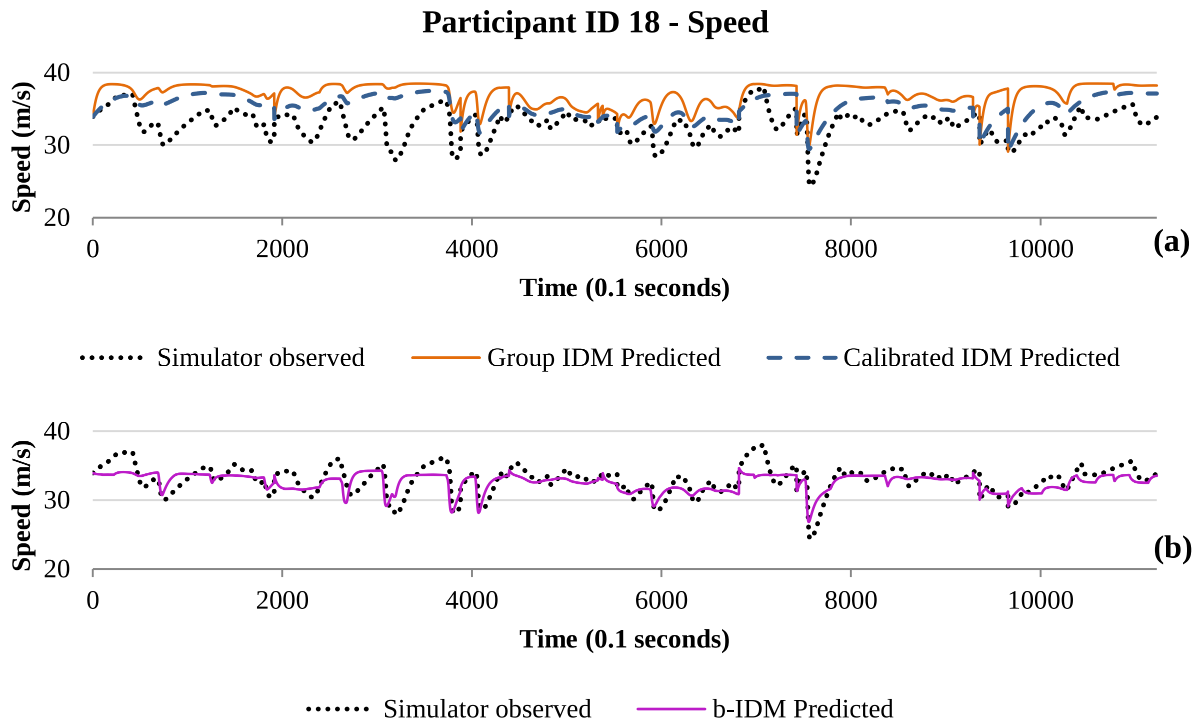


Figure 7.11 Speed validation plots for participant ID 18 showing (a) Calibrated and group IDM predicted and (b) b-IDM predicted

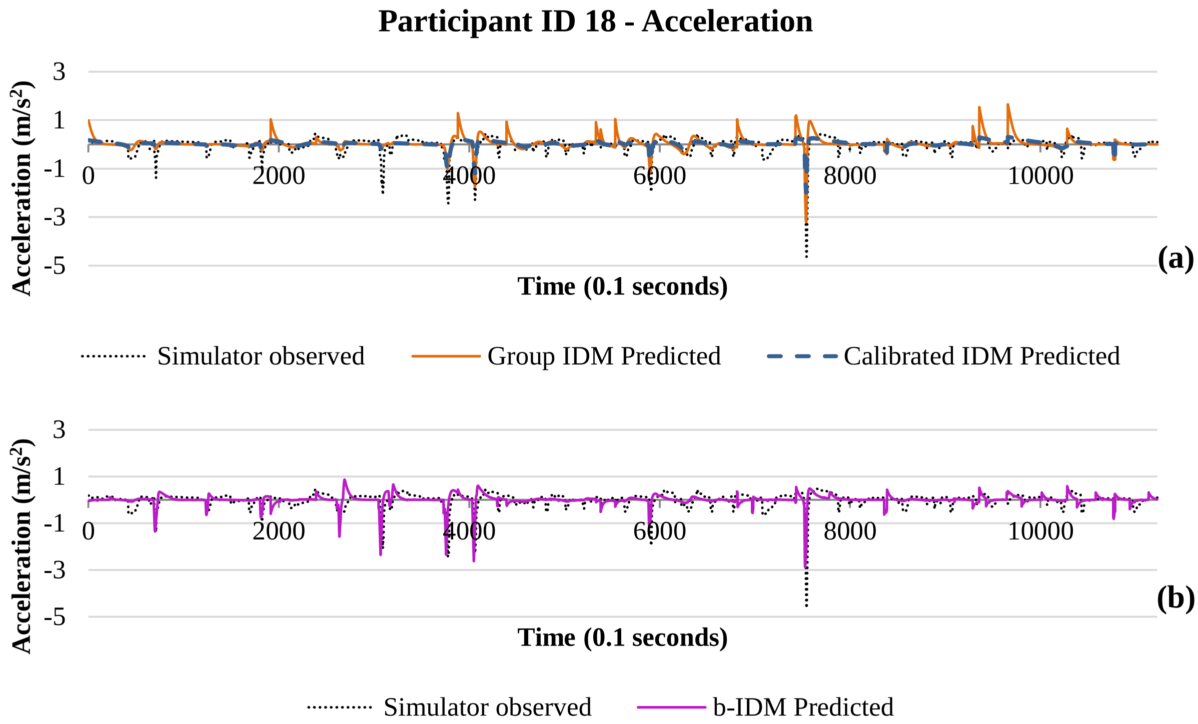


Figure 7.12 Acceleration validation plots for participant ID 18 showing (a) Calibrated and group IDM predicted and (b) b-IDM predicted

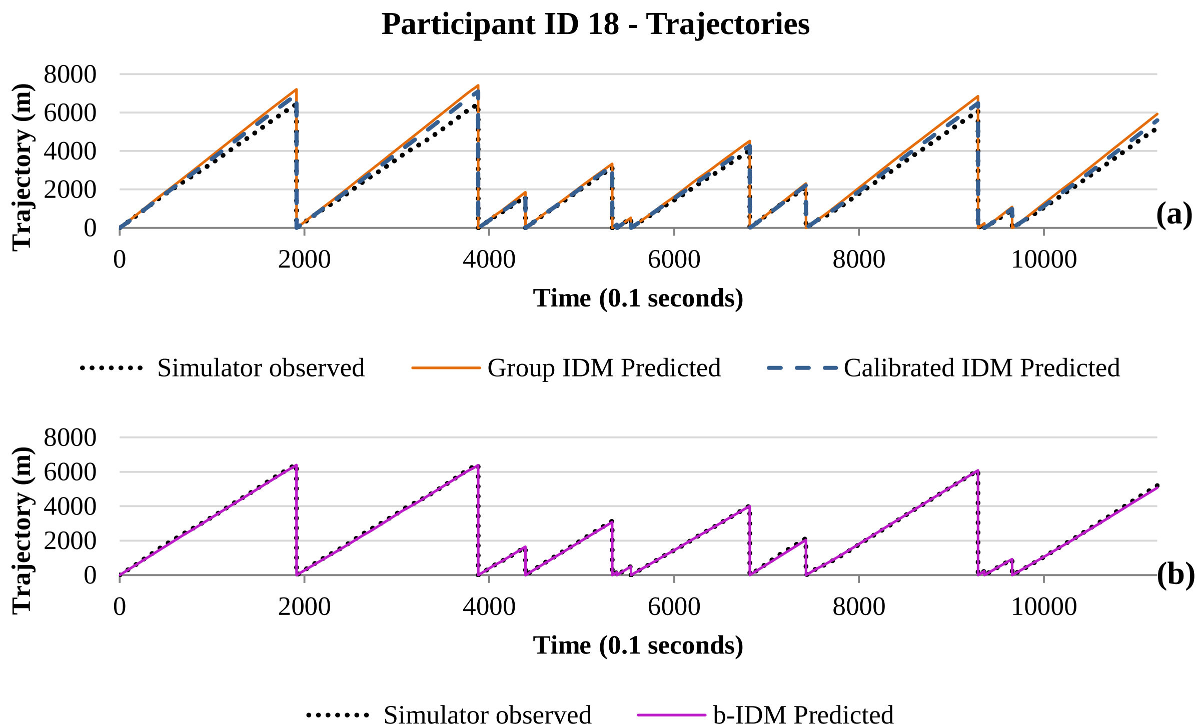


Figure 7.13 Trajectory validation plots for participant ID 18 showing (a) Calibrated and group IDM predicted and (b) b-IDM predicted

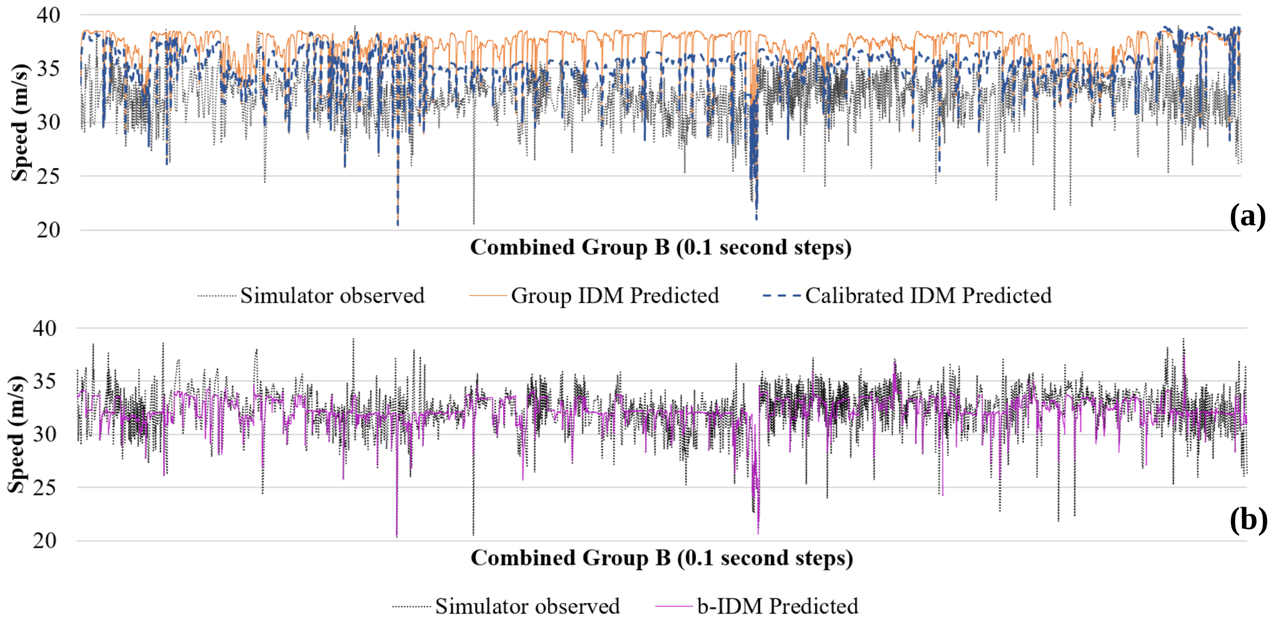


Figure 7.14 Speed plots for the entire group B validation set showing (a) Calibrated and group IDM predicted and (b) b-IDM predicted

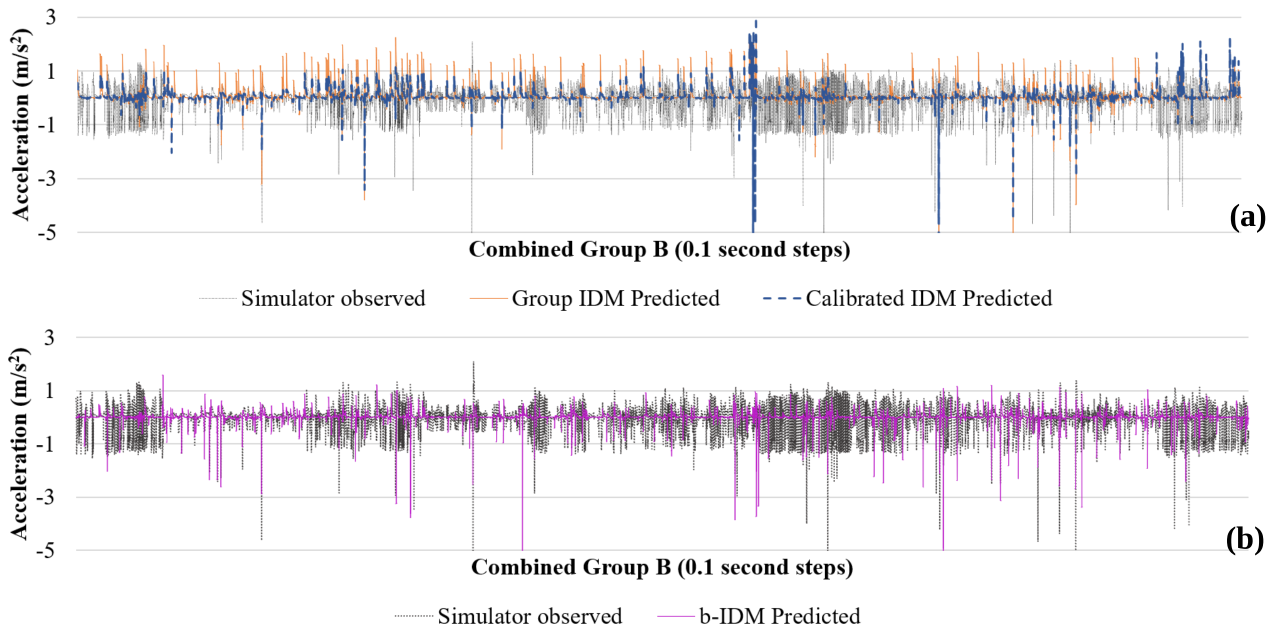


Figure 7.15 Acceleration plots for the entire group B validation set showing (a) Calibrated and group IDM predicted and (b) b-IDM predicted

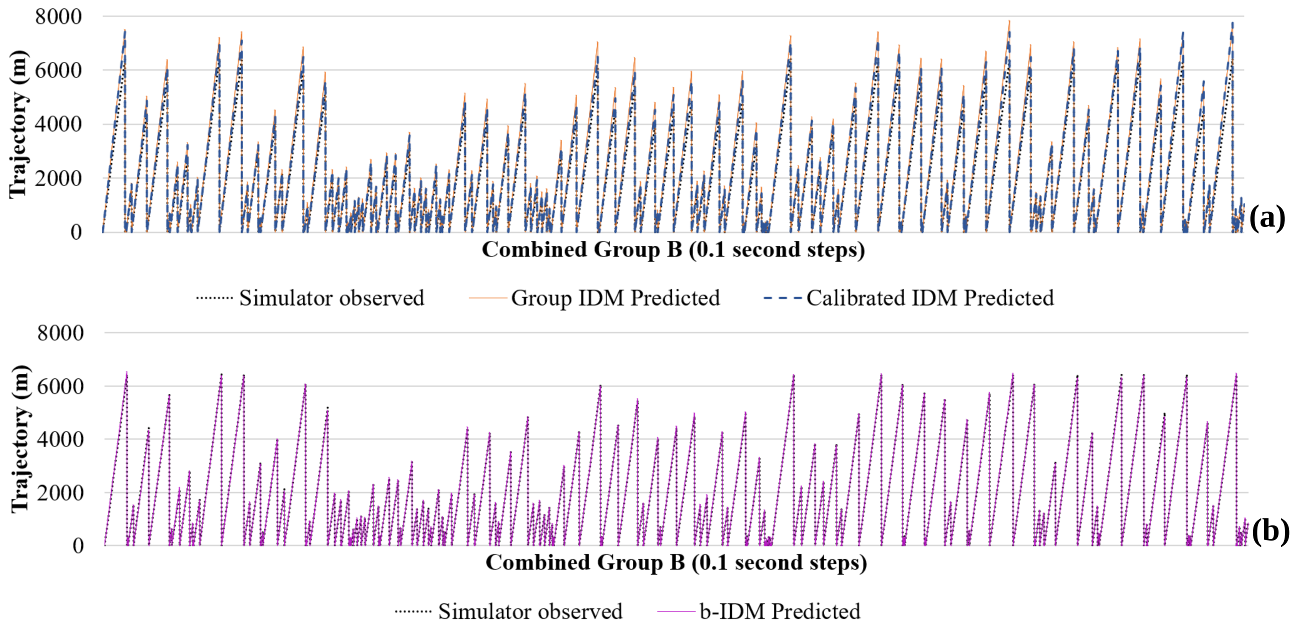


Figure 7.16 Trajectory plots for the entire group B validation set showing (a) Calibrated and group IDM predicted and (b) b-IDM predicted

The individual participant and group validation charts show a much better fit from the b-IDM. The following section quantifies the observed results using goodness of fit metrics.

7.5 b-IDM Validation Metrics Summary

To determine the goodness of fit, the normalized root mean square error (NRMSE) and mean absolute percentage error (MAPE), shown in equations 7.4 and 7.5 were used. NRMSE normalizes the data with respect to the range of the time series, thus allowing for an easier comparison of the errors. The NRMSE is expressed as a percentage in the results.

$$\%\,NRMSE = \frac{\sqrt{\sum_{t=1}^{n}(\hat{y}_t - y_t)^2/n}}{y_{max} - y_{min}} \times 100\,\% \tag{7.4}$$

$$MAPE = \frac{100\,\%}{n}\sum_{t=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{7.5}$$

Where,

y represents the parameters obtained from the models (i.e. speed, acceleration, and trajectory)

$\hat{y}_t$ represents the estimated parameter values output from the models at time t

y_t represents the actual value of the parameter at time t

n represents the number of individual time points (0.1 second time steps)

y_{max} is the maximum value of y_t from t = 1 to t = n

y_{min} is the minimum value of y_t from t = 1 to t = n.

Table 7.7 Goodness of fit comparisons using % NRMSE

Variable	NRMSE (%)					
	Group A			Group B		
	Calibrated IDM	Group IDM	b-IDM	Calibrated IDM	Group IDM	b-IDM
Speed	20.22	30.13	8.32	21.17	28.69	8.14
Acceleration	6.09	6.36	6.05	5.98	6.24	5.76
Trajectories	3.92	5.82	0.59	4.57	6.47	0.63

Table 7.8 Goodness of fit comparisons using MAPE

Variable	MAPE (%)					
	Group A			Group B		
	Calibrated IDM	Group IDM	b-IDM	Calibrated IDM	Group IDM	b-IDM
Speed	8.62	13.77	3.09	10.68	15.55	3.63
Acceleration	136.45	160.74	127.6	155.37	191.84	143.3
Trajectories	6.81	11.28	1.5	8.96	13.83	1.75

The goodness of fit comparisons suggest that the b-IDM resulted in a much better fit with respect to speed and trajectories. However, acceleration did not result in a substantial improvement. This is expected as most car-following models are calibrated using speeds and trajectories due to the highly variable nature of acceleration. The obtained results are shown in tables 7.7 and 7.8 and figure 7.17.

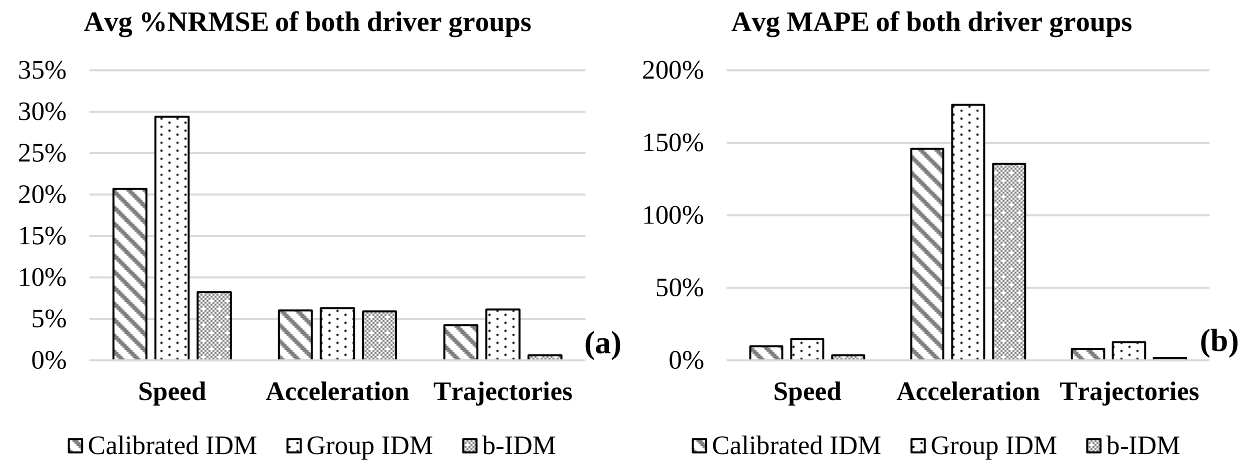


Figure 7.17 Goodness of fit averages (a) % NRMSE and (b) MAPE for both driver groups

Although the MAPE results in much poorer goodness of fit for acceleration, this was expected due to the mean values of acceleration being closer to zero. The MAPE is usually not recommended for values close to zero as it significantly overestimates the error, however, similar results to the % NRMSE were observed with the speeds and trajectories suggesting a better b-IDM fit. The calibrated IDM resulted in a better fit than the uncalibrated group IDM. This was expected due to the individual-specific parameters used. Overall, the b-IDM resulted in much closer predictions even though group traits were used.

In conclusion, the general form of the biobehavioral parameter α was modeled to be expressed as follows:

$$\boldsymbol{\alpha} = \boldsymbol{e}^{\mu_0 - \mu_1 \boldsymbol{Distraction}} \times \boldsymbol{LA}^{\mu_2} \times \boldsymbol{SA}^{\mu_3} \times \boldsymbol{WL\_HR}^{\mu_4} \times \boldsymbol{Lead\ v(t)}^{\mu_5} \tag{7.6}$$

Where,

$\mu_0, \mu_1, \mu_2, \mu_3, \mu_4, \mu_5$ are all coefficients that can be established from a group of participants.

Chapter 8 Conclusions

This chapter briefly discusses the purpose of this research along with summarizing the established findings. Recommendations for future research are also provided.

8.1 Purpose

A framework designed to utilize the task-capability interface (TCI) to incorporate biobehavioral parameters and predict changes to driving performance, specifically to car-following, was presented. Ninety drivers were recruited to validate the framework by participating in virtual scenarios within a driving simulator environment. The scenarios were created to capture all the necessary parameters by varying the situation complexity of individual tasks. Participants had to complete an extensive behavioral questionnaire that could be used to correlate subjective and experimental data.

A biobehavioral extension to the IDM (i.e. b-IDM), using the collected data, was developed to easily calibrate predicted and observed values by grouping individual driver performance and behavioral traits. The model was validated and found to be an effective way of utilizing behavioral and performance variables to efficiently predict car-following behavior.

8.2 Conclusions

The overall objective of incorporating biobehavioral architecture into the intelligent driver model (IDM) was achieved. Several physiological and driving performance variables were examined in this research. The following conclusions were derived from the methodology, experimentation, and data analysis:

- The developed theoretical framework (figure 3.2) proved to be an effective method by utilizing the TCI to monitor changes in cognitive workload (WL), situation awareness (SA), and level of activation (LA) of drivers.

- The developed simulator scenario effectively captured varying WL and SA as noted from the NASA-TLX and SART scores. Averaged driving performance measures such as speed, SDLP, and headway were also observed to significantly differ between the six tasks.
- It was discovered that a four-way interaction between WL, SA, LA, and performance was being experienced by the driver at any given time point. For example, an increase in WL due to a complex task leads to a reduction in driving speed but the newly decreased driving speed could improve SA and make the task less complex, thus reducing WL.
- A new method of quantifying SA was developed by using probe questions, regions of interest, and gaze paths to track driver comprehension.
- Participants were successfully clustered into two groups with significantly different driving performance traits. However, these differed performance traits did not correspond to any substantial cognitive or behavioral characteristics obtained from the questionnaires.
- It was observed that the overall driving performance cannot be predicted solely based on demographic and subjective data. Driving metrics were found to be a crucial part of the puzzle and cannot be entirely substituted for subjective data. However, speed was noted to be a consistent metric in both formats.
- The following variables were crucial to the developed b-IDM: WL from normalizing HR (*WL_HR*), normalized LA (*LA*), normalized SA (*SA*), presence of distraction (*Distraction*), and leader velocity (*Lead v(t)*).

- Although the developed models resulted in low R-squared values, all selected variables were highly significant. Low R-squared are generally expected in behavioral models due to the high variance between individuals in terms of cognitive, physical, and mental properties.
- The developed model was validated using a 75/25 data split. Large improvements were seen to the overall fit of the IDM, especially with respect to the speed and trajectory predictions.
- Grouping driver traits proved to be a useful tool in decreasing individual-specific calibration efforts.
- Although the findings of this research were validated, the use of a driving simulator does not guarantee similar results in naturalistic settings. Using instrumented vehicles to collect similar physiological and performance measures would further refine the model. Also, using a much larger sample size to both build and validate the model might improve the overall fit and predictability.

A few challenges experienced during the execution of this research were as follows:

- The main limitation of the framework was the assumption that changes to driving performance were sequential. The change in equilibrium between driver capability and task demand simultaneously led to changes in WL, SA, LA, and driving performance.
- The process of synchronizing all the physiological measures to the driving simulator data and appropriately resampling the data for further analysis was intensive. Several VBA and MATLAB codes were developed to prepare the dataset.

- Incomplete data due to equipment malfunction, corrupt files, and simulator sickness posed a huge challenge to the aggregation and analysis. Also, the relatively large data files required substantial computational power and experienced lots of system crashes.

8.3 Recommendations and Future Research

This research provided some valuable insights into using biobehavioral variables to enhance the calibration and prediction of car-following models. The main focus of this dissertation was the IDM; however, applying the same theories to other models might add to the scalability of the theorized methodology.

The inclusion of distractions in the developed model provides a new take on predicting speeds and trajectories of distracted drivers and how these values affect the overall traffic flow. This could be a useful addition to microsimulation models. More detailed analysis using various naturalistic driving trajectories might aid in better understanding the car-following and lane changing dynamics of distracted driving.

As more car manufacturers are standardizing partial automation features such as adaptive cruise control (ACC) and automatic lane following (ALF) in their vehicles, predicting car-following behavior when engaged in these modes can further benefit traffic flow and demand predictions. A key focus area would be to understand car-following behavior right before engaging or right after disengaging automation systems. The TCI could be used to determine the levels of WL and SA at the instance automation is engaged. Once engaged in automation, the task-automation interface (TAI) determines when a driver, engaged in automation, decides to take over due to an imbalance resulting from the demand of the task and trust in automation capability. A theoretical framework, shown in figure 8.1, was established to facilitate the development of experimental strategies to collect the required variables.

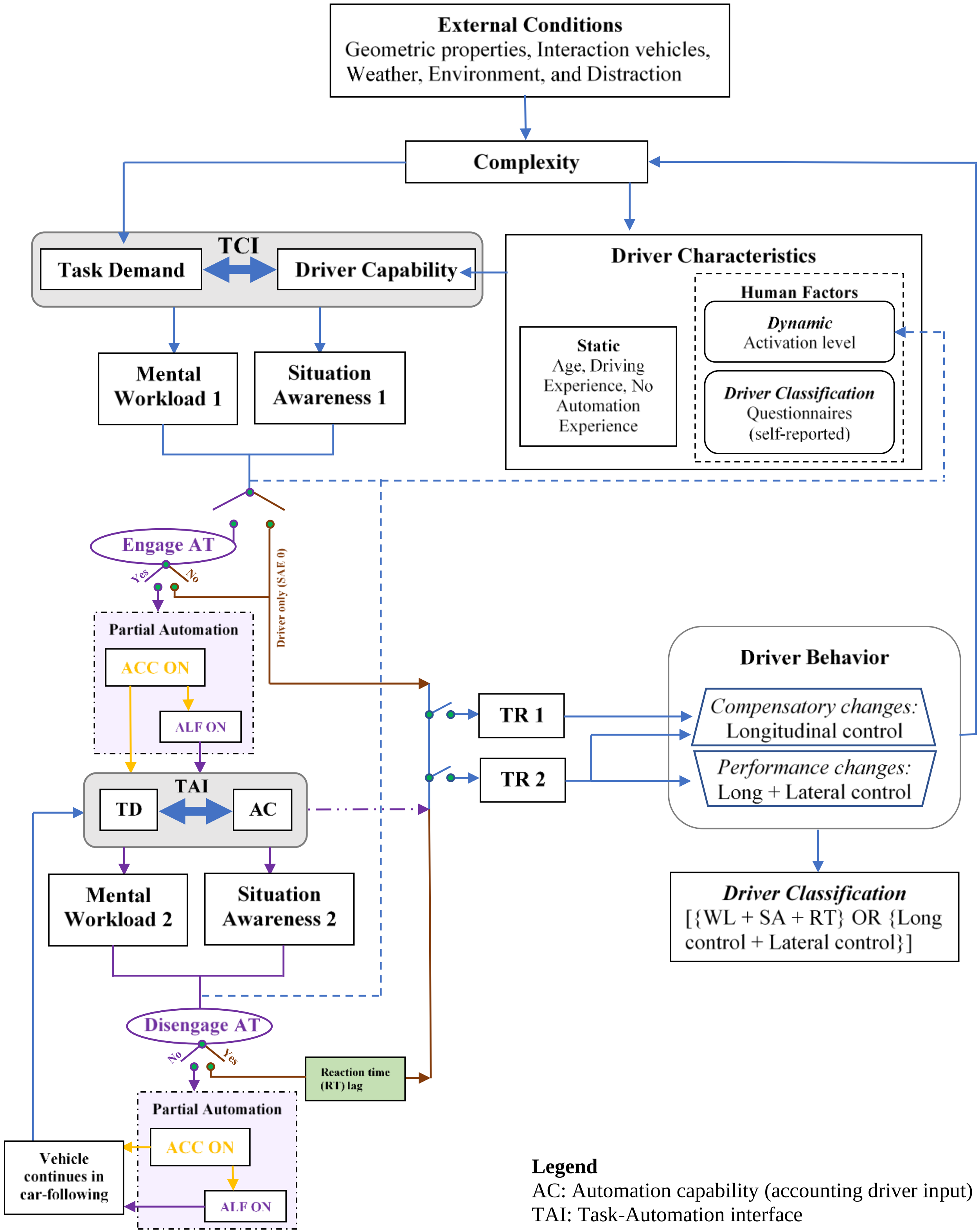


Figure 8.1 Extended framework to include automation

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Appendix A IRB Approval Letter

THE UNIVERSITY OF KANSAS
Research

Date: February 11, 2019

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

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

RE: **Approval of Modification**

The IRB reviewed the submission referenced below on 2/11/2019. Approval expires on 7/16/2019.

IRB Action: APPROVED	**Effective date: 2/11/2019**	**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:	Modification	
Review Date:	2/11/2019	
Documents Reviewed:	• HRPP_Consent form_amended , • Human Research Protocol_Aggressiveness Study_Amended, • Flyer_study advertising, • EyeTracker_EyeWorks_Sim Solutions Car.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 B Flyer for Recruiting Participants

KU SCHOOL OF ENGINEERING
The University of Kansas

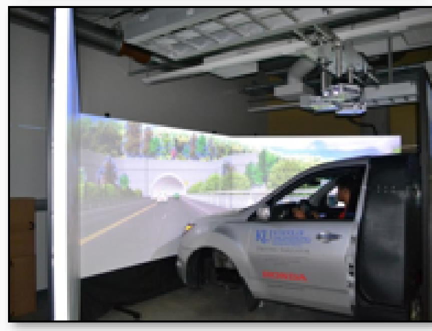
Study sponsored by:

MID-AMERICA TRANSPORTATION CENTER

Participants Needed for Driving Simulator Research

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

Flyer valid from **10/01/2018 to 05/31/2019**



Experimental Procedure:

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

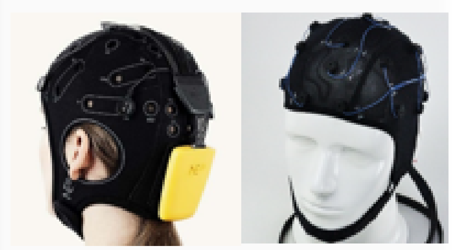
Participants will be required to drive for no more than **70 minutes** including breaks. Information on braking, reaction time, lateral position, speed, time gap, acceleration, and electrical activity in the brain will be collected using electroencephalogram (EEG), eye tracking, heart rate chest strap, 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 dry 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:

[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

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

____
Participant's Signature

RESEARCHER CONTACT INFORMATION

Dr. Alexandra Kondyli, PhD
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Appendix D Prescreening and Behavioral Questionnaire

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 behavior 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. You will be asked about physical/mental health conditions, personality traits, and driving history including accidents and traffic violations. The questionnaire will be used as a screening tool to determine eligible participants for the driving simulator intervention. Participants will be given a unique identifier, following participant invitation and participation, links between study code numbers and direct identifiers will be immediately destroyed.

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 1 year of driving experience and no less than 1000 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.

On completion of the questionnaires, participants will be contacted with their respective appointment date/time for the driving simulator study. On completion of the 80-minute driving simulator study, participants will receive a $50 gift card (cash value) as compensation for their time.

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) 312-0845

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

Participant information

Age:

Highest level of education:

E-mail address:

Participant information cont.

Which hand do you write with?

- ○ Right
- ○ Left
- ○ Both

What was the first language that you spoke?

Do you speak other languages?

- Yes
- No

If so, which?

And, at what age did you learn it?

Participant information cont.

Have you been diagnosed with any of the following?

- Attention Deficit Hyperactivity Disorder (ADHD)
- Dyslexia
- Other learning disabilities. Please specify:
- Depression. When and duration:

Have you ever sustained head injury?

- Yes
- No

If yes please list and describe:

Are you taking any prescription medication?

- Yes
- No

If yes, please list and describe:

Demographics

Gender:

- Male
- Female
- Other:
- Prefer not to disclose

Ethnicity:

- Hispanic or Latino
- Not Hispanic or Latino
- Prefer not to disclose

Race:

- American Indian/ Alaskan Native
- Asian
- Native Hawaiian/ Other Pacific Islander
- Black/ African American
- White
- More than one race
- Other:
- Prefer not to disclose

Screening questionnaire

What is your occupation?

What is the highest educational qualification you have or are working towards (high school, undergraduate degree, graduate school)? Also state the specialization if any.

Do you possess a valid U.S. Driver's license?

- Yes
- No

Date driver's license was first obtained?

State your average annual mileage (approximate)?

If you have a vehicle, what is the make-year of your current vehicle?

Is your vehicle equipped with Anlocking brakes (ABS)?

- Yes
- No

Do you currently have an acvve vehicle insurance? Select all valid:

- Liability
- Comprehensive
- Collision

How much do you enjoy driving? (0 = not at all; 10 = love it)

How often do you drive?

- Never
- Sometimes
- About half the time
- Often
- Always

How often do you use your cell phone while driving?

- Never
- Sometimes
- About half the time
- Most of the time
- Always

Number of accidents/ crashes in the last 5 years?

- 0 - 1
- 2 - 3
- > 3

Number of traffic violations/tickets received in the last 2 years?

- 0 - 1
- 2 - 3
- > 3

How close do you like to follow/tail the lead vehicle while driving at 70 mph?

Very close	Close	Regular	Slightly far	Not close at all
O	O	O	O	O

Provide a value in seconds and distance for the previous question

How close do you like to follow/tail the lead vehicle while driving at 50 mph?

Very close	Close	Regular	Slightly far	Not close at all
O	O	O	O	O

Provide a value in seconds and distance for the previous question

How close do you like to follow/tail the lead vehicle while driving at 30 mph?

Very close	Close	Regular	Slightly far	Not close at all
O	O	O	O	O

Provide a value in seconds and distance for the previous question

What speed do you usually drive at in a 70 mph roadway?

What speed do you usually drive at in a 50 mph roadway?

What speed do you usually drive at in a 30 mph roadway?

How often do you check your rear and side mirrors in a 20 minute drive?

- Less than 5 times
- 5 to 10 times
- 10 to 20 times
- > 20 times

While driving to work, do you allow cars to merge ahead of you?

- Never
- Rarely
- Often

When merging from an on-ramp, do you try to merge ahead or behind the approaching vehicle?

- Ahead
- Behind

Have your co-passengers ever mentioned about your braking intensity? (last 2 years)

- Yes
- No

If so, how often?

- Less than 3 times
- 3 to 5 times
- 6 to 10 times

What is the bumper to bumper distance you prefer when completely stopped in traffic (0 mph)?

- Feet
- Car lengths

How long do you typically wait after deciding to change a lane?

- < 3 seconds
- 3 - 6 seconds
- > 6 seconds

Medical history (eye condions, heart condions, known arrhythmia, epilepsy, seizures, hearing aid, pregnancy, arthritis, motion sickness)?

- No knowledge of the above mentioned conditions
- If yes, please specify

Experience with automation

Have you ever used any form of automation apart from cruise control in any land vehicle?

- Yes
- No

If yes, does your current vehicle have any of the following automation systems: adaptive cruise control, emergency braking assist, lane keep assist, automatic lane changing? select all that apply

- None
- Adaptive cruise control
- Emergency braking assist
- Lane keep assist
- Automatic lane changing
- Other

If yes, how comfortable are you with using the above mentioned systems? (scale 1 to 5)

- 1 (Not comfortable at all)
- 2
- 3
- 4
- 5 (Extremely comfortable)

If your vehicle is NOT equipped with any of the above systems, how willing are you to try these systems? (scale 1 to 5)

- 1 (Not willing)
- 2
- 3
- 4
- 5 (Very willing)

PANAS

This scale consists of a number of words that describe different feelings and emotions. Read each item and slide the bar accordingly to indicate the appropriate answer under the word.

Indicate to what extent you have felt this way during the past week.

Use the following scale to record your answers.

(1) = Very slightly or not at all (2) = A little (3) = Moderately (4) = Quite a bit (5) = Extremely

	1	2	3	4	5
Interested					
Distressed					
Excited					
Upset					
Strong					
Guilty					
Scared					
Hostile					
Enthusiastic					
Proud					
Irritable					
Alert					
Ashamed					

	1	2	3	4	5
Inspired					
Nervous					
Determined					
Attentive					
Jittery					
Active					
Afraid					

NFC_Scale

For each of the statements below, please indicate to what extent the statement is characteristic of you. If the statement is extremely uncharacteristic of you (not at all like you) please indicate by choosing the appropriate option.

	Extremely uncharacteristic	Somewhat uncharacteristic	Uncertain	Somewhat characteristic	Extremely characteristic
I would prefer complex to simple problems	○	○	○	○	○
I like to have the responsibility of handling a situation that requires a lot of thinking	○	○	○	○	○
Thinking is not my idea of fun	○	○	○	○	○
I would rather do something that requires little thought than something that is sure to challenge my thinking abilities	○	○	○	○	○
I try to anticipate and avoid situations where there is a likely chance I will have to think in depth about something	○	○	○	○	○
I find satisfaction in deliberating hard and long for hours	○	○	○	○	○
I only think as hard as I have to	○	○	○	○	○
I prefer to think about small, daily projects to long-term ones	○	○	○	○	○

	Extremely uncharacteristic	Somewhat uncharacteristic	Uncertain	Somewhat characteristic	Extremely characteristic
I like tasks that require little thought once I've learned them	○	○	○	○	○
The idea of relying on thought to make my way to the top appeals to me	○	○	○	○	○
I really enjoy a task that involves coming up with new solutions to problems	○	○	○	○	○
Learning new ways to think doesn't excite me very much	○	○	○	○	○
I prefer my life to be filled with puzzles that I must solve	○	○	○	○	○
The notion of thinking abstractly is appealing to me	○	○	○	○	○
I would prefer a task that is intellectual, difficult, and important than one that is somewhat important but does not require much thought	○	○	○	○	○
I feel relief rather than satisfaction after completing a task that required a lot of mental effort	○	○	○	○	○
It's enough for me that something gets the job done; I don't care how it works	○	○	○	○	○
I usually end up deliberating about issues even when they do not affect me personally	○	○	○	○	○

NEO-FFI

Read each statement carefully. For each statement indicate the response that best represents your opinion.

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
I am not a worrier	○	○	○	○	○
I like to have a lot of people around me	○	○	○	○	○

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
I don't like to waste my time daydreaming	O	O	O	O	O
I try to be courteous to everyone I meet	O	O	O	O	O
I keep my belongings clean and neat	O	O	O	O	O
I often feel inferior to others	O	O	O	O	O
I laugh easily	O	O	O	O	O
Once I find the right way to do something I stick to it	O	O	O	O	O
I often get into arguments with my family and coworkers	O	O	O	O	O
I'm pretty good about pacing myself so as to get things done on time	O	O	O	O	O
When I'm under a great deal of stress, sometimes I feel like I'm going to pieces	O	O	O	O	O
I don't consider myself especially "lighthearted"	O	O	O	O	O
I am intrigued by the patterns I find in art and nature	O	O	O	O	O
Some people think I'm selfish and egotistical	O	O	O	O	O
I am not a very methodical person	O	O	O	O	O
I rarely feel lonely and blue	O	O	O	O	O
I really enjoy talking to people	O	O	O	O	O
I believe letting students hear controversial speakers can only confuse and mislead them	O	O	O	O	O
I would rather cooperate with others than compete with them	O	O	O	O	O
I try to perform all the tasks assigned to me conscientiously	O	O	O	O	O

NEO-FFI pt. 2

Continued

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
I often feel tense and jittery	O	O	O	O	O
I like to be where the action is	O	O	O	O	O
Poetry has little or no effect on me	O	O	O	O	O
I tend to be cynical and skeptical of others' intentions	O	O	O	O	O
I have a clear set of goals and work toward them in an orderly fashion	O	O	O	O	O
Sometimes I feel completely worthless	O	O	O	O	O
I usually prefer to do things alone	O	O	O	O	O

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
I often try new foreign foods	O	O	O	O	O
I believe that most people will take advantage of you if you let them	O	O	O	O	O
I waste a lot of time before settling down to work	O	O	O	O	O
I rarely feel fearful or anxious	O	O	O	O	O
I often feel as if I'm bursting with energy	O	O	O	O	O
I seldom notice the moods or feelings that different environments produce	O	O	O	O	O
Most people I know like me	O	O	O	O	O
I work hard to accomplish my goals	O	O	O	O	O
I often get angry at the way people treat me	O	O	O	O	O
I am a cheerful, high-spirited person	O	O	O	O	O
I believe we should look to our religious authorities for decisions on moral issues	O	O	O	O	O
Some people think of me as cold and calculating	O	O	O	O	O
When I make a commitment, I can always be counted on to follow through	O	O	O	O	O

NEO-FFI pt. 3

Continued

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Too often, when things go wrong, I get discouraged and feel like giving up	O	O	O	O	O
I am not a cheerful optimist	O	O	O	O	O
Sometimes when I am reading poetry or looking at a work of art, I feel a chill or wave of excitement	O	O	O	O	O
I'm hard-headed and tough-minded in attitudes	O	O	O	O	O
Sometimes I am not as dependable or reliable as I should be	O	O	O	O	O
I am seldom sad or depressed	O	O	O	O	O
My life is fast-paced	O	O	O	O	O
I have little interest in speculating on the nature of the universe or human condition	O	O	O	O	O
I generally try to be thoughtful and considerate	O	O	O	O	O
I am a productive person who always gets the job done	O	O	O	O	O
I often feel helpless and want someone else to solve my problems	O	O	O	O	O

	Strongly disagree	Disagree	Neutral	Agree	Strongly agree
I am a very active person	O	O	O	O	O
I have a lot of intellectual curiosity	O	O	O	O	O
If I dont like people, I let them know it	O	O	O	O	O
I never seem to be able to get organized	O	O	O	O	O
At times I have been so ashamed I just want to hide	O	O	O	O	O
I would rather go my own way than be a leader of others	O	O	O	O	O
I often enjoy playing with theories or abstract ideas	O	O	O	O	O
If necessary, I am willing to manipulate people to get what I want	O	O	O	O	O
I strive for excellence in everything I do	O	O	O	O	O

Cognitive Reflection Test (CRT)

A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost?

If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?

In a lake, there is a patch of lily pads. Every day, the patch doubles in size.
If it takes 48 days for the patch to cover the enre lake, how long would it take for the patch to cover half of the lake?

Interpersonal Reactivity Index

The following statements inquire about your thoughts and feelings in a variety of situations. For each item, indicate how well it describes you by choosing the appropriate option on the scale at the top of the page. READ EACH ITEM CAREFULLY BEFORE RESPONDING. Answer as honestly as you can. Thank you.

	Does not describe me well at all	Describes me poorly	Neutral	Describes me slightly well	Describes me very well
I daydream and fantasize, with some regularity, about things that might happen to me.	O	O	O	O	O
I often have tender, concerned feelings for people less fortunate than me.	O	O	O	O	O
I sometimes find it difficult to see things from the "other guy's" point of view.	O	O	O	O	O
Sometimes I don't feel very sorry for other people when they are having problems.	O	O	O	O	O
I really get involved with the feelings of the characters in a novel.	O	O	O	O	O
In emergency situations, I feel apprehensive and ill-at-ease.	O	O	O	O	O
I am usually objective when I watch a movie or play, and I don't often get completely caught up in it.	O	O	O	O	O
I try to look at everybody's side of a disagreement before I make a decision.	O	O	O	O	O
When I see someone being taken advantage of, I feel kind of protective towards them.	O	O	O	O	O
I sometimes feel helpless when I am in the middle of a very emotional situation.	O	O	O	O	O
I sometimes try to understand my friends better by imagining how things look from their perspective.	O	O	O	O	O

	Does not describe me well at all	Describes me poorly	Neutral	Describes me slightly well	Describes me very well
Becoming extremely involved in a good book or movie is somewhat rare for me.	O	O	O	O	O
When I see someone get hurt, I tend to remain calm.	O	O	O	O	O
Other people's misfortunes do not usually disturb me a great deal.	O	O	O	O	O
If I'm sure I'm right about something, I don't waste much time listening to other people's arguments.	O	O	O	O	O
After seeing a play or movie, I have felt as though I were one of the characters.	O	O	O	O	O
Being in a tense emotional situation scares me.	O	O	O	O	O
When I see someone being treated unfairly, I sometimes don't feel very much pity for them.	O	O	O	O	O
I am usually pretty effective in dealing with emergencies.	O	O	O	O	O
I am often quite touched by things that I see happen.	O	O	O	O	O
I believe that there are two sides to every question and try to look at them both.	O	O	O	O	O
I would describe myself as a pretty soft-hearted person.	O	O	O	O	O
When I watch a good movie, I can very easily put myself in the place of a leading character.	O	O	O	O	O
I tend to lose control during emergencies.	O	O	O	O	O
When I'm upset at someone, I usually try to "put myself in his shoes" for a while.	O	O	O	O	O
When I am reading an interesting story or novel, I imagine how I would feel if the events in the story were happening to me.	O	O	O	O	O
When I see someone who badly needs help in an emergency, I go to pieces.	O	O	O	O	O
Before criticizing somebody, I try to imagine how I would feel if I were in their place.	O	O	O	O	O

Empathy Assessment Index

Please answer every prompt

	Yes	No
I am open to listening to the points of view of others.	O	O
I can imagine what it's like to be in someone else's shoes.	O	O
If a person is poor, I believe it is the result of bad personal choices.	O	O
When I see a stranger crying, I feel like crying.	O	O
I believe unemployment is brought on by individuals' failures.	O	O
I can tell how I am feeling emotionally by noticing how my body feels.	O	O
When something exciting happens, I get so excited I feel out of control.	O	O

	Yes	No
I consider other people's point of view in discussions.	O	O
Seeing someone dance makes me want to move my feet.	O	O
When someone insults me or verbally attacks me, I don't let it bother me.	O	O
I am not aware of how I feel about a situation until after the situation is over.	O	O
I believe poverty is brought on by individuals' failures.	O	O
When a friend is sad and it affects me deeply, it does not interfere with my own quality of life.	O	O
When I see a friend crying, I feel like crying.	O	O
I feel what another person is feeling, even when I do not know the person.	O	O
I believe adults who are poor deserve social assistance.	O	O
I am aware of my thoughts.	O	O
When I am with a sad person, I feel sad myself.	O	O
I believe government should support our well-being.	O	O
Watching a happy movie makes me feel happy.	O	O
I can tell the difference between someone else's feelings and my own.	O	O
I have angry outbursts.	O	O
I have a physical reaction (such as shaking, crying or going numb) when I am upset.	O	O
When I am with a happy person, I feel happy myself.	O	O

	Yes	No
When I care deeply for people, it feels like their emotions are my own.	O	O
I think society should help out children in need.	O	O
When I am upset or unhappy, I get over it quickly.	O	O
I can imagine what it is like to be poor.	O	O
I can explain to others how I am feeling.	O	O
I can agree to disagree with other people.	O	O
I get overwhelmed by other people's anxiety.	O	O
When a friend is happy, I become happy.	O	O
I believe government should be expected to help individuals.	O	O
I like to view both sides of an issue.	O	O
Emotional evenness describes me well.	O	O
Friends view me as a moody person.	O	O
It is easy for me to see other people's point of view.	O	O
I am aware of how other people think of me.	O	O
When I get upset, I need a lot of time to get over it.	O	O
When a friend is sad, I become sad.	O	O
I can distinguish my friend's feelings from my own.	O	O
I have large emotional swings.	O	O
I can imagine what the character is feeling in a well written book.	O	O
Hearing laughter makes me smile.	O	O
I rush into things without thinking.	O	O

	Yes	No
I think society should help out adults in need.	O	O
I watch other people's feelings without being overwhelmed by them.	O	O
I am comfortable helping a person of a different race or ethnicity than my own.	O	O
I believe the United States economic system allows for anyone to get ahead.	O	O
I can simultaneously consider my point of view and another person's point of view.	O	O

Baron-Cohen and Wheelwright

Below is a list of statements. Please read each statement carefully and rate how strongly you agree or disagree with it by circling your answer. There are no right or wrong answers, or trick questions. Please do not skip any statement.

	Strongly agree	Slightly agree	Slightly disagree	Strongly disagree
I can easily tell if someone else wants to enter a conversation.	O	O	O	O
I prefer animals to humans.	O	O	O	O
I try to keep up with the current trends and fashions.	O	O	O	O
I find it difficult to explain to others things that I understand easily, when they don't understand it first time.	O	O	O	O
I dream most nights.	O	O	O	O
I really enjoy caring for other people.	O	O	O	O
I try to solve my own problems rather than discussing them with others.	O	O	O	O
I find it hard to know what to do in a social situation.	O	O	O	O
I am at my best first thing in the morning.	O	O	O	O

	Strongly agree	Slightly agree	Slightly disagree	Strongly disagree
People often tell me that I went too far in driving my point home in a discussion.	O	O	O	O
It doesn't bother me too much if I am late meeting a friend.	O	O	O	O
Friendships and relationships are just too difficult, so I tend not to bother with them.	O	O	O	O
I would never break a law, no matter how minor.	O	O	O	O
I often find it difficult to judge if something is rude or polite.	O	O	O	O
In a conversation, I tend to focus on my own thoughts rather than on what my listener might be thinking.	O	O	O	O
I prefer practical jokes to verbal humor.	O	O	O	O
I live life for today rather than the future.	O	O	O	O
When I was a child, I enjoyed cutting up worms to see what would happen.	O	O	O	O
I can pick up quickly if someone says one thing but means another.	O	O	O	O
I tend to have very strong opinions about morality.	O	O	O	O
It is hard for me to see why some things upset people so much.	O	O	O	O
I find it easy to put myself in somebody else's shoes.	O	O	O	O
I think that good manners are the most important thing a parent can teach their child.	O	O	O	O
I like to do things on the spur of the moment.	O	O	O	O
I am good at predicting how someone will feel.	O	O	O	O

	Strongly agree	Slightly agree	Slightly disagree	Strongly disagree
I am quick to spot when someone in a group is feeling awkward or uncomfortable.	O	O	O	O
If I say something that someone else is offended by, I think that that's their problem, not mine.	O	O	O	O
If anyone asked me if I liked their haircut, I would reply truthfully, even if I didn't like it.	O	O	O	O
I can't always see why someone should have felt offended by a remark.	O	O	O	O
People often tell me that I am very unpredictable.	O	O	O	O

Baron-Cohen and Wheelwright continued

Continued

	Strongly agree	Slightly agree	Slightly disagree	Strongly disagree
I can easily tell if someone else wants to enter a conversation.	O	O	O	O
I prefer animals to humans.	O	O	O	O
I try to keep up with the current trends and fashions.	O	O	O	O
I find it difficult to explain to others things that I understand easily, when they don't understand it first time.	O	O	O	O
I dream most nights.	O	O	O	O
I really enjoy caring for other people.	O	O	O	O
I try to solve my own problems rather than discussing them with others.	O	O	O	O
I find it hard to know what to do in a social situation.	O	O	O	O
I am at my best first thing in the morning.	O	O	O	O

	Strongly agree	Slightly agree	Slightly disagree	Strongly disagree
People often tell me that I went too far in driving my point home in a discussion.	O	O	O	O
It doesn't bother me too much if I am late meeting a friend.	O	O	O	O
Friendships and relationships are just too difficult, so I tend not to bother with them.	O	O	O	O

Psychological Entitlement Scale

Please respond to the following items using the number that best reflects your own beliefs.

	Strongly disagree	Moderately disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Moderately agree	Strongly agree
I honestly feel I'm just more deserving than others.	O	O	O	O	O	O	O
Great things should come to me.	O	O	O	O	O	O	O
If I were on the Titanic, I would deserve to be on the first lifeboat!	O	O	O	O	O	O	O
I demand the best because I'm worth it.	O	O	O	O	O	O	O
I do not necessarily deserve special treatment.	O	O	O	O	O	O	O
I deserve more things in my life.	O	O	O	O	O	O	O
People like me deserve and extra break now and and then.	O	O	O	O	O	O	O
Things should go my way.	O	O	O	O	O	O	O
I feel entitled to more of everything.	O	O	O	O	O	O	O

Moral Dilemmas

Footbridge: An empty runaway trolley is speeding down a set of tracks toward five railway workmen. There is a footbridge above the tracks in between the runaway trolley and the five workmen. On this footbridge is a railway workman wearing a large, heavy backpack. If nothing is done, the trolley will proceed down the main tracks and cause the deaths of the five workmen. It is possible to avoid these five deaths. Joe is a bystander who understands what is going on and who happens to be standing right behind the workman on the footbridge. Joe sees that he can avoid the deaths of the five workmen by pushing the workman with the heavy backpack off of the footbridge and onto the tracks below. The trolley will collide with the workman, and the combined weight of the workman and the backpack will be enough to stop the trolley, avoiding the deaths of the five workmen. But the collision will cause the death of the workman with the backpack.

Question: Is it morally acceptable for Joe to push the workman off of the footbridge in order to avoid the deaths of the five workmen, causing the death of the single workman instead?

Everyday Moral Dilemmas (Negative)

You will now read a series of brief stories in which somebody (the actor) describes a particular situation. The people are males and females and are of a variety of different ages. You will be asked to provide a rating about each story. Each scale will be from 1 to 7. Only whole number responses are permissible.

I go online a lot to meet people. I talk to a number of different people and lie to all of them. I lie about facts such as my job, looks, and where I'm from.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

After I got in the Marine Corps, a friend of mine and I were trying to get false IDs so that we could get into the bars and clubs. We asked the clerk to change our dates of birth. We told her that the dates were wrong.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

I was in a French class with a guy named Jason. He found a copy of a test we were going to have. I bought it from him for a dollar.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

I remember when public transportation buses started charging a dollar. My friends and I would tear the dollar into 4 pieces and fold it up so it looked like a dollar. I would use a dollar for four rides.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

Years ago, my partner and I were friends with another couple. Then I started going out with one of the people in the other relationship secretly. It was really awkward when all four of us would have dinner together.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

When I was 17 years old I had two boyfriends. I would see one and then go visit the other. Sometimes one would drive up to my house as the other was driving away. Neither of them ever found out.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

I slept with one of my math teachers and I really hope nobody ever finds out about it. At the time he said he was separated from his wife, so I knew that he was married.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

When my partner was very sick a few years ago he had to walk very slowly. He needed a cane and couldn't move fast. I was very impatient with him and told him to move faster.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

When I was in high school, this old man died. Some guys and I went into his house and I took a pair of old work boots. I put them in the trunk of my car.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

I was seeing a married man named Frank in my early twenties. He wasn't 100% sure that he wanted to be with me because he was married and had kids. So, we had been together for a year and a half when I decided to cheat on Frank with a man at work.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

I was thirteen years old and I went into the grocery store where I lived. There was a comb that I wanted in the store, so I just took it. I didn't really need it but I just wanted the thrill of stealing it and nobody catching me.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

A little while ago I had to go to the DMV to get my drivers license renewed. They told me that I had to take a written test in which I had three attempts to pass. I failed the first two times so I cheated on the final attempt.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

I took my sister's ring that was given to her by our father's aunt. I had never met our father's aunt but my sister spent some time with her. I took the ring because I didn't think that my sister deserved it.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

I worked in a cosmetics department store in the 80's. I started stealing clothes by pretending to ring them up, as if I was buying them, and then just putting them in my bag. I kept taking clothes and eventually the store found out.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

I was married for three years when I became attracted to a woman at work. One night when my wife was away with friends I was unfaithful to her. I then continued to have an affair.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

A couple of years ago, I was out on the streets using drugs. I had a very young attractive girlfriend. I used to let her do whatever she wanted to do, like prostitution and stuff like that.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

I was responsible for the financial wellbeing of the women members in my family. They really needed all the money that they had and could get. So, through a bit of "creative reporting" on their taxes, I ended up cheating the government out of about $100,000.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

I was getting a massage at the gym and the massage therapist came on to me. I was dating a guy named Brad at the time though. I was unfaithful to Brad and had sex with the man who was massaging me.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

I used to work as a legal assistant. I lied to clients all of the time, the attorney I worked for lied all the time too. We just lie to our clients so things will work out the best for us.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

I have cheated pretty much all of my life. The most recent time was because I was in a long distance relationship. There were so many opportunities to cheat that I just gave into the temptation.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

I cheated on my present boyfriend. I didn't understand why he did not want to get married. I felt like he didn't want to get married because of me and because he didn't want to be with me, so I thought it was okay to have an affair.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

Ten years ago I was staying with a friend who lived in a house of a very famous man. There were many autographed books in the house. I stole one of the books, which was autographed by a very famous celebrity.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

There was a time for about a month that I was kind of into crystal methane. At the time I snuck around and did it in my house. My mother didn't know that I was doing it in the bathroom.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

I was in a relationship with a girl named Pam that I didn't really want to be with anymore. I was attracted to another girl named Annie who I hung out with often. So, she and I engaged in very loud sexual play on my couch so that Pam would hear us in the other room.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

I put a poster that I had on EBay. There was a man who bid on it and paid with a system that sent the money directly to me. He was kind of a jerk during the whole transaction, so I decided not to send the poster and just keep the money.

YOUR MORAL JUDGMENT:

Extremely inappropriate	Moderately inappropriate	Slightly inappropriate	Neither appropriate nor inappropriate	Slightly appropriate	Moderately appropriate	Extremely appropriate
1	2	3	4	5	6	7

Thank you for your participation

Appendix E SART Questionnaire

Instability of Situation
How changeable is the situation? Is the situation highly unstable and likely to change suddenly (high), or is it very stable and straight forward (low)?

1	**2**	**3**	**4**	**5**	**6**	**7**

Complexity of Situation
How complicated is the situation? Is it complex with many interrelated components (high) or is it simple and straightforward (low)?

1	**2**	**3**	**4**	**5**	**6**	**7**

Variability of Situation
How many variables are changing in the situation? Are there large number of factors varying (high) or are there very few variables changing (low)?

1	**2**	**3**	**4**	**5**	**6**	**7**

Arousal
How aroused are you in the situation? Are you alert and ready for activity (high) or do you have a low degree of alertness (low)?

1	**2**	**3**	**4**	**5**	**6**	**7**

Concentration of Attention
How much are you concentrating on the situation? Are you concentrating on many aspects of the situation (high) or focused on only one (low)?

1	**2**	**3**	**4**	**5**	**6**	**7**

Division of Attention
How much is your attention divided in this situation? Are you concentrating on many aspects of the situation (high) or focused on only one (low)?

1	**2**	**3**	**4**	**5**	**6**	**7**

Spare Mental Capacity
How much mental capacity do you have to spare in the situation? Do you have sufficient to attend to many variables (high) or nothing to spare at all (low)?

1	**2**	**3**	**4**	**5**	**6**	**7**

Information Quantity
How much information have you gained about the situation? Have you received and understood a great deal of knowledge (high) or very little (low)?

1	**2**	**3**	**4**	**5**	**6**	**7**

Information Quality
How good is the information you have gained about the situation? Is the knowledge communicated very useful (high) or is it insufficient (low)?

1	**2**	**3**	**4**	**5**	**6**	**7**

Familiarity with Situation
How familiar are you with the situation? Do you have a great deal of relevant experience (high) or is it a new situation (low)?

1	**2**	**3**	**4**	**5**	**6**	**7**

Appendix F Participant Demographics

ID	Age	Gender	Age of license	Annual mileage	Education level	Enjoy driving	Cellphone usage	Crash history	Ticket history	Current Insurance
1	23	1	9	6500	2	7	8	1	1	1
2	28	2	15	15000	5	6	4	1	1	3
3	22	1	2	4000	2	8	3	1	1	1
4	21	1	3	7500	2	9	8	1	1	2
5	21	1	0	10000	2	8	3	1	1	2
6	20	1	4	10000	2	10	8	1	1	2
7	18	1	3	6000	2	10	3	1	1	3
8	19	1	4	7000	2	10	3	1	1	3
9	22	1	0	10000	2	7	4	2	1	3
10	19	1	1	2000	2	7	2	1	1	1
11	19	1	5	7000	2	10	10	1	1	1
12	20	1	4	8000	2	5	1	1	1	2
13	21	1	6	6000	2	8	4	1	1	3
14	19	1	3	7000	2	9	3	1	1	NA
15	21	1	6	10000	2	10	3	1	1	3
16	20	1	3	20000	2	6	4	1	1	3
17	37	2	23	10000	3	4	1	1	1	1
18	23	1	8	5000	2	7	7	1	1	1
19	19	1	3	15000	2	10	2	1	2	1
20	18	1	3	20000	2	10	10	1	3	1
21	19	1	4	7500	2	9	1	2	1	1
22	22	1	7	12000	3	10	8	1	2	3
23	21	1	0	1000	2	NA	4	1	1	1
24	21	1	5	10000	2	7	4	1	1	2
25	18	1	4	6000	2	10	3	1	1	3
26	21	2	6	12000	2	7	3	1	1	NA
27	20	2	5	6000	2	6	3	1	1	3
28	21	2	0	10000	2	8	4	1	1	1
29	59	2	26	6000	2	9	1	2	1	1
30	51	2	33	25000	3	8	3	1	1	3
31	23	2	8	20000	2	8	4	1	1	3
32	21	2	7	8000	2	9	1	1	1	1
33	50	2	35	10000	2	7	6	1	1	1
34	22	2	0	10000	4	8	2	1	1	3
35	19	2	4	12500	2	10	2	1	3	1
36	18	2	0	6500	2	7	4	1	1	3
37	19	2	0	10000	2	8	1	1	1	2
38	19	2	4	1000	2	9	4	1	1	3
39	21	2	6	1000	2	6	5	1	1	2
40	19	2	4	15000	2	8	7	1	1	1
41	20	2	4	12000	2	10	10	1	1	3

ID	Age	Gender	Age of license	Annual mileage	Education level	Enjoy driving	Cellphone usage	Crash history	Ticket history	Current Insurance
42	21	2	4	25000	2	6	2	1	1	1
43	20	2	5	10000	2	8	1	1	2	3
44	22	2	0	5000	2	9	4	2	1	2
45	20	2	5	10000	2	7	5	1	3	1
46	54	2	38	25000	4	10	7	1	1	3
47	21	2	4	9000	2	8	8	1	1	2
48	19	2	3	10000	2	8	4	1	1	1
49	20	1	5	5000	2	8	1	1	1	1
50	23	1	7	10000	4	8	2	1	1	3
51	27	1	8	30000	3	10	2	1	1	1
52	46	1	28	20000	3	9	4	1	1	1
53	48	1	31	12000	3	8	1	1	1	1
54	27	1	0	8000	5	10	NA	2	1	3
55	31	1	17	10000	5	7	3	1	1	3
56	46	1	29	1700	5	4	2	1	1	1
57	29	1	14	15000	5	6	3	1	2	3
58	26	1	0	13000	3	5	2	2	1	3
59	36	1	20	15000	2	10	2	1	1	1
60	49	1	33	45000	3	8	4	1	1	1
61	25	1	0	11000	1	10	3	1	1	3
62	46	1	30	20000	3	10	3	1	1	3
63	38	1	22	45000	3	7	6	2	1	1
64	35	2	20	2000	2	6	1	1	1	1
65	26	2	2	12000	4	10	7	1	1	1
66	42	2	26	16000	3	9	3	1	1	3
67	40	2	22	27000	3	9	NA	1	1	1
68	26	2	3	10000	5	NA	5	1	1	3
69	42	2	27	2000	3	7	4	1	1	2
70	36	2	22	19000	5	8	6	1	1	3
71	34	2	19	40000	3	10	2	2	1	3
72	48	2	32	8000	5	8	1	1	1	3
73	31	2	17	10000	1	10	9	1	1	3
74	30	2	15	13000	5	9	4	1	1	3
75	32	2	16	24000	5	NA	7	1	1	2
76	28	2	12	12000	3	6	4	1	1	3
77	56	1	37	1200	5	5	1	1	1	1
78	58	1	45	7500	1	9	2	1	1	1
79	61	1	46	15000	2	10	5	1	1	3
80	53	1	37	18000	2	10	1	1	1	1
81	56	1	41	20000	2	10	2	1	1	1
82	56	1	41	5000	1	8	1	1	1	1
83	25	1	9	11000	2	8	4	1	1	3
84	53	2	36	10000	2	10	1	1	1	3

ID	Age	Gender	Age of license	Annual mileage	Education level	Enjoy driving	Cellphone usage	Crash history	Ticket history	Current Insurance
85	60	2	46	1000	1	6	NA	1	1	3
86	64	2	49	8000	3	8	NA	1	1	3
87	57	2	41	10000	5	9	2	1	1	3
88	57	2	41	13000	3	8	5	1	1	3
89	20	2	5	12000	2	6	3	1	1	1
90	55	2	40	15000	3	10	3	1	1	3
Mean	**31.4**	**1.5**	**14.6**	**12043.3**	**2.6**	**8.2**	**3.8**	**1.1**	**1.1**	**NA**
SD	**14.2**	**0.5**	**14.6**	**8561.1**	**1.1**	**1.6**	**2.4**	**0.3**	**0.4**	**NA**

*NA indicates missing or not completed information.

Education level {1: High school; 2: Current college student; 3: Finished college; 4: Current graduate student; 5: Finished graduate school with at least a master's degree}

Current insurance {1: Liability; 2: Comprehensive; 3: Collision}

Appendix G Behavioral Questionnaires Total Scores

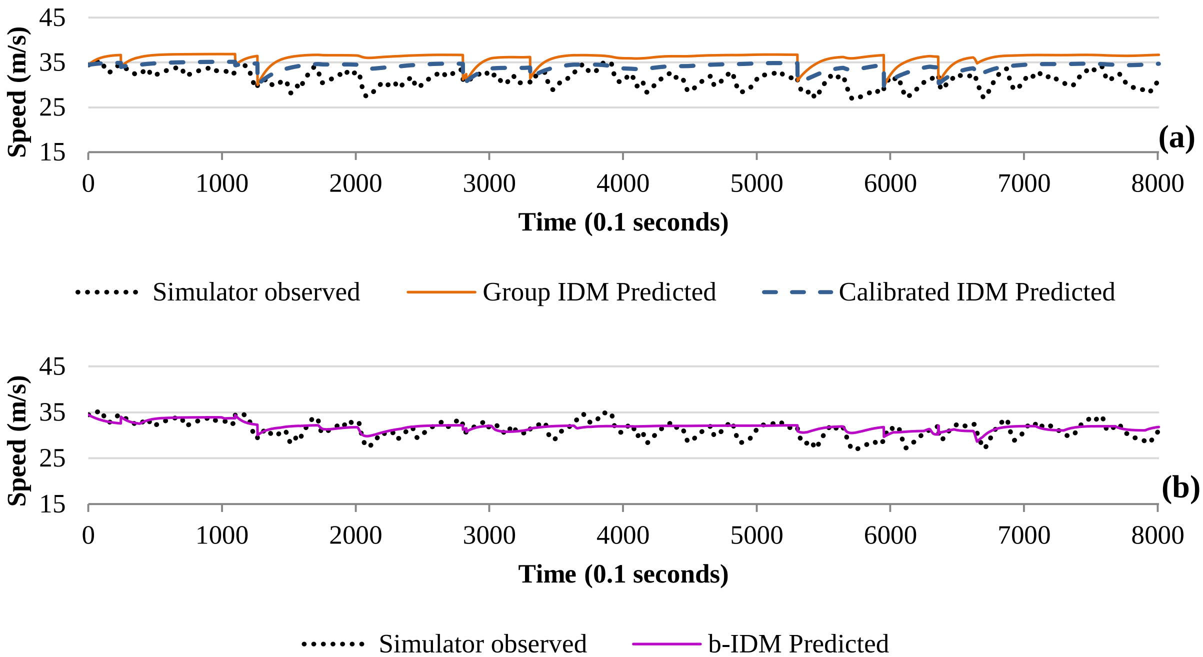
ID	PANAS	Neuroticism	CRT score	IRI	PES	Moral dilemmas
1	5	55	3	52	33	3
2	-11	50	0	84	34	1
3	28	32	1	59	32	2
4	19	37	3	77	50	1
5	30	38	2	65	39	2
6	29	54	3	52	29	1
7	33	47	1	71	40	1
8	30	70	3	62	17	1
9	14	33	2	47	31	1
10	22	57	0	48	40	2
11	23	44	2	64	30	2
12	25	58	0	78	41	1
13	38	51	1	66	23	1
14	13	33	2	65	25	1
15	21	35	2	56	42	1
16	-2	39	2	83	33	2
17	18	63	1	84	42	2
18	12	53	1	72	27	2
19	24	52	3	58	24	1
20	35	52	3	81	9	3
21	26	30	3	48	15	1
22	2	43	3	73	20	1
23	28	40	2	63	39	1
24	17	52	3	82	18	2
25	19	66	3	69	35	2
26	6	25	0	44	30	1
27	26	44	3	59	25	2
28	31	52	1	78	49	1
29	22	49	2	62	31	1
30	12	57	2	66	32	1
31	37	54	2	71	23	2
32	16	56	0	72	25	1
33	37	56	1	26	24	2
34	17	54	3	95	18	1
35	26	36	1	76	23	1
36	-1	48	3	46	34	1
37	8	43	0	70	36	1
38	8	41	3	66	35	1
39	7	39	1	67	28	1
40	16	49	3	84	37	2
41	3	22	0	68	29	1
42	8	45	3	59	36	2

ID	PANAS	Neuroticism	CRT score	IRI	PES	Moral dilemmas
43	24	46	0	83	32	1
44	21	48	0	80	38	1
45	21	56	0	78	37	1
46	32	38	0	54	23	2
47	35	31	1	70	27	1
48	7	52	0	90	23	2
49	27	64	3	58	28	1
50	34	48	3	45	28	1
51	37	57	0	58	24	2
52	29	42	2	56	36	1
53	17	50	2	61	18	2
54	28	55	2	66	33	1
55	17	64	2	71	33	1
56	30	56	1	37	36	1
57	1	36	3	69	15	2
58	16	46	2	69	39	2
59	27	58	1	67	44	3
60	22	53	2	80	35	2
61	19	52	3	58	29	2
62	38	54	2	71	19	2
63	12	46	3	70	47	2
64	27	51	3	65	38	1
65	25	52	3	76	33	2
66	17	43	3	71	23	3
67	21	38	1	65	18	2
68	15	33	2	77	38	2
69	-11	43	3	82	20	2
70	14	39	3	65	34	1
71	25	29	1	52	39	2
72	33	58	2	72	31	2
73	0	25	0	60	43	2
74	13	54	1	77	23	1
75	18	57	2	37	31	2
76	15	43	2	71	35	1
77	0	28	2	51	36	1
78	0	NA	0	47	22	2
79	29	60	3	80	21	2
80	36	51	0	57	38	2
81	25	54	3	70	26	2
82	14	31	1	46	34	2
83	17	51	3	67	24	2
84	37	54	0	62	36	2
85	38	26	1	65	29	0

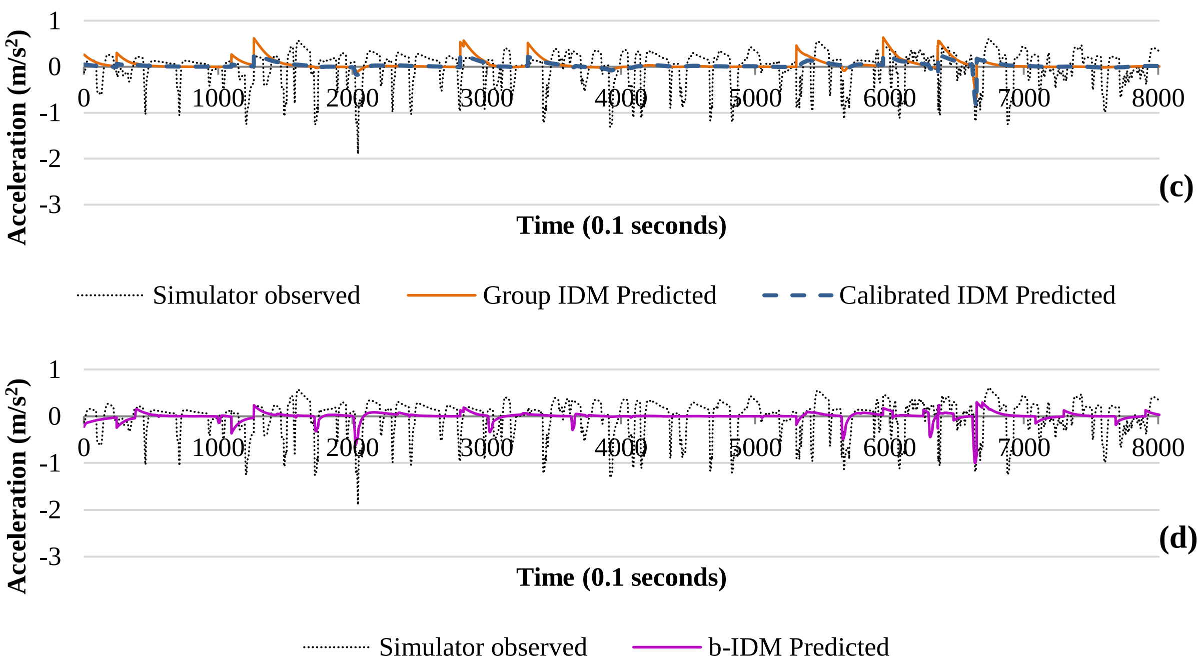
ID	PANAS	Neuroticism	CRT score	IRI	PES	Moral dilemmas
86	36	63	1	61	27	2
87	34	59	2	69	25	2
88	26	41	3	63	23	1
89	-4	43	3	63	31	2
90	33	45	0	65	33	2
Mean	**22.4**	**46.9**	**2.2**	**65.5**	**30.4**	**1.6**
SD	**12.0**	**10.5**	**1.1**	**12.5**	**8.2**	**0.6**

Group A Participants

Participant ID 5 - Speed



Participant ID 5 - Acceleration



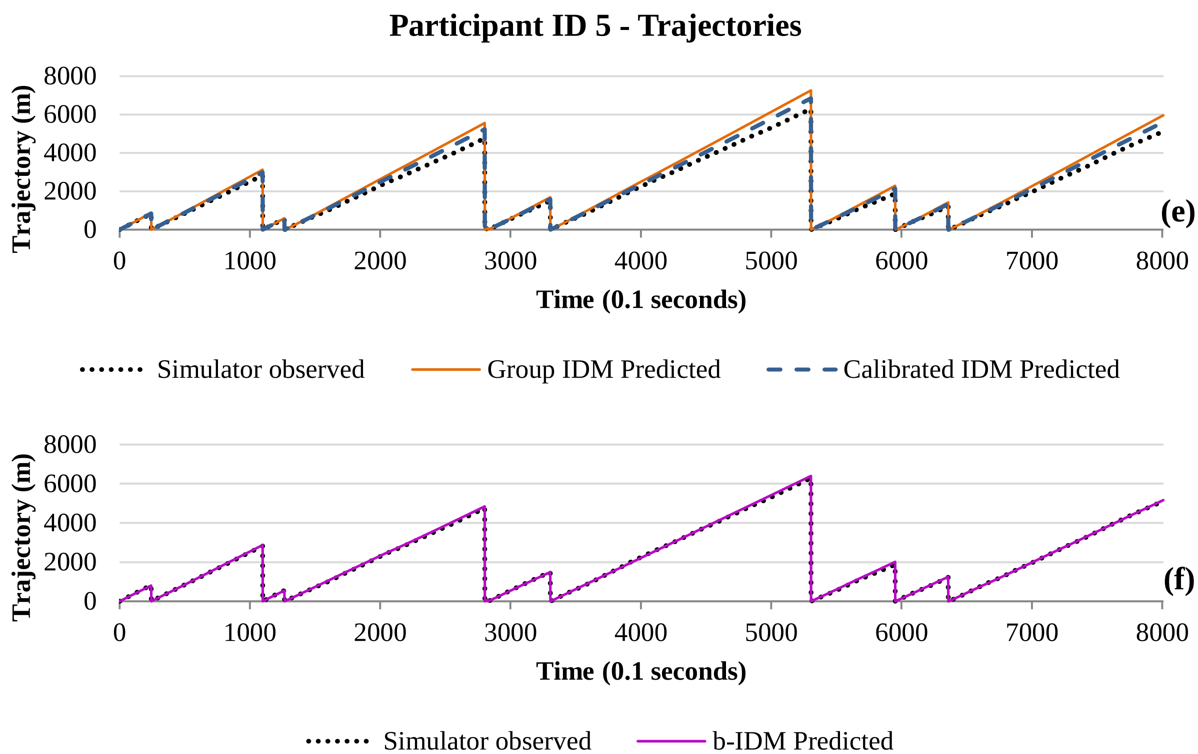
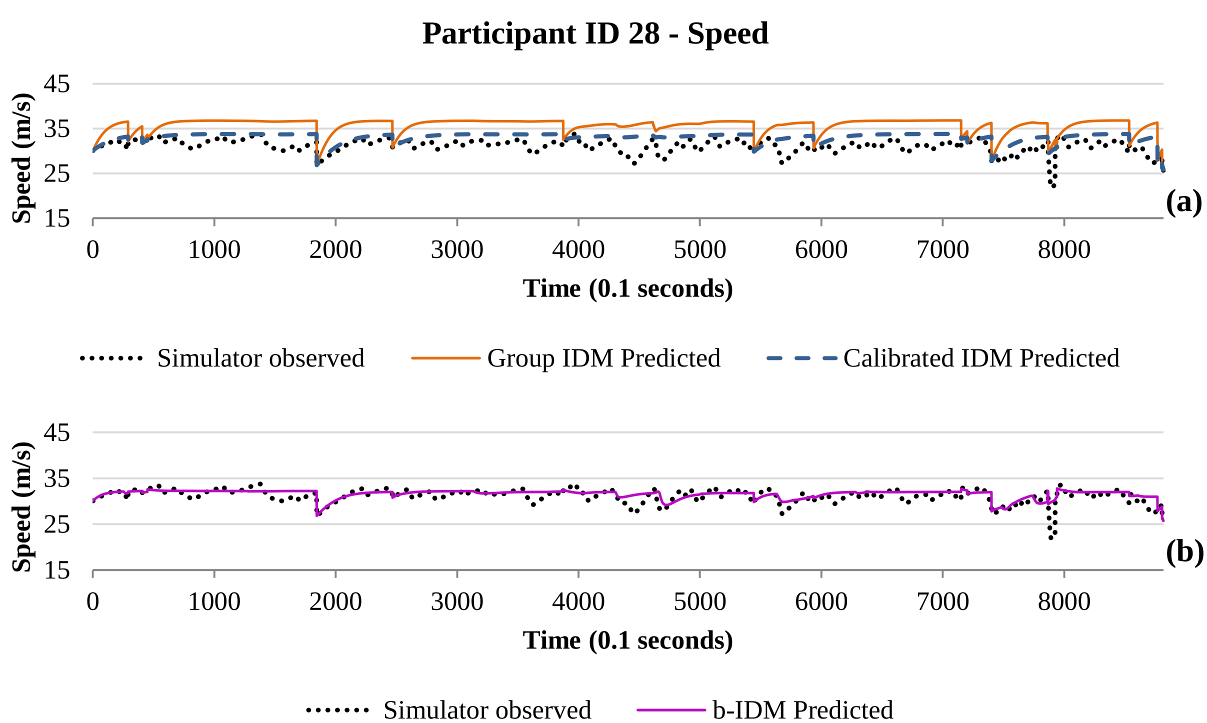


Figure H.1 Comparison plots for participant 5 showing (a) Calibrated and group IDM predicted speed, (b) b-IDM predicted speed, (c) Calibrated and group IDM predicted acceleration, (d) b-IDM predicted acceleration, (e) Calibrated and group IDM predicted trajectories, and (f) b-IDM predicted trajectories



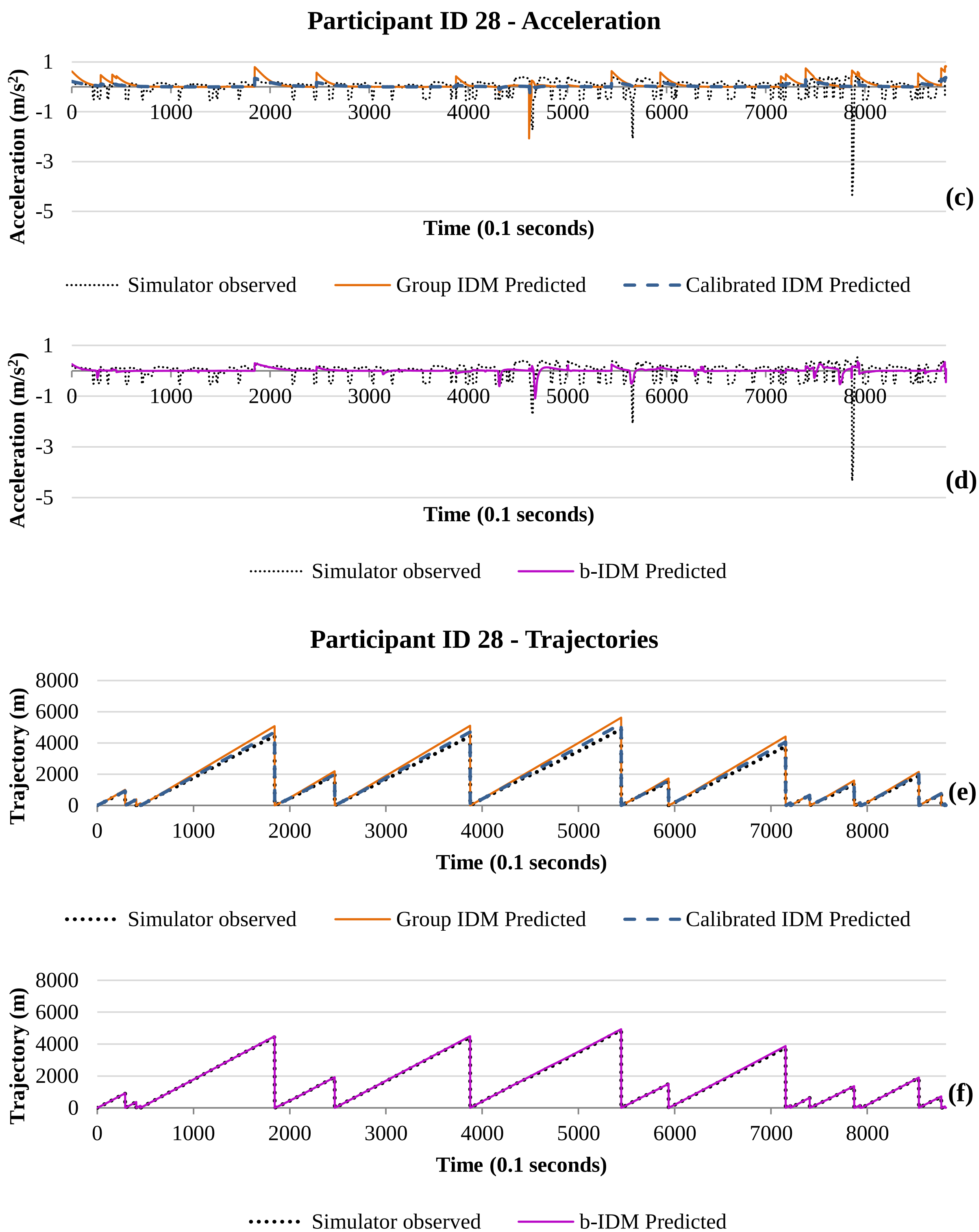
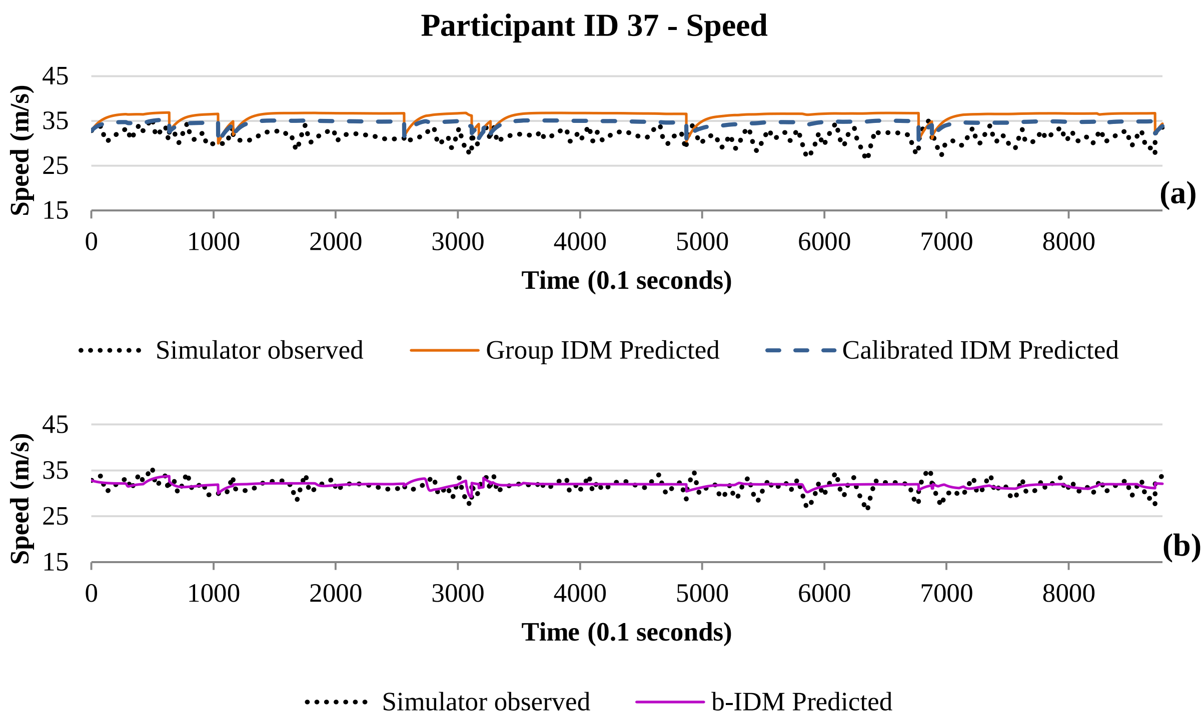
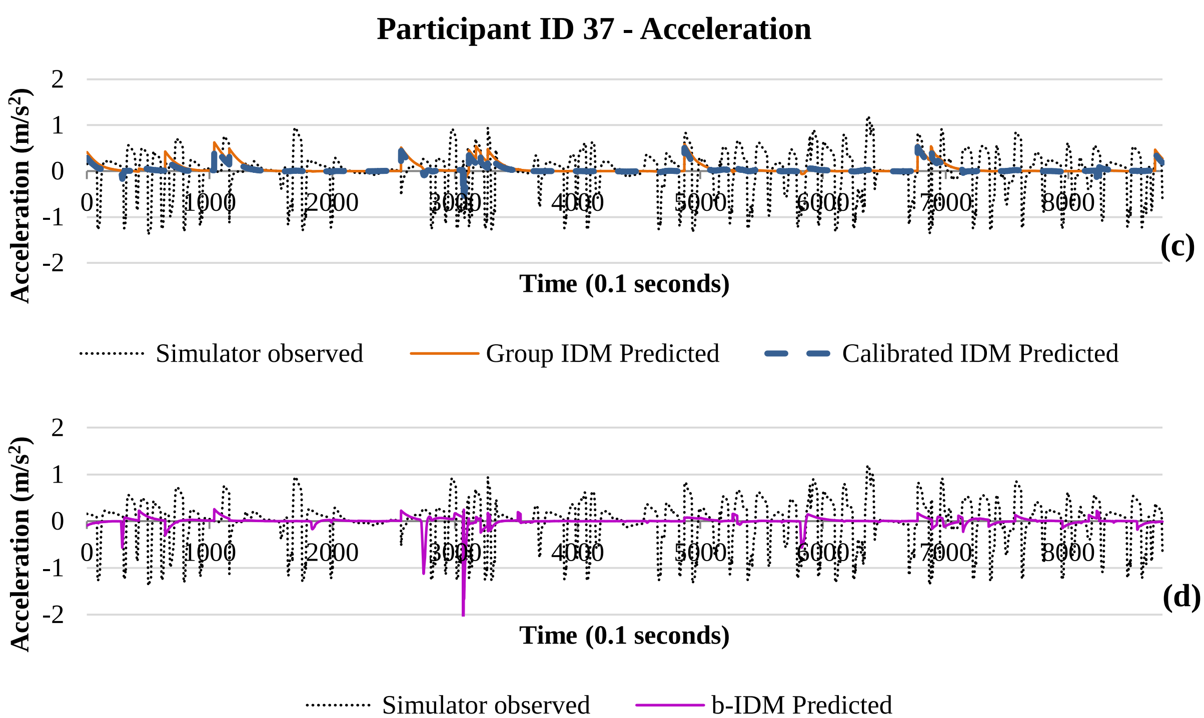


Figure H.2 Comparison plots for participant 28 showing (a) Calibrated and group IDM predicted speed, (b) b-IDM predicted speed, (c) Calibrated and group IDM predicted acceleration, (d) b-IDM predicted acceleration, (e) Calibrated and group IDM predicted trajectories, and (f) b-IDM predicted trajectories


Participant ID 37 - Speed
Speed (m/s)
45
35
25
15
0
1000
2000
3000
4000
5000
6000
7000
8000
Time (0.1 seconds)
(a)
Simulator observed
Group IDM Predicted
Calibrated IDM Predicted
Speed (m/s)
45
35
25
15
0
1000
2000
3000
4000
5000
6000
7000
8000
Time (0.1 seconds)
(b)
Simulator observed
b-IDM Predicted


Participant ID 37 - Acceleration
Acceleration (m/s²)
2
1
0
-1
-2
0
1000
2000
3000
4000
5000
6000
7000
8000
Time (0.1 seconds)
(c)
Simulator observed
Group IDM Predicted
Calibrated IDM Predicted
Acceleration (m/s²)
2
1
0
-1
-2
0
1000
2000
3000
4000
5000
6000
7000
8000
Time (0.1 seconds)
(d)
Simulator observed
b-IDM Predicted

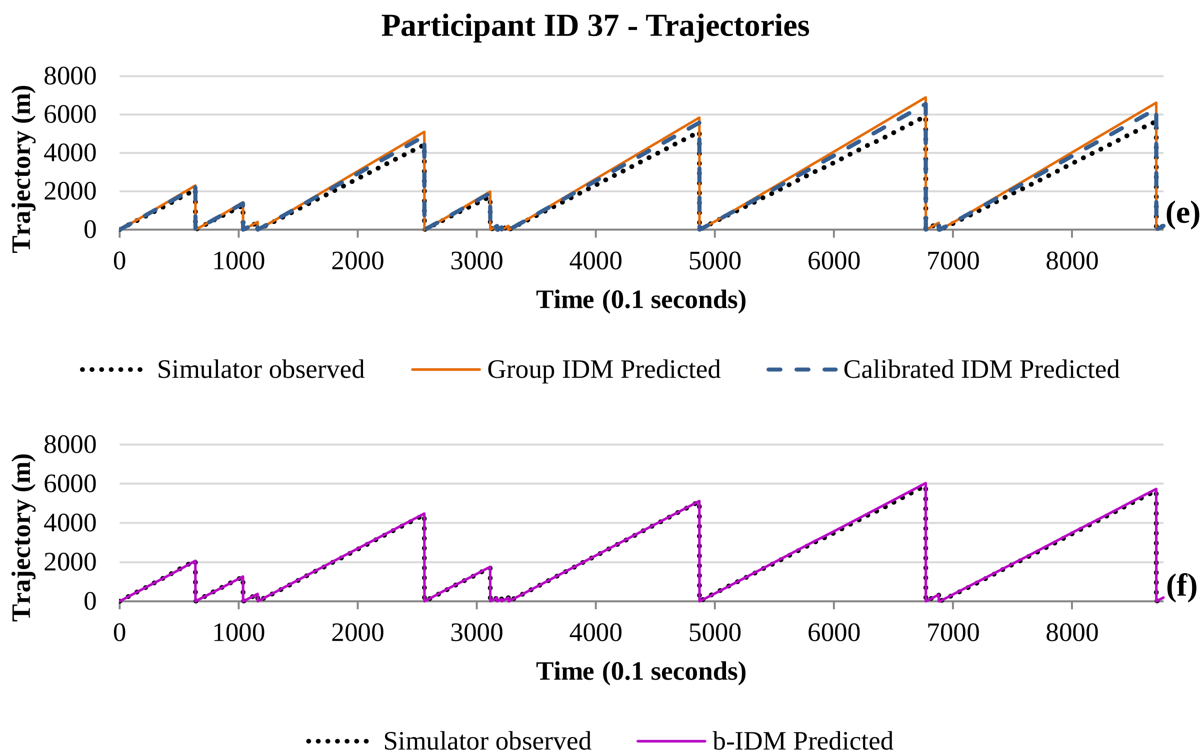
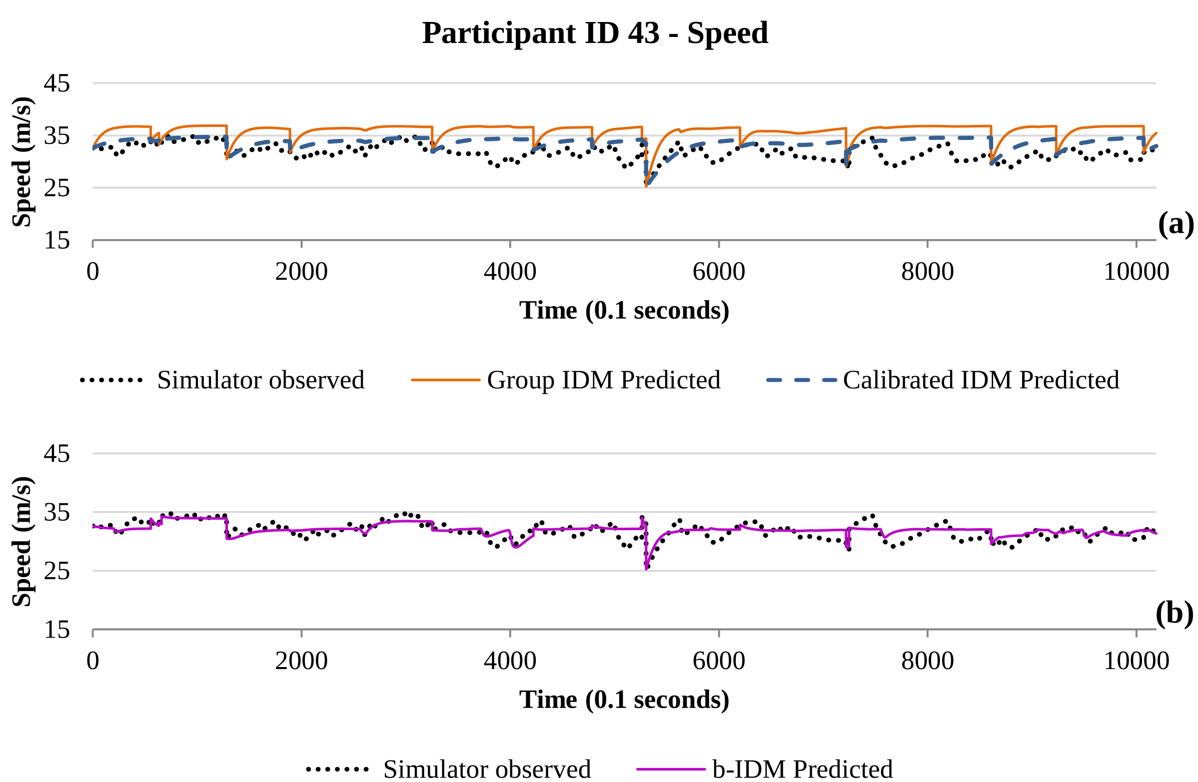


Figure H.3 Comparison plots for participant 37 showing (a) Calibrated and group IDM predicted speed, (b) b-IDM predicted speed, (c) Calibrated and group IDM predicted acceleration, (d) b-IDM predicted acceleration, (e) Calibrated and group IDM predicted trajectories, and (f) b-IDM predicted trajectories



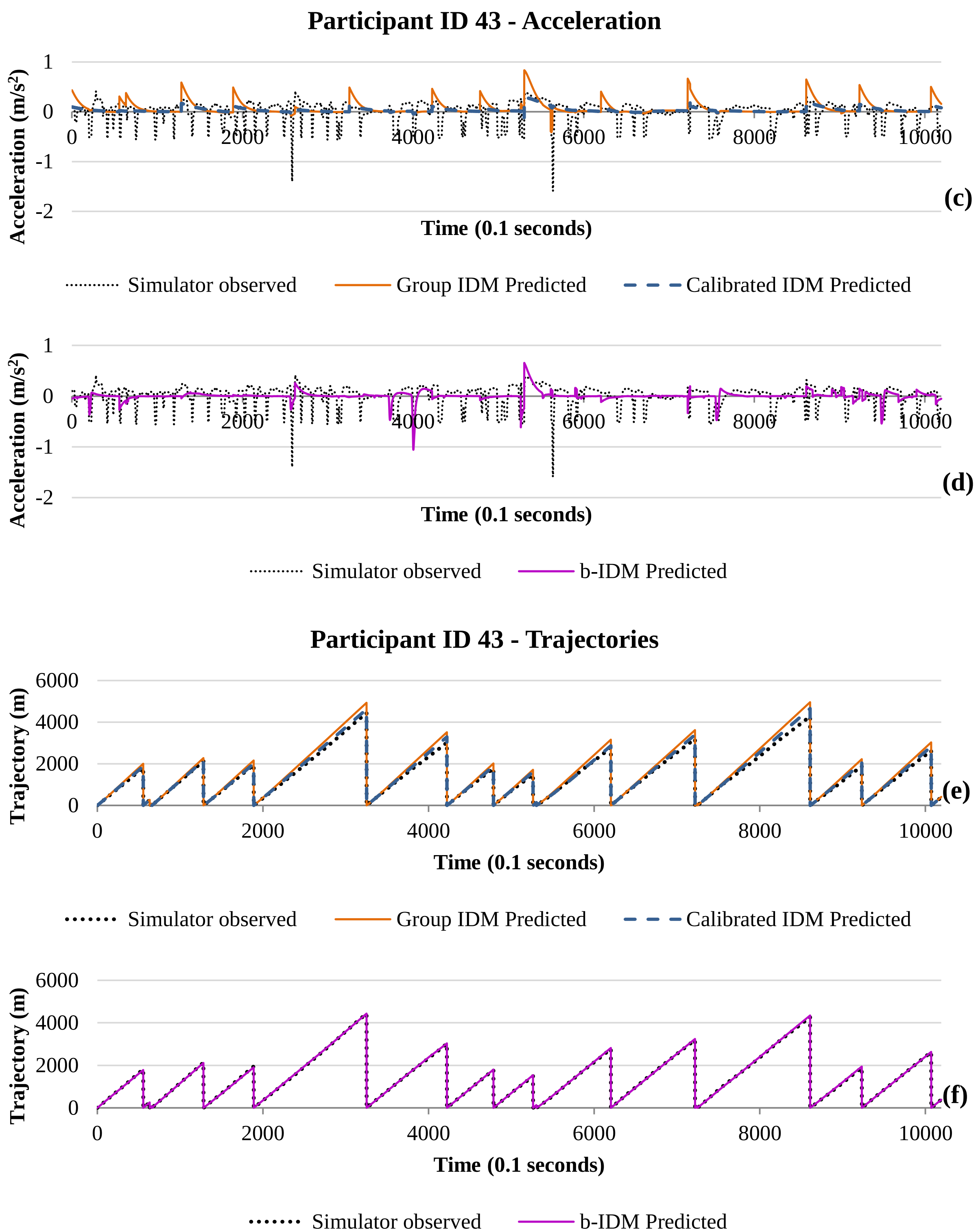
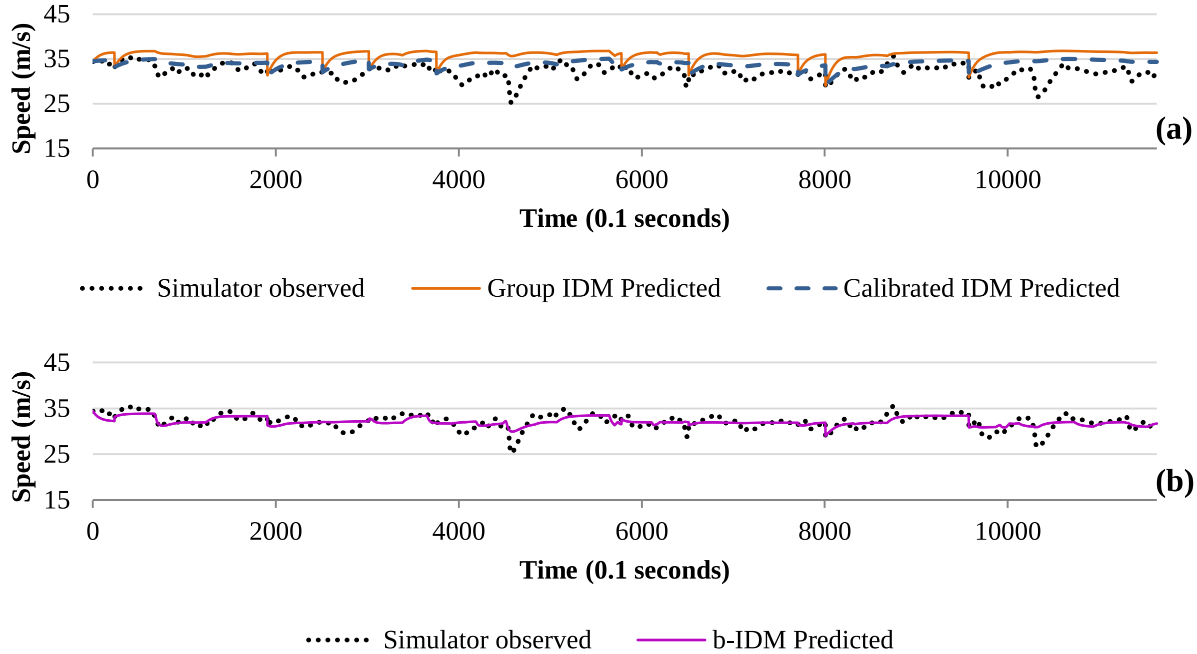
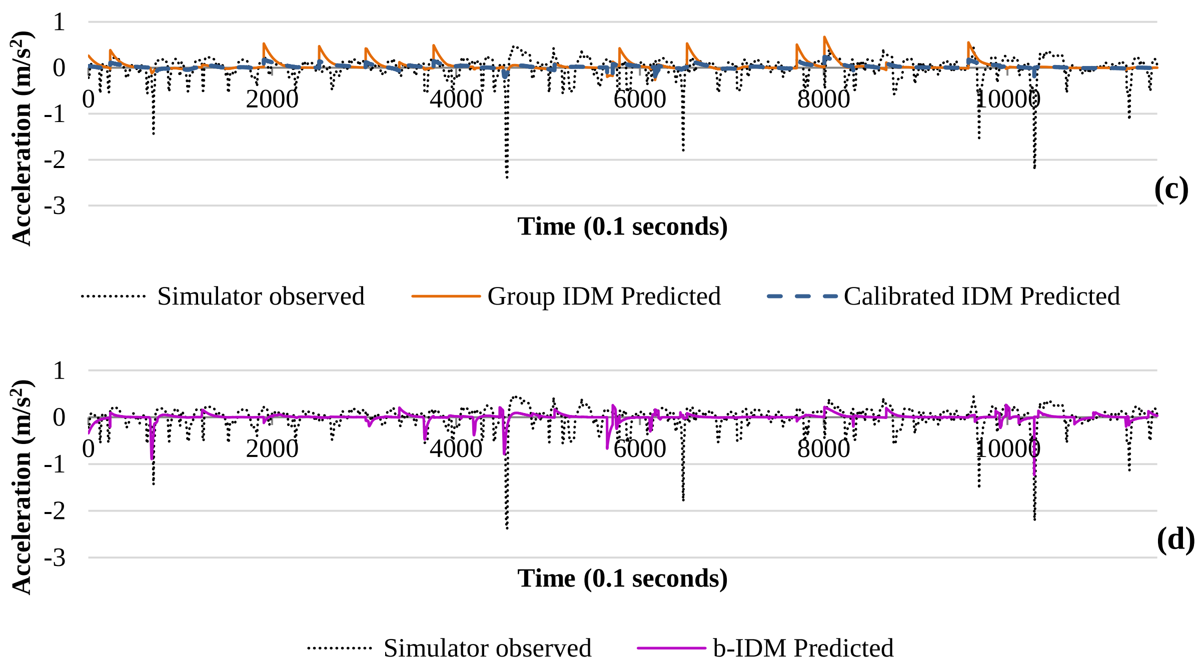


Figure H.4 Comparison plots for participant 43 showing (a) Calibrated and group IDM predicted speed, (b) b-IDM predicted speed, (c) Calibrated and group IDM predicted acceleration, (d) b-IDM predicted acceleration, (e) Calibrated and group IDM predicted trajectories, and (f) b-IDM predicted trajectories

Participant ID 51 - Speed



Participant ID 51 - Acceleration



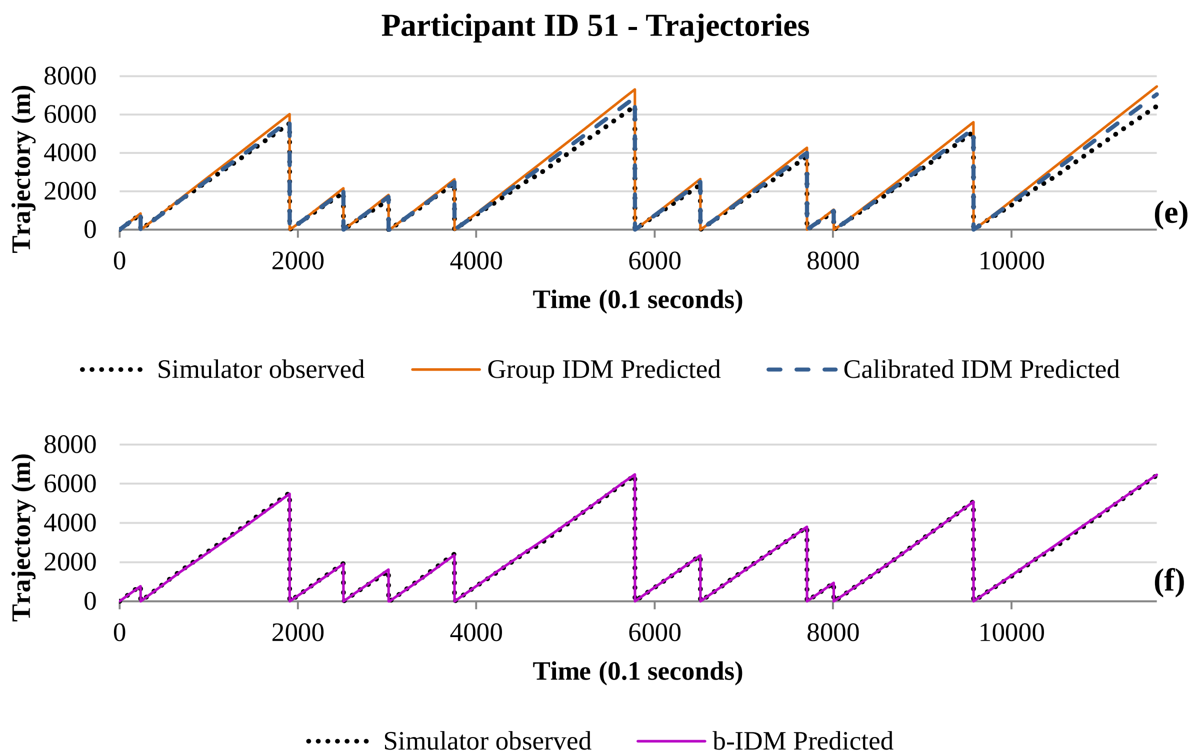
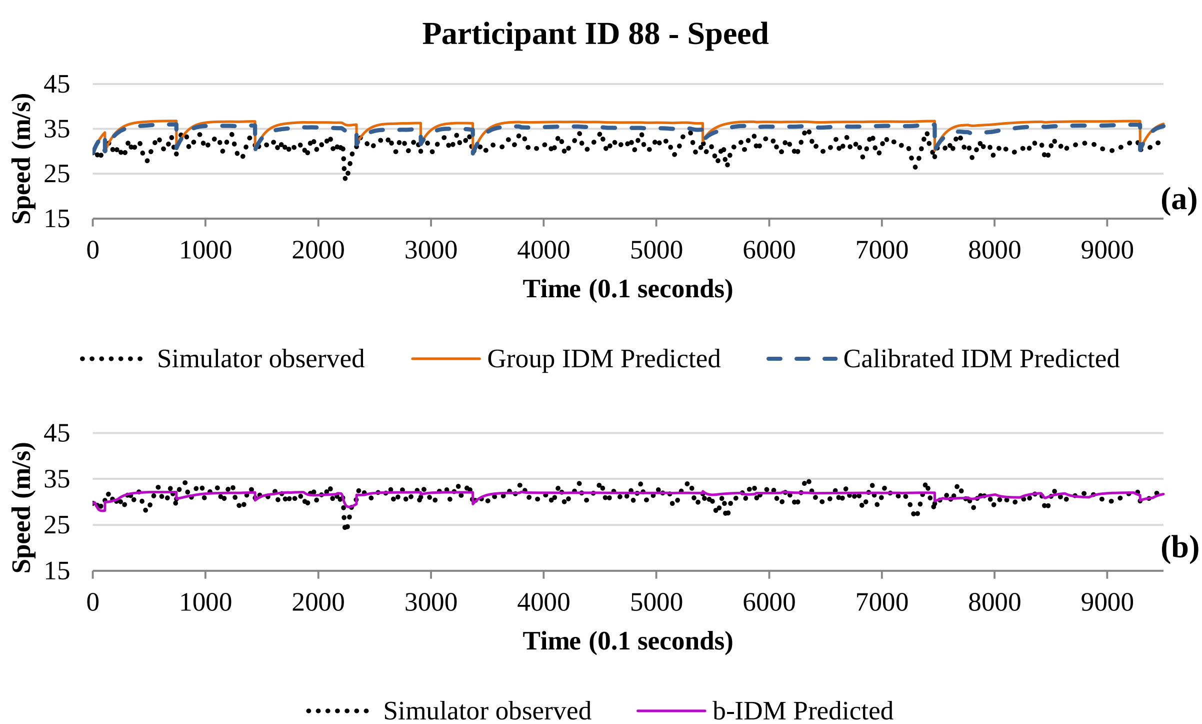


Figure H.5 Comparison plots for participant 51 showing (a) Calibrated and group IDM predicted speed, (b) b-IDM predicted speed, (c) Calibrated and group IDM predicted acceleration, (d) b-IDM predicted acceleration, (e) Calibrated and group IDM predicted trajectories, and (f) b-IDM predicted trajectories



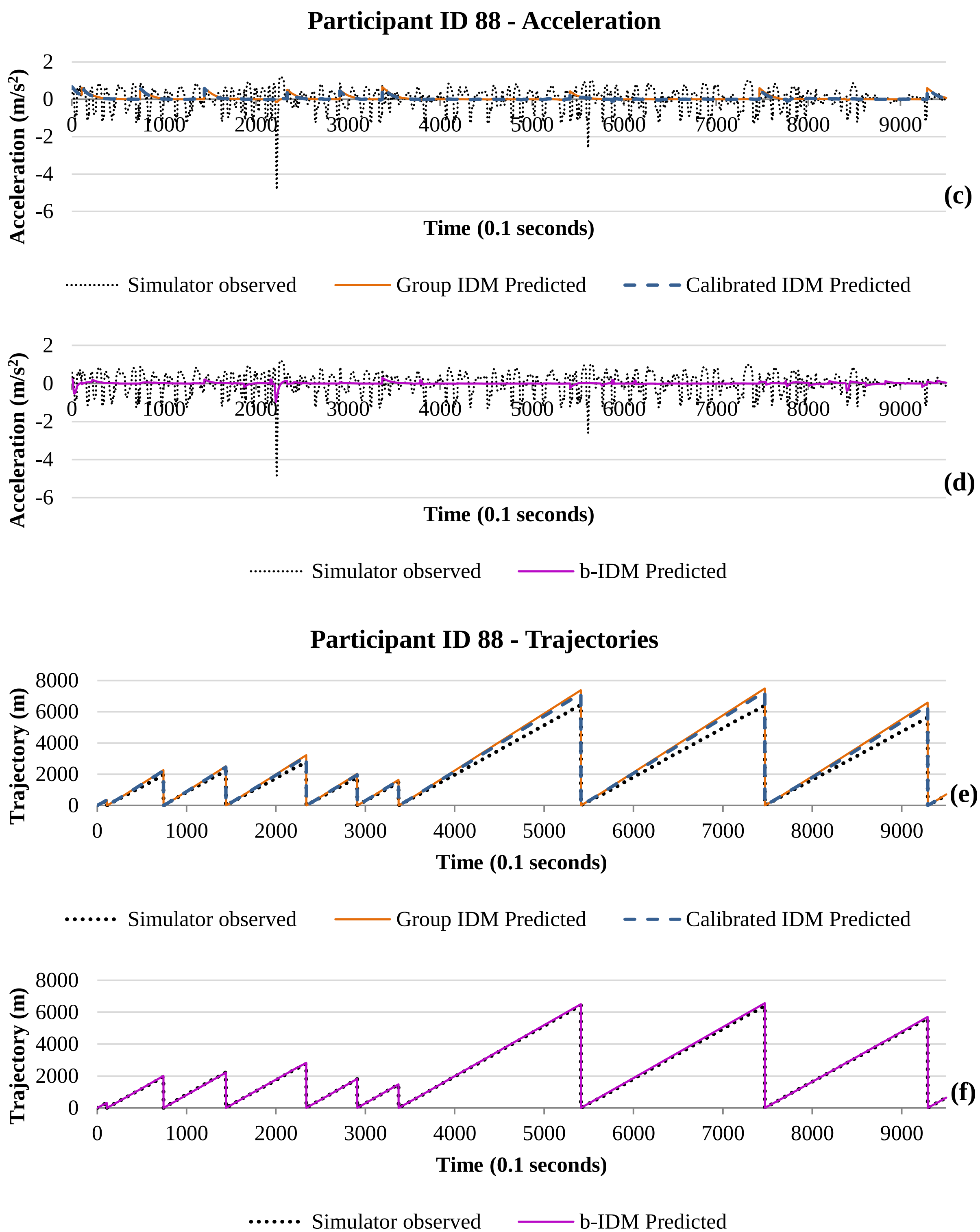
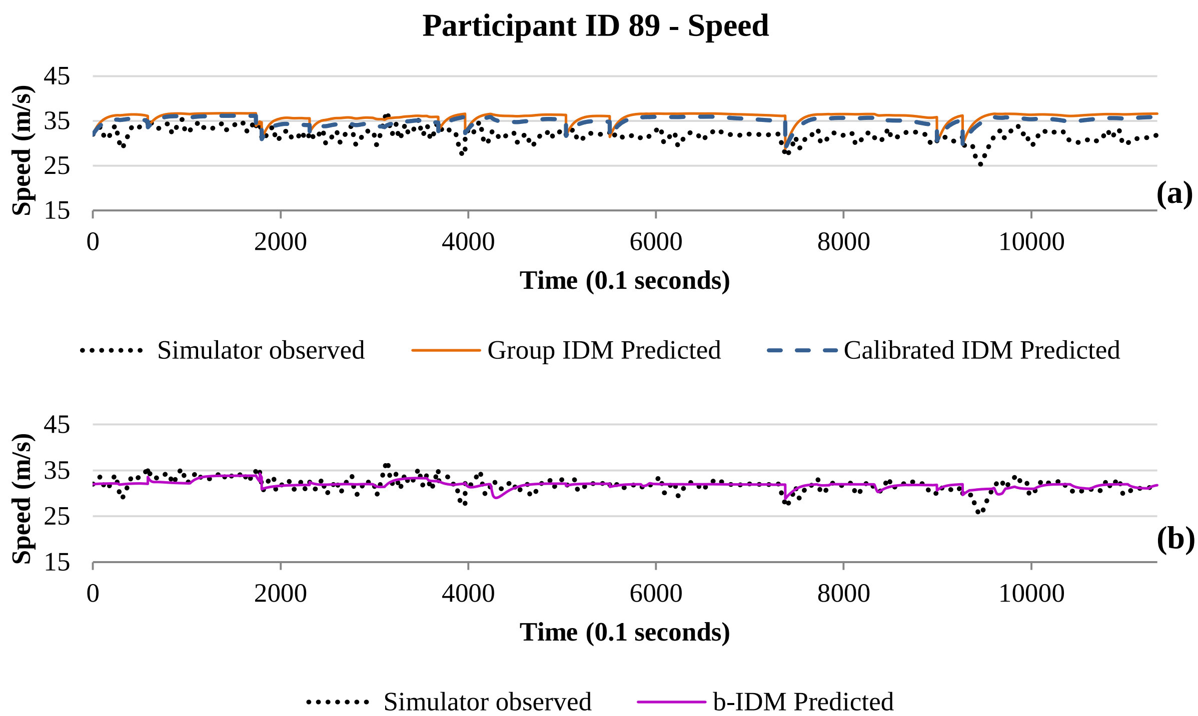
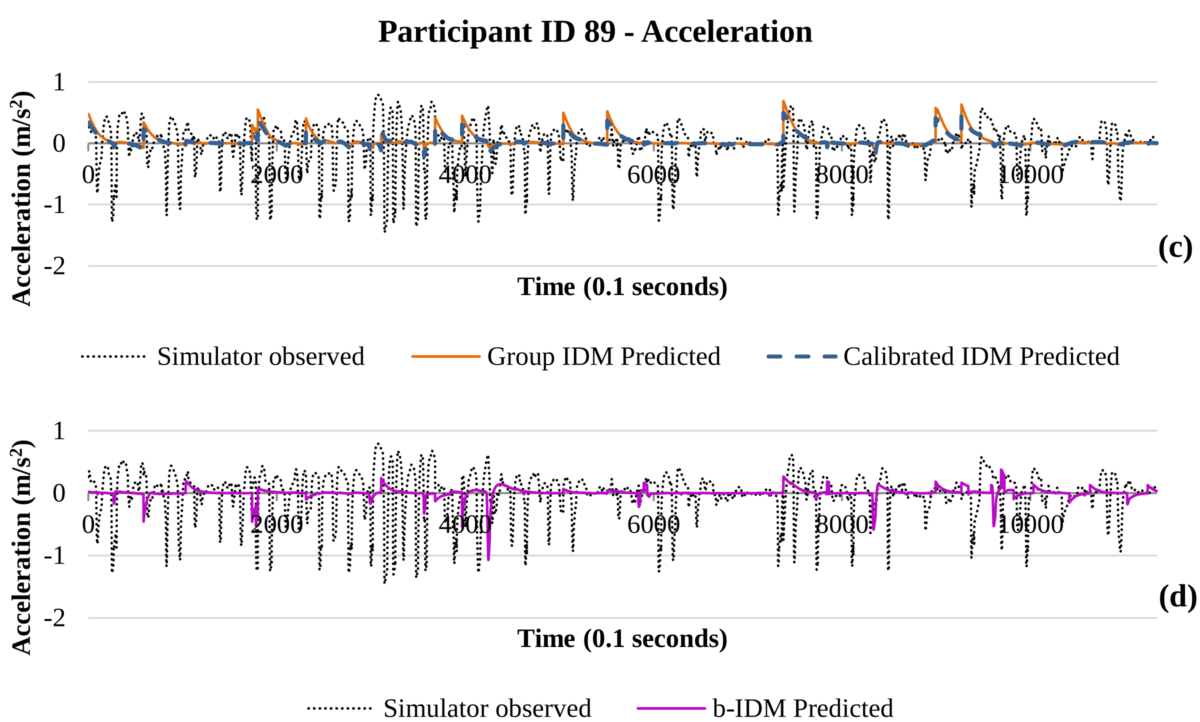


Figure H.6 Comparison plots for participant 88 showing (a) Calibrated and group IDM predicted speed, (b) b-IDM predicted speed, (c) Calibrated and group IDM predicted acceleration, (d) b-IDM predicted acceleration, (e) Calibrated and group IDM predicted trajectories, and (f) b-IDM predicted trajectories


Participant ID 89 - Speed
Speed (m/s)
45
35
25
15
0
2000
4000
6000
8000
10000
Time (0.1 seconds)
(a)
Simulator observed
Group IDM Predicted
Calibrated IDM Predicted
(b)
b-IDM Predicted


Participant ID 89 - Acceleration
Acceleration (m/s²)
1
0
-1
-2
2000
4000
6000
8000
10000
Time (0.1 seconds)
(c)
Simulator observed
Group IDM Predicted
Calibrated IDM Predicted
(d)
b-IDM Predicted

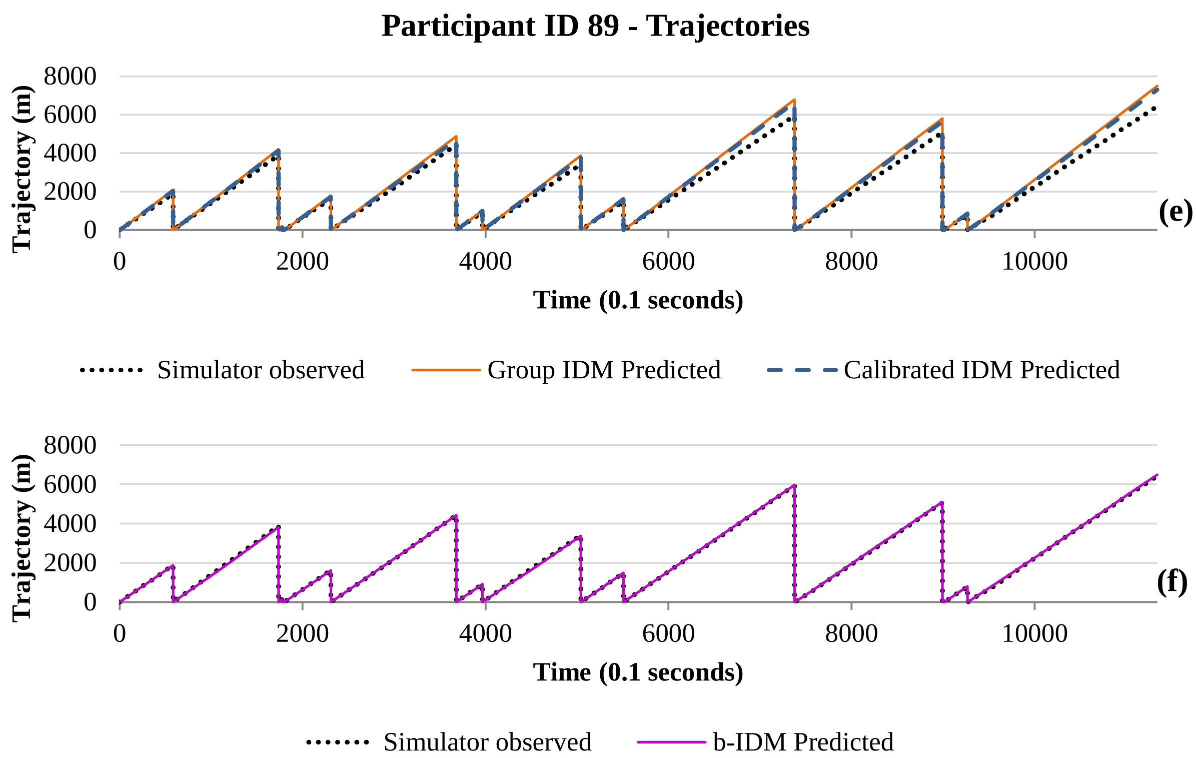
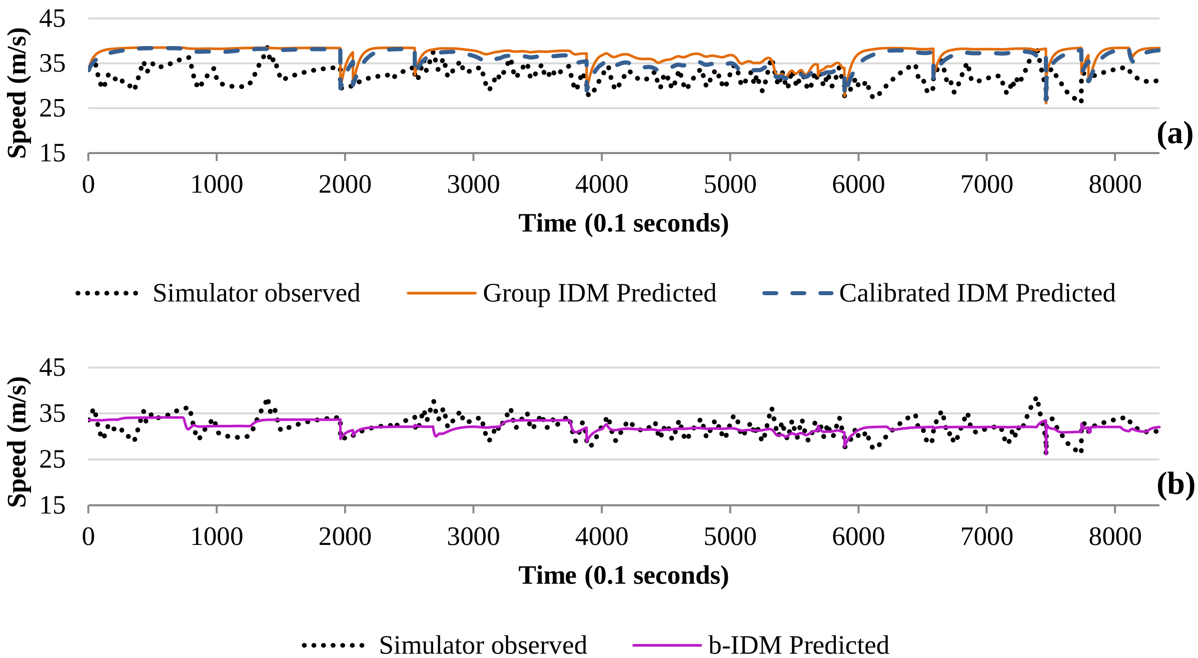


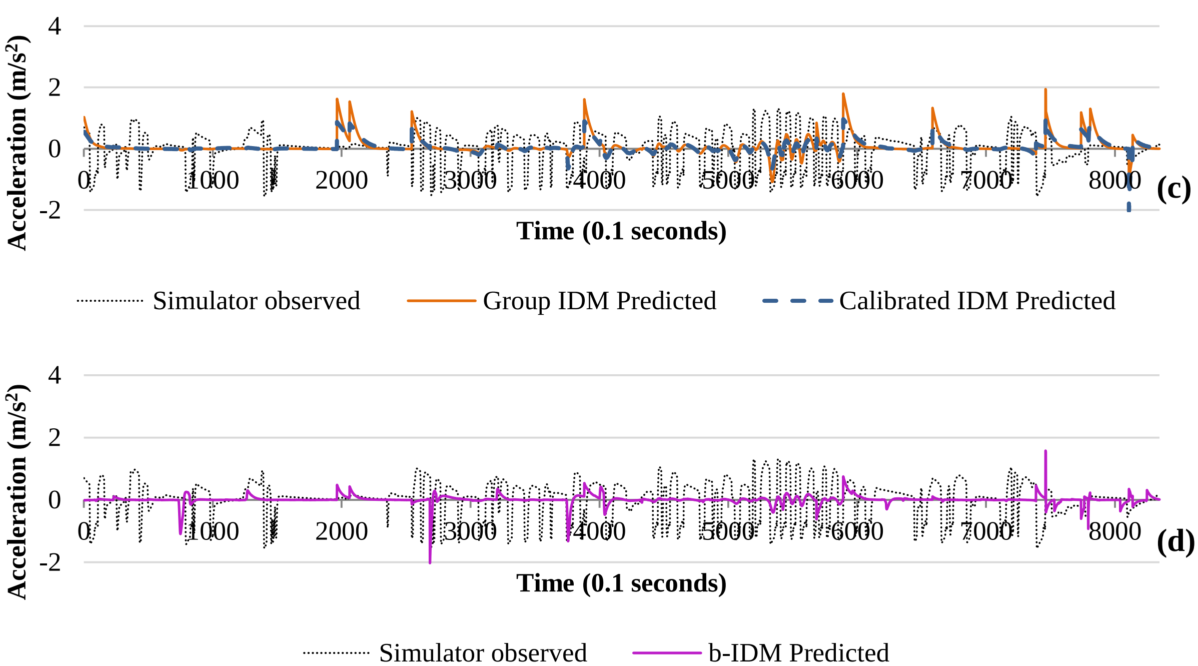
Figure H.7 Comparison plots for participant 89 showing (a) Calibrated and group IDM predicted speed, (b) b-IDM predicted speed, (c) Calibrated and group IDM predicted acceleration, (d) b-IDM predicted acceleration, (e) Calibrated and group IDM predicted trajectories, and (f) b-IDM predicted trajectories

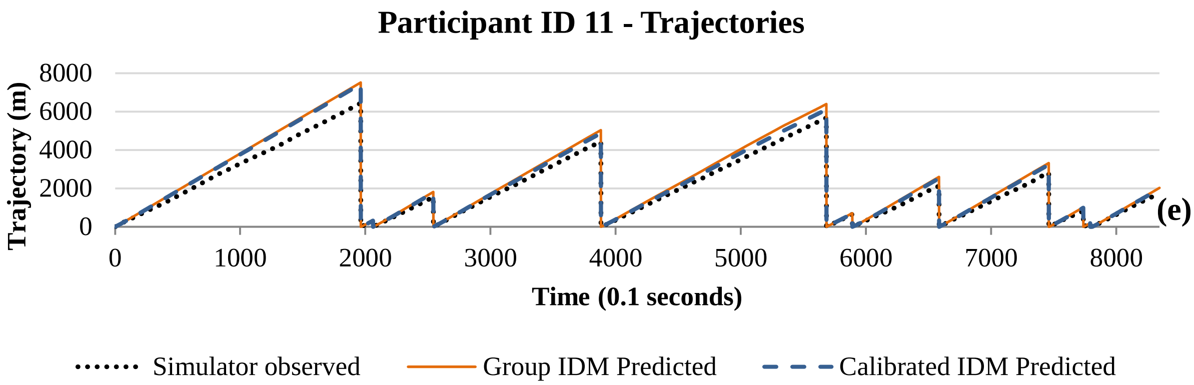
Group B Participants

Participant ID 11 - Speed



Participant ID 11 - Acceleration





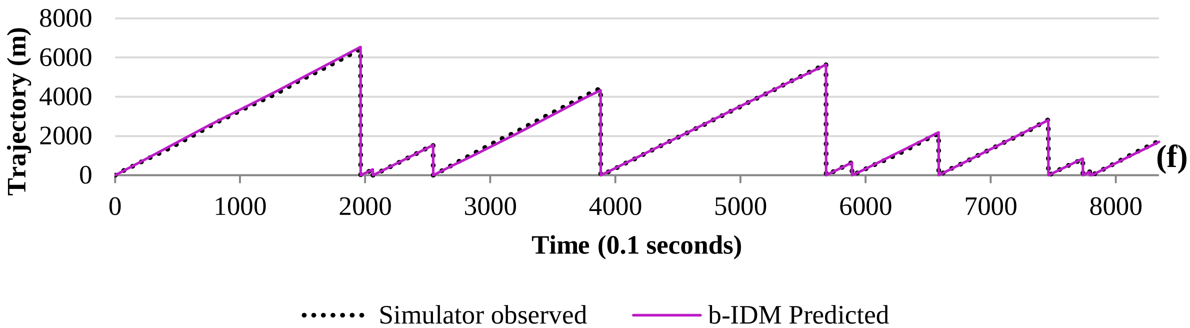
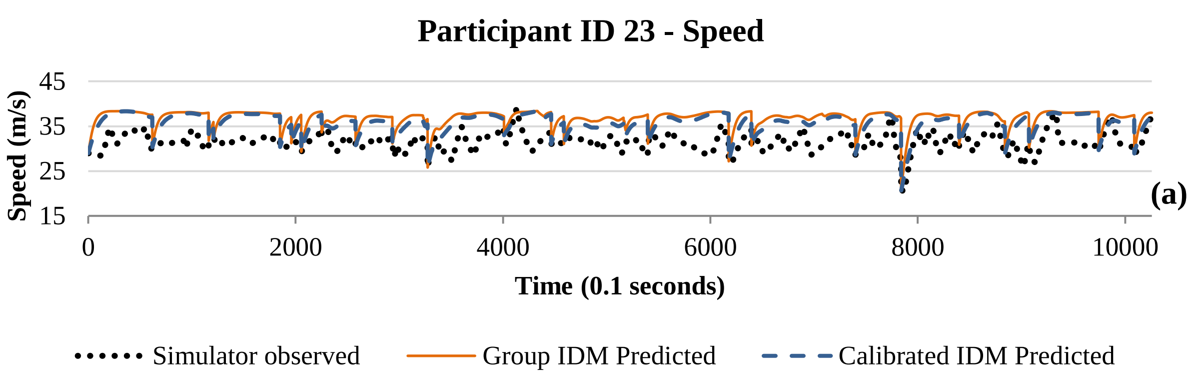
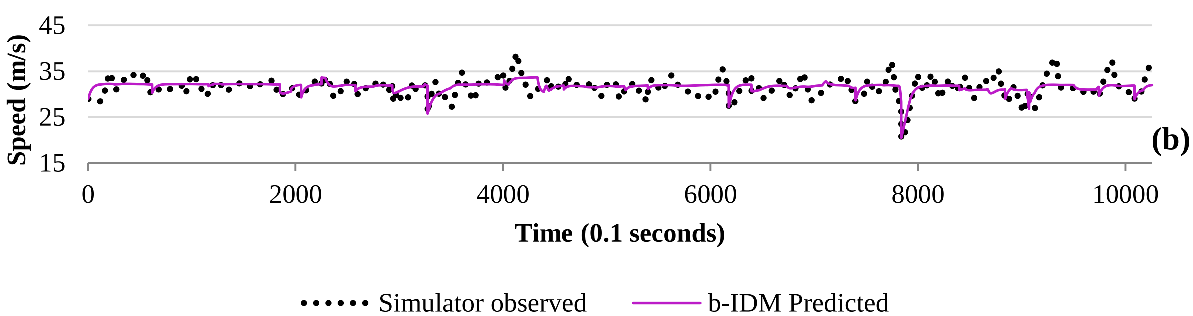


Figure H.8 Comparison plots for participant 11 showing (a) Calibrated and group IDM predicted speed, (b) b-IDM predicted speed, (c) Calibrated and group IDM predicted acceleration, (d) b-IDM predicted acceleration, (e) Calibrated and group IDM predicted trajectories, and (f) b-IDM predicted trajectories





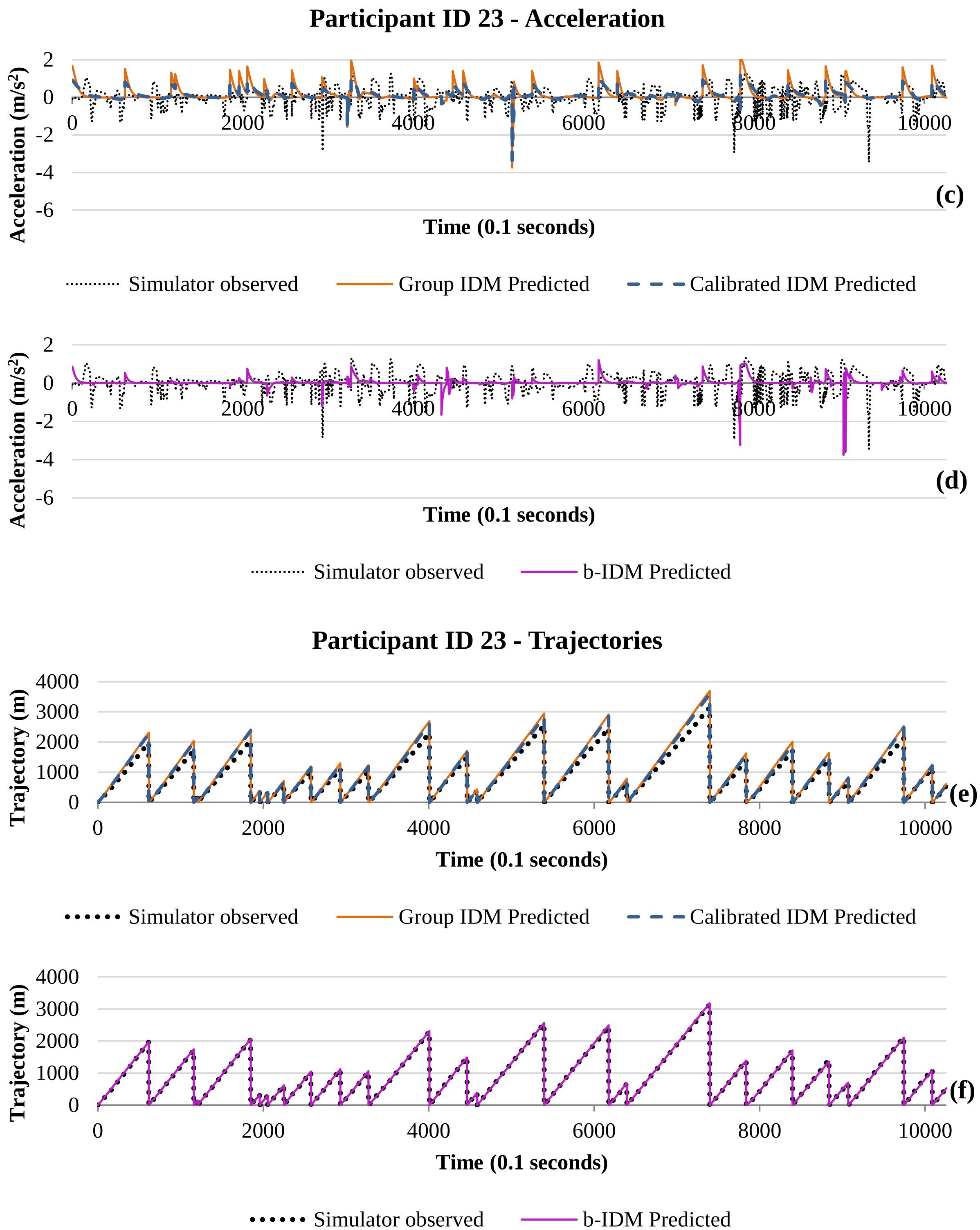
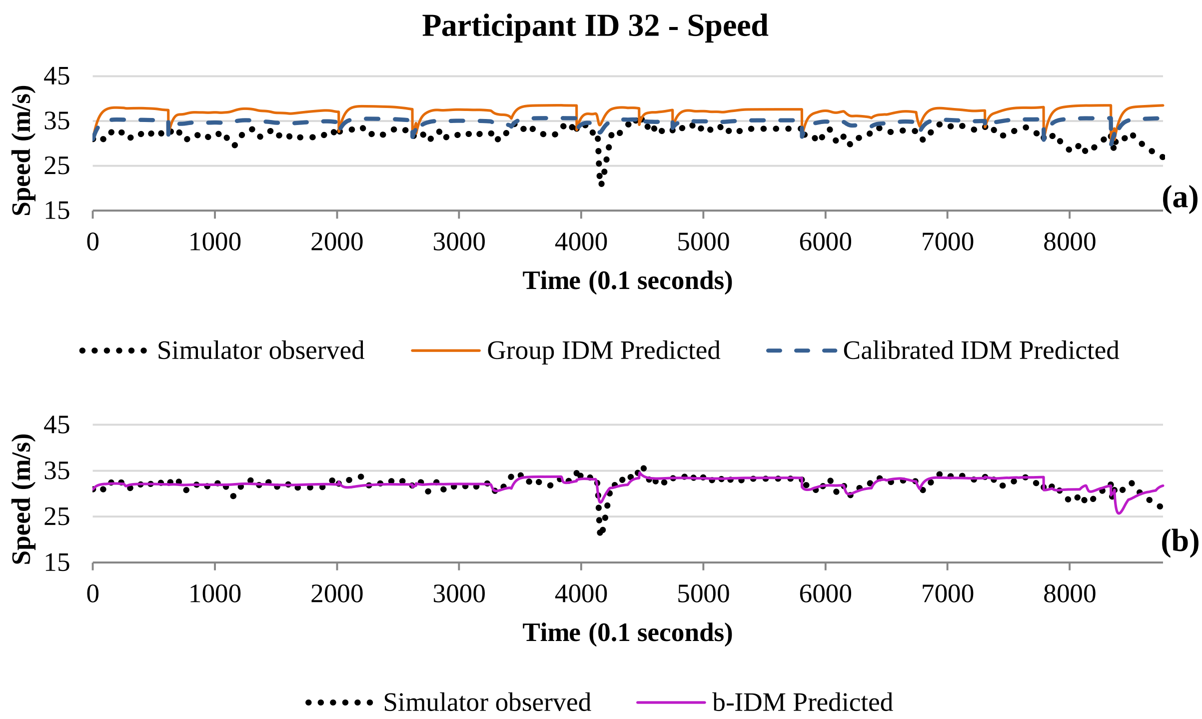
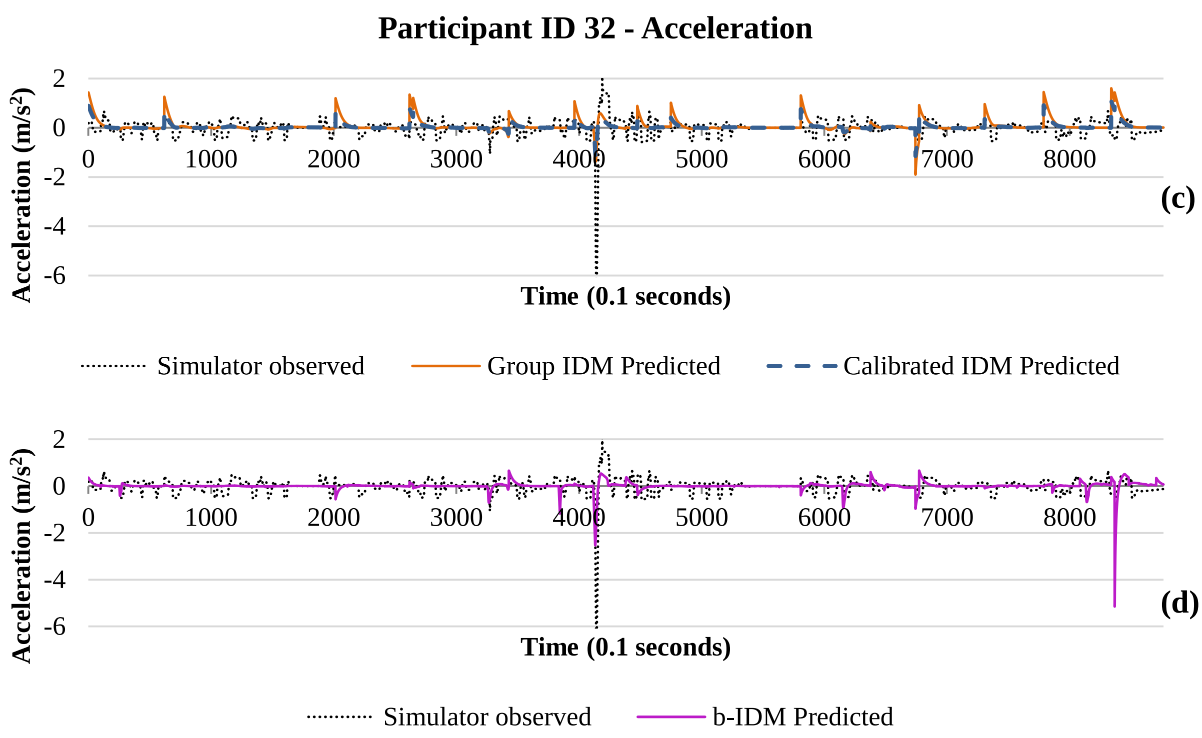


Figure H.9 Comparison plots for participant 23 showing (a) Calibrated and group IDM predicted speed, (b) b-IDM predicted speed, (c) Calibrated and group IDM predicted acceleration, (d) b-IDM predicted acceleration, (e) Calibrated and group IDM predicted trajectories, and (f) b-IDM predicted trajectories


Participant ID 32 - Speed
Speed (m/s)
45
35
25
15
0
1000
2000
3000
4000
5000
6000
7000
8000
Time (0.1 seconds)
(a)
Simulator observed
Group IDM Predicted
Calibrated IDM Predicted
(b)
b-IDM Predicted


Participant ID 32 - Acceleration
Acceleration (m/s^2)
2
0
-2
-4
-6
0
1000
2000
3000
4000
5000
6000
7000
8000
Time (0.1 seconds)
(c)
Simulator observed
Group IDM Predicted
Calibrated IDM Predicted
(d)
b-IDM Predicted

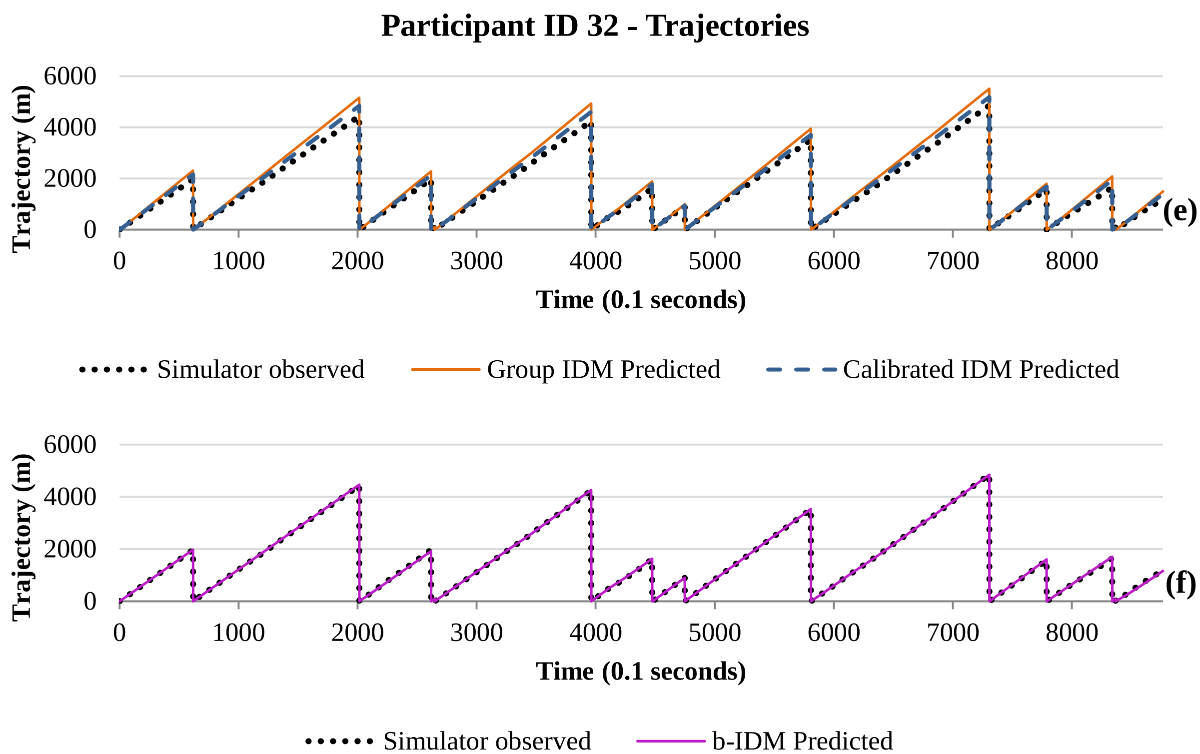
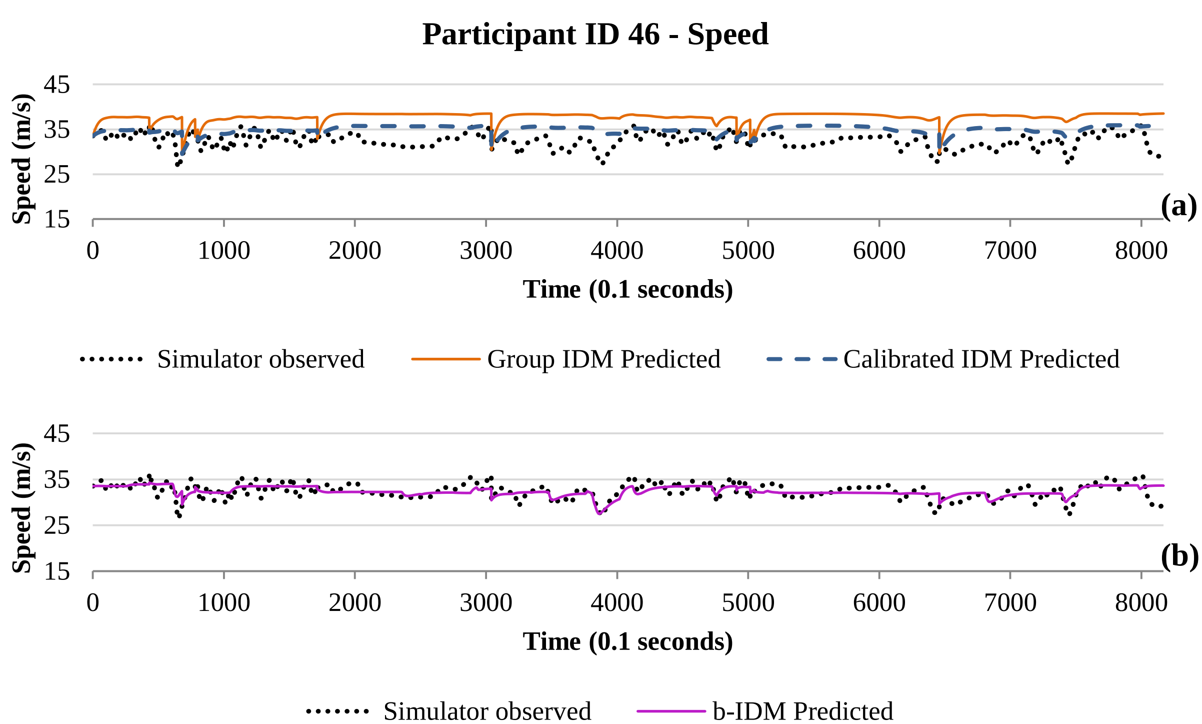


Figure H.10 Comparison plots for participant 32 showing (a) Calibrated and group IDM predicted speed, (b) b-IDM predicted speed, (c) Calibrated and group IDM predicted acceleration, (d) b-IDM predicted acceleration, (e) Calibrated and group IDM predicted trajectories, and (f) b-IDM predicted trajectories



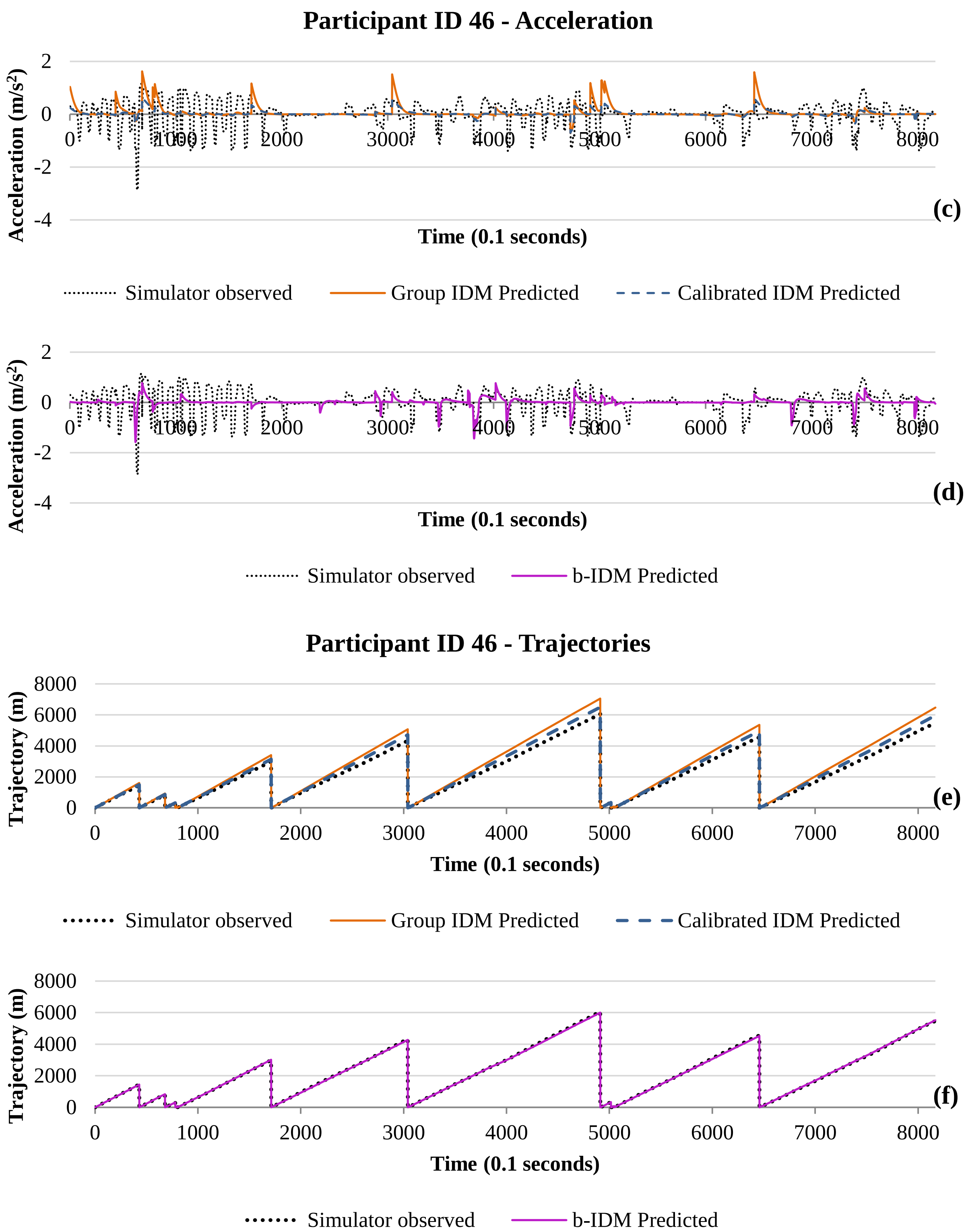
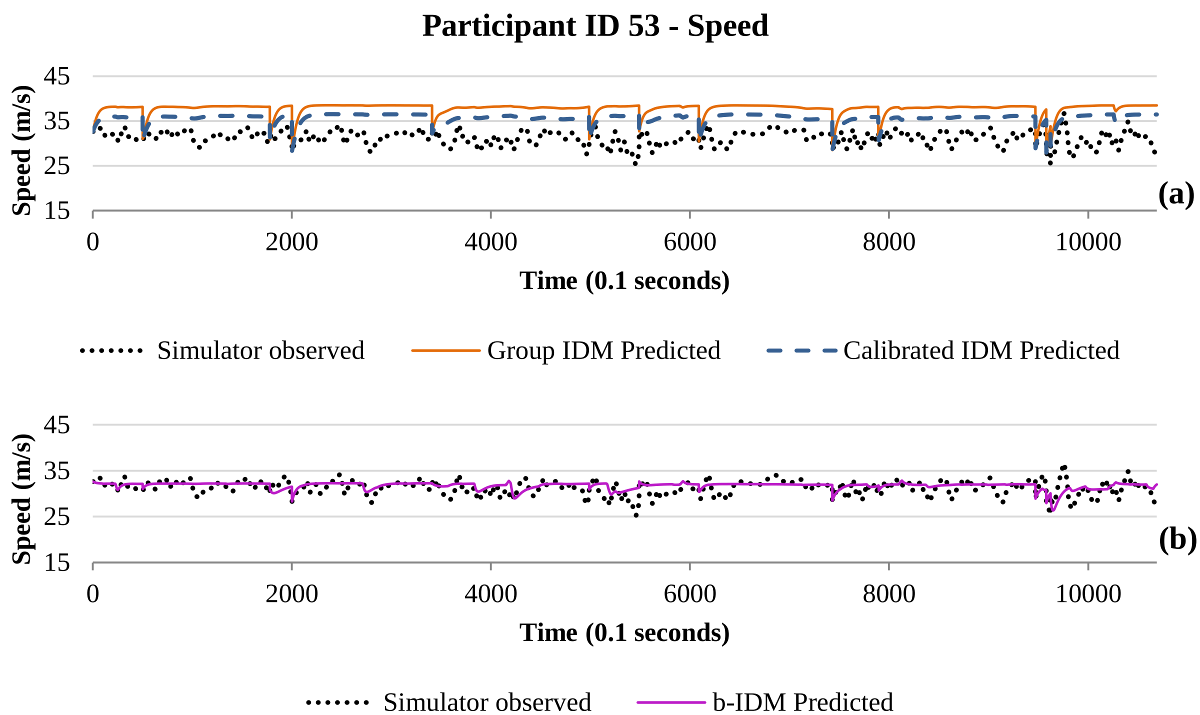
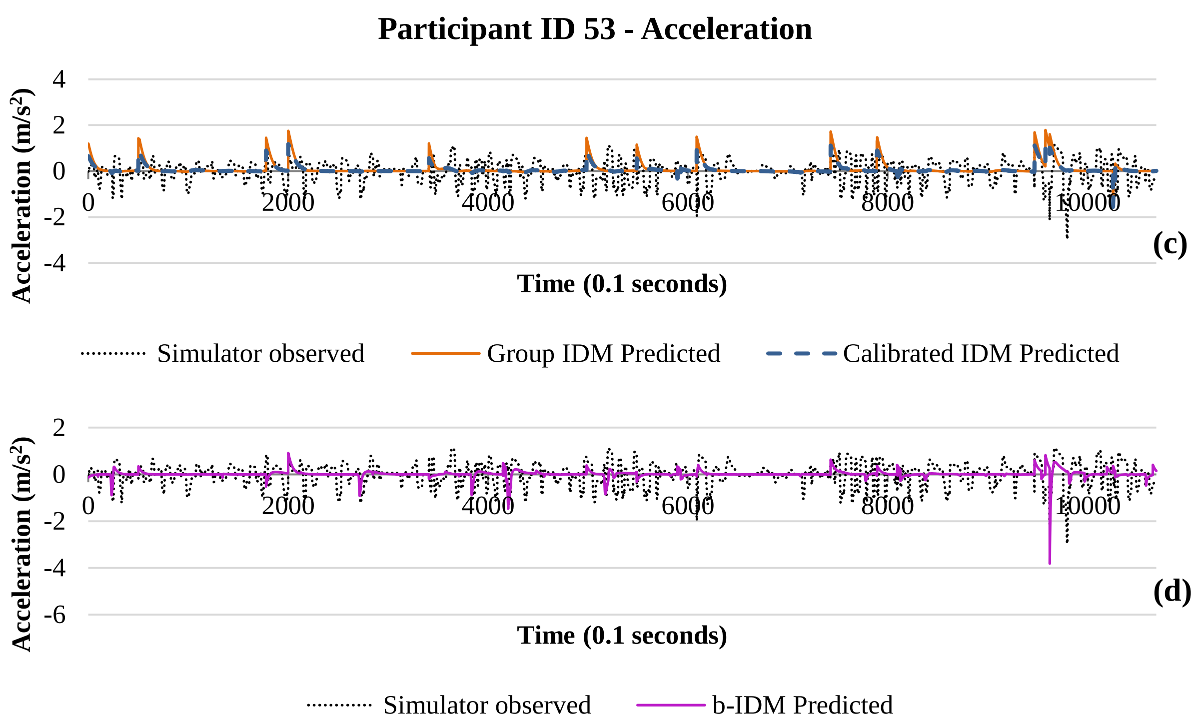
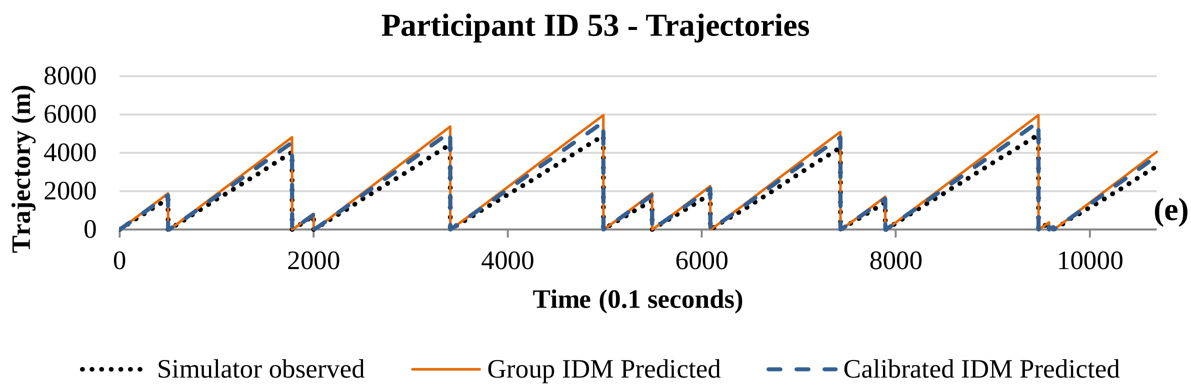


Figure H.11 Comparison plots for participant 46 showing (a) Calibrated and group IDM predicted speed, (b) b-IDM predicted speed, (c) Calibrated and group IDM predicted acceleration, (d) b-IDM predicted acceleration, (e) Calibrated and group IDM predicted trajectories, and (f) b-IDM predicted trajectories


Participant ID 53 - Speed
Speed (m/s)
45
35
25
15
0
2000
4000
6000
8000
10000
Time (0.1 seconds)
(a)
Simulator observed
Group IDM Predicted
Calibrated IDM Predicted
Speed (m/s)
45
35
25
15
0
2000
4000
6000
8000
10000
Time (0.1 seconds)
(b)
Simulator observed
b-IDM Predicted


Participant ID 53 - Acceleration
Acceleration (m/s²)
4
2
0
-2
-4
0
2000
4000
6000
8000
10000
Time (0.1 seconds)
(c)
Simulator observed
Group IDM Predicted
Calibrated IDM Predicted
Acceleration (m/s²)
2
0
-2
-4
-6
0
2000
4000
6000
8000
10000
Time (0.1 seconds)
(d)
Simulator observed
b-IDM Predicted



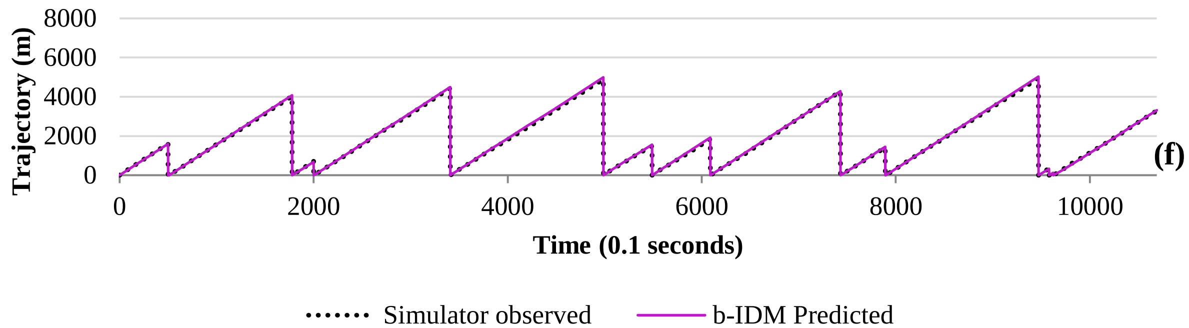
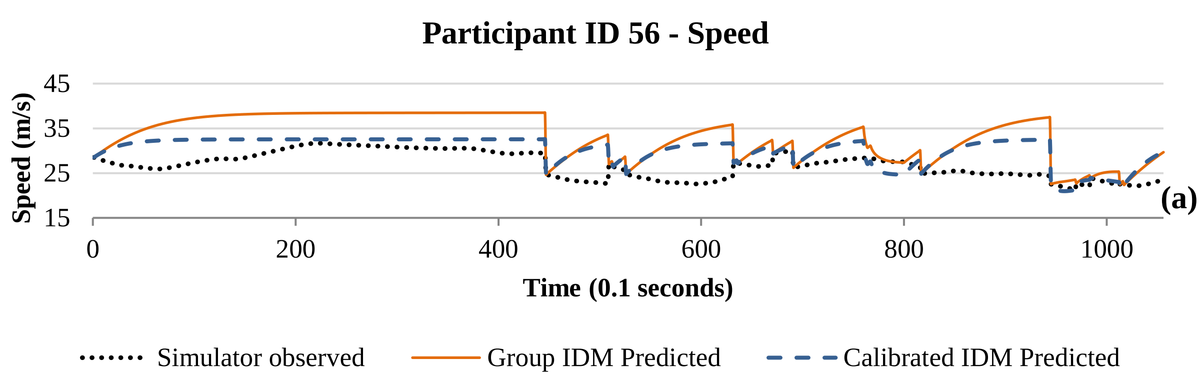
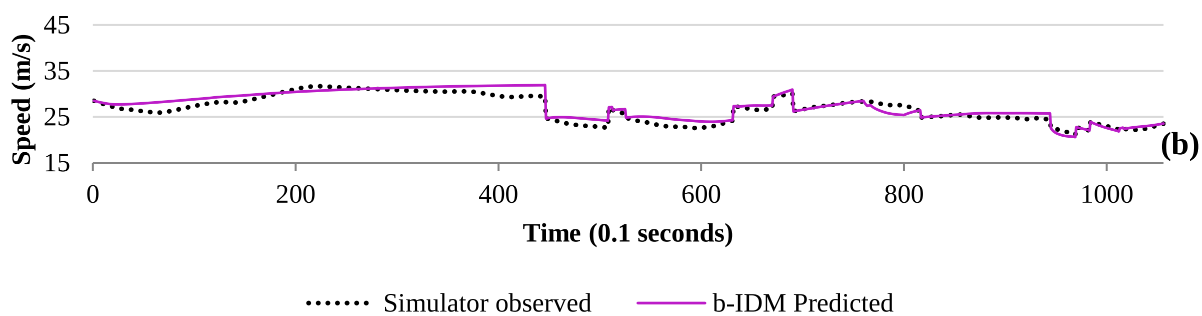
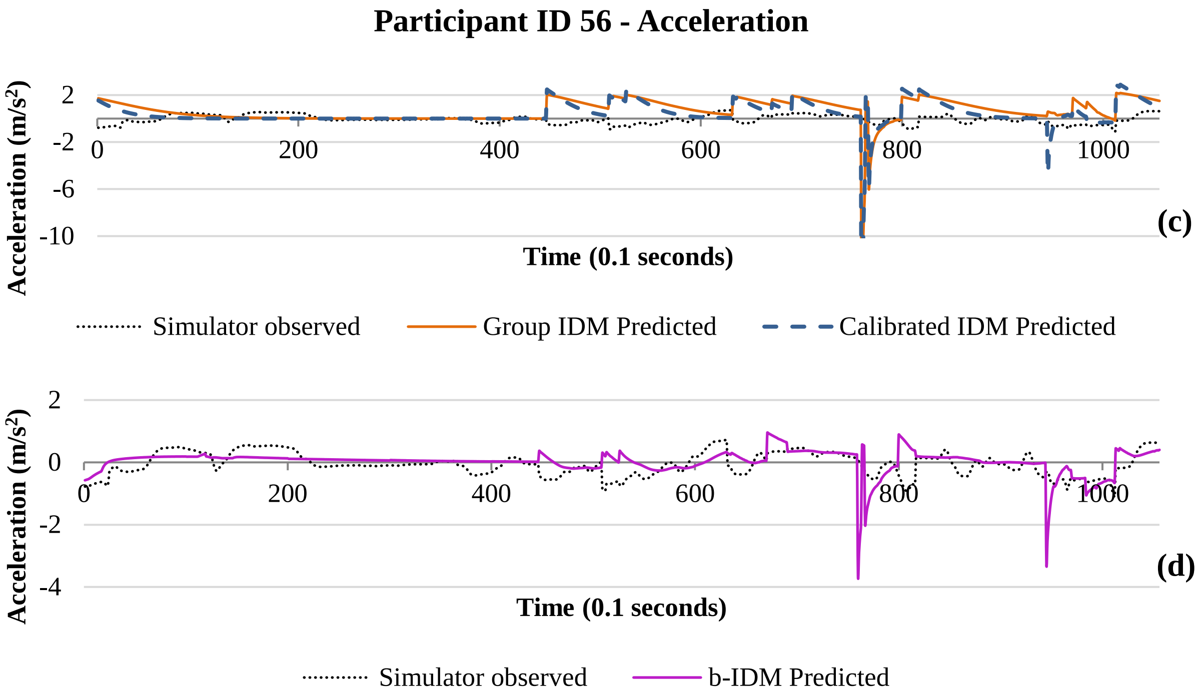


Figure H.12 Comparison plots for participant 53 showing (a) Calibrated and group IDM predicted speed, (b) b-IDM predicted speed, (c) Calibrated and group IDM predicted acceleration, (d) b-IDM predicted acceleration, (e) Calibrated and group IDM predicted trajectories, and (f) b-IDM predicted trajectories







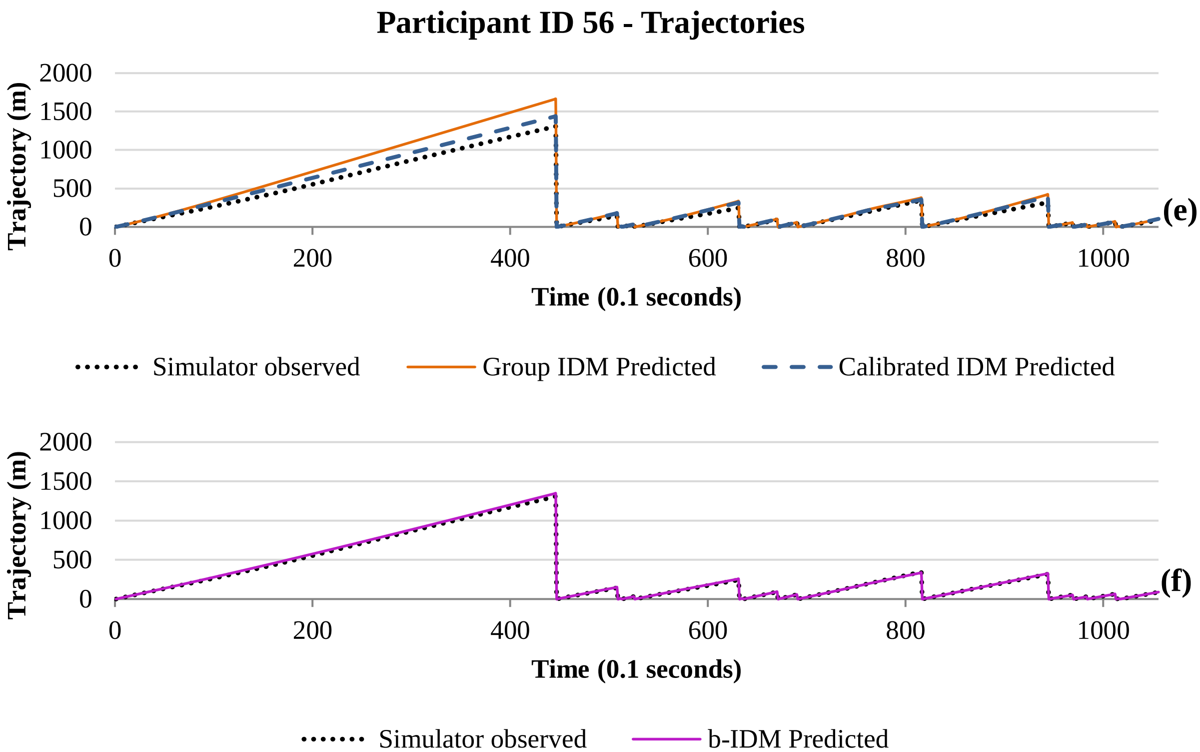
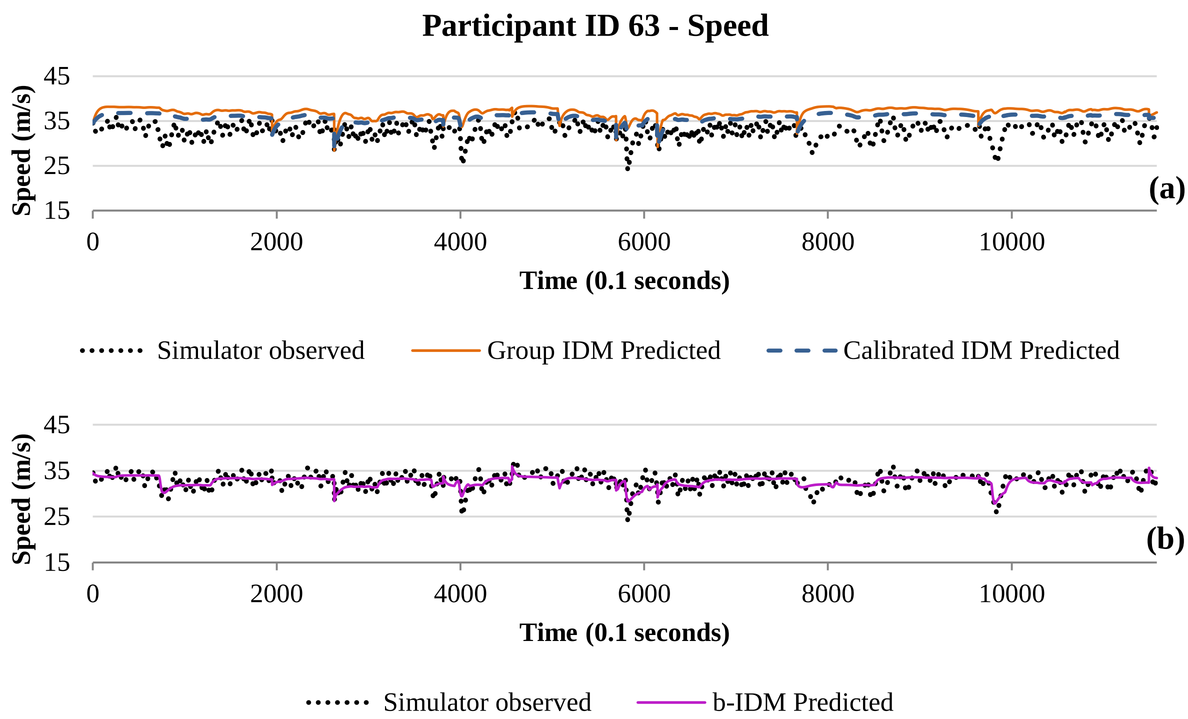
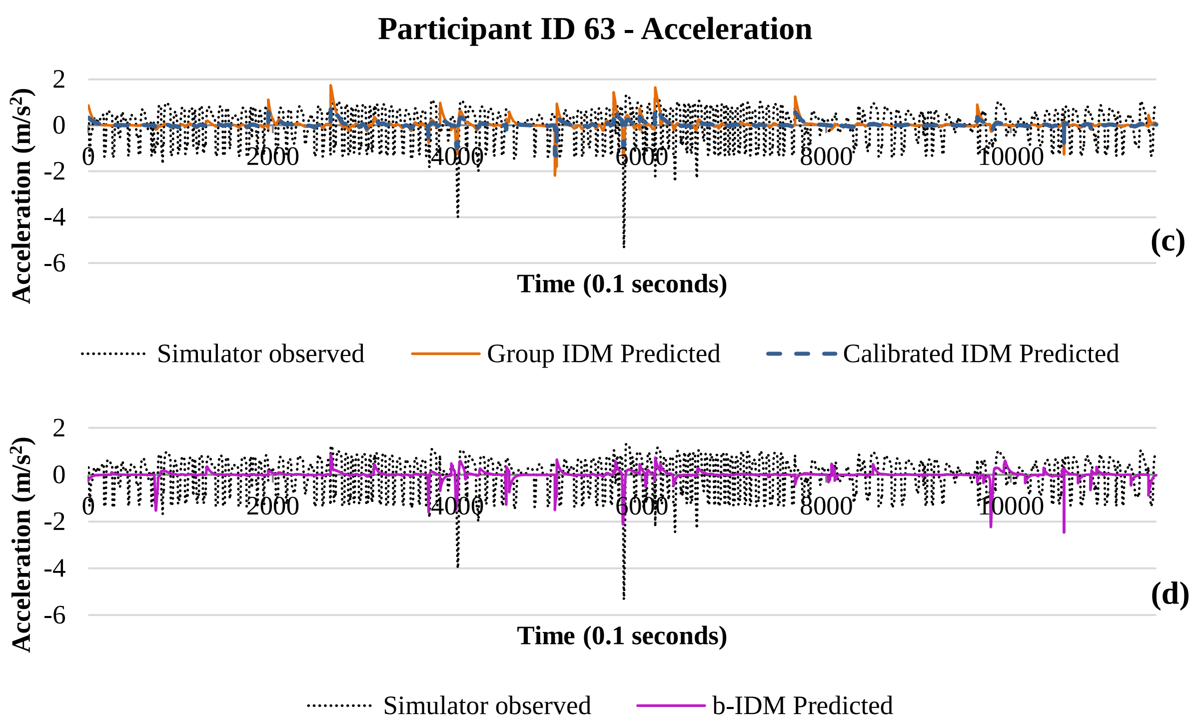


Figure H.13 Comparison plots for participant 56 showing (a) Calibrated and group IDM predicted speed, (b) b-IDM predicted speed, (c) Calibrated and group IDM predicted acceleration, (d) b-IDM predicted acceleration, (e) Calibrated and group IDM predicted trajectories, and (f) b-IDM predicted trajectories


Participant ID 63 - Speed
Speed (m/s)
45
35
25
15
0
2000
4000
6000
8000
10000
Time (0.1 seconds)
(a)
Simulator observed
Group IDM Predicted
Calibrated IDM Predicted
Speed (m/s)
Time (0.1 seconds)
(b)
Simulator observed
b-IDM Predicted


Participant ID 63 - Acceleration
Acceleration (m/s²)
2
0
-2
-4
-6
0
2000
4000
6000
8000
10000
Time (0.1 seconds)
(c)
Simulator observed
Group IDM Predicted
Calibrated IDM Predicted
Acceleration (m/s²)
Time (0.1 seconds)
(d)
Simulator observed
b-IDM Predicted

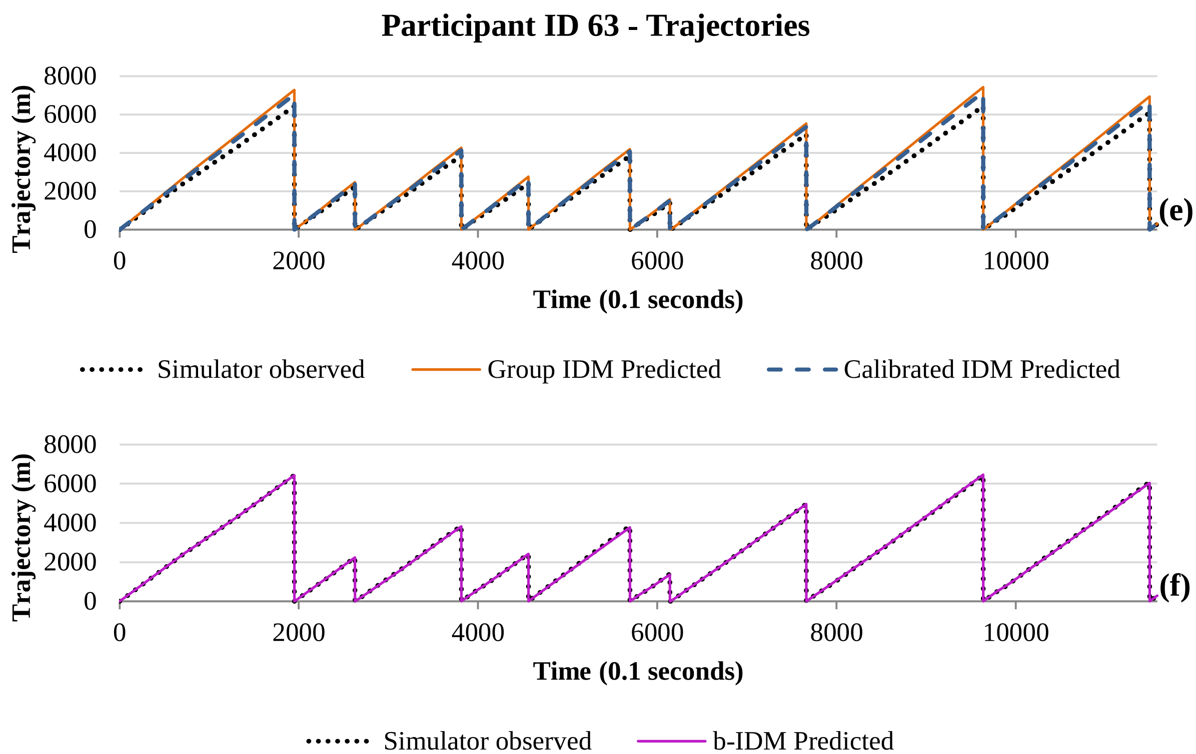
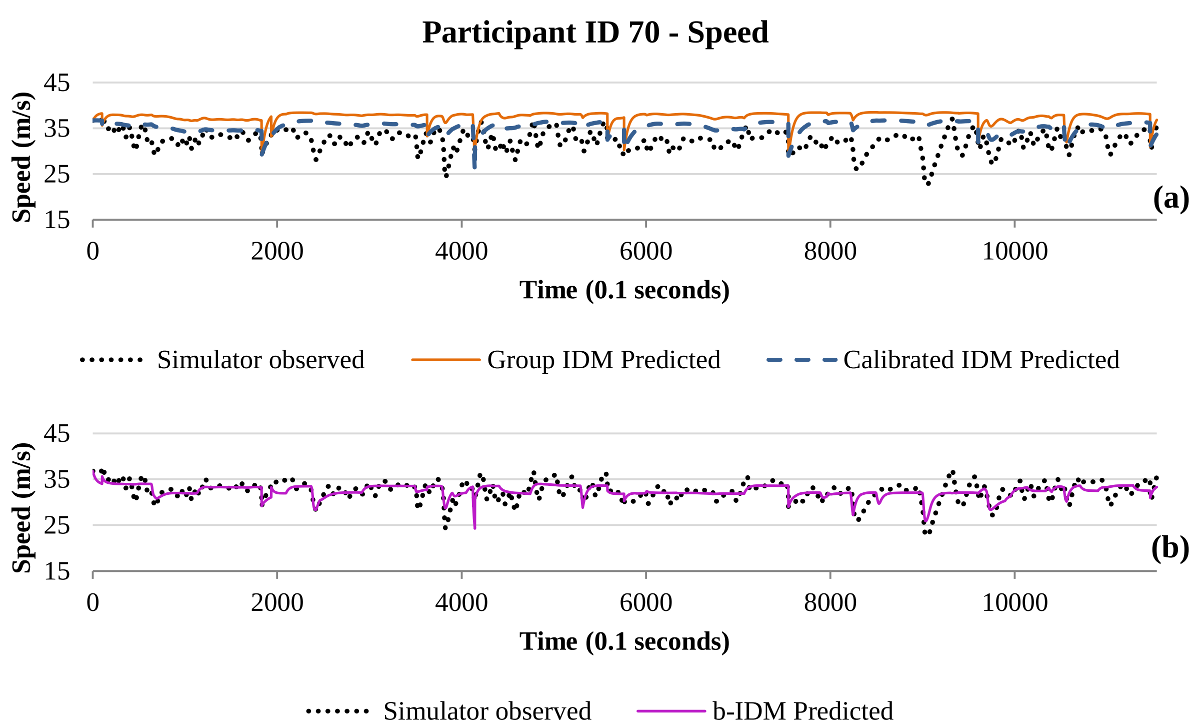


Figure H.14 Comparison plots for participant 63 showing (a) Calibrated and group IDM predicted speed, (b) b-IDM predicted speed, (c) Calibrated and group IDM predicted acceleration, (d) b-IDM predicted acceleration, (e) Calibrated and group IDM predicted trajectories, and (f) b-IDM predicted trajectories



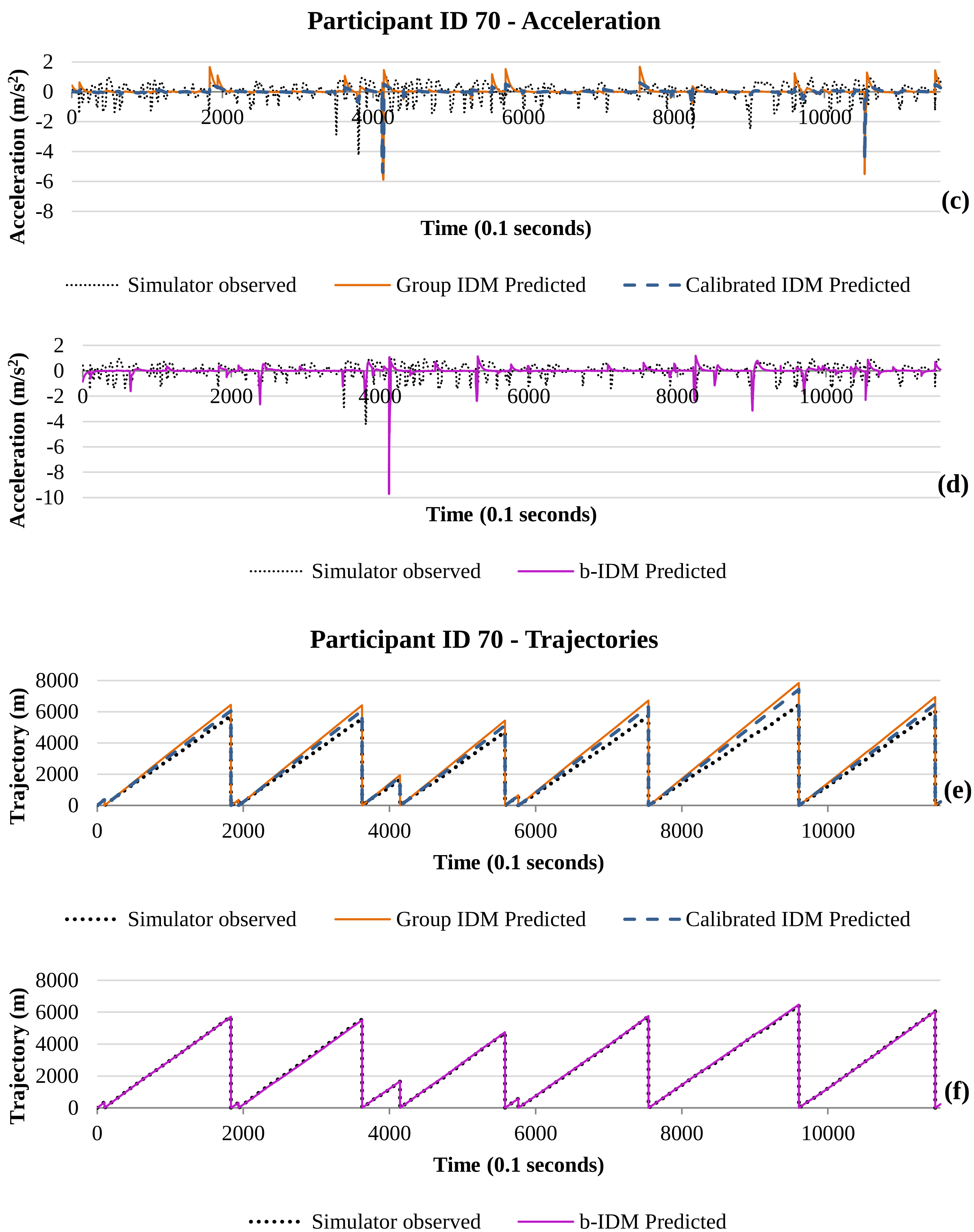
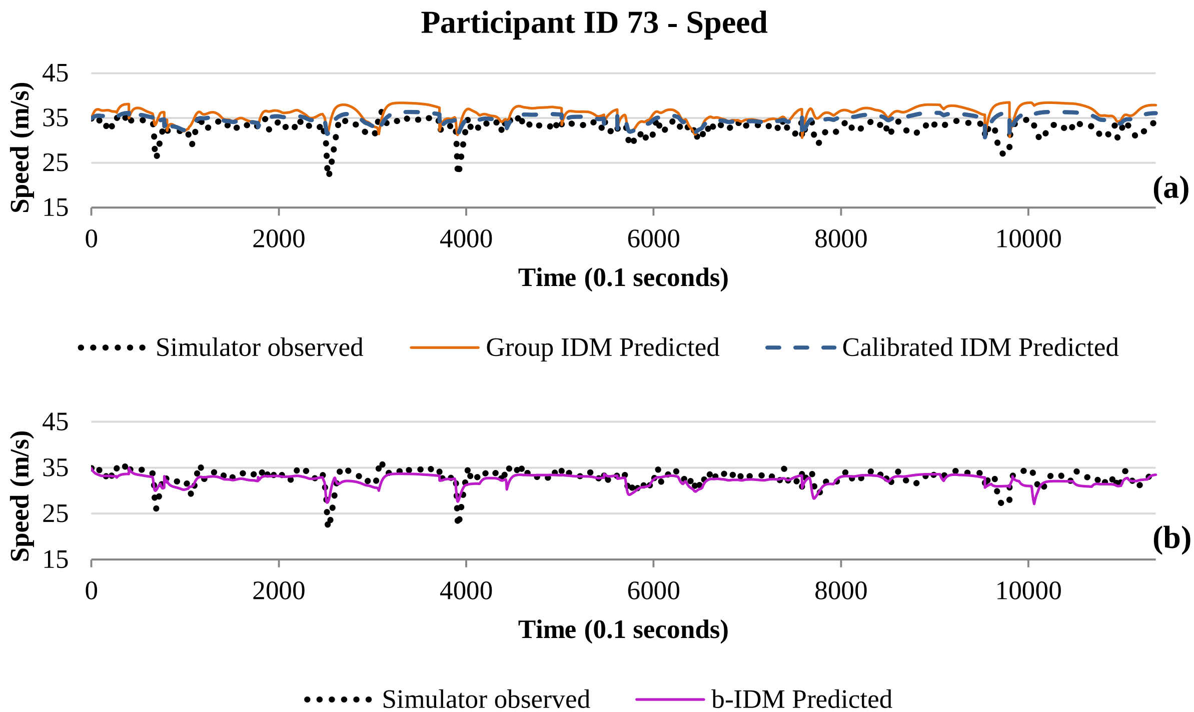
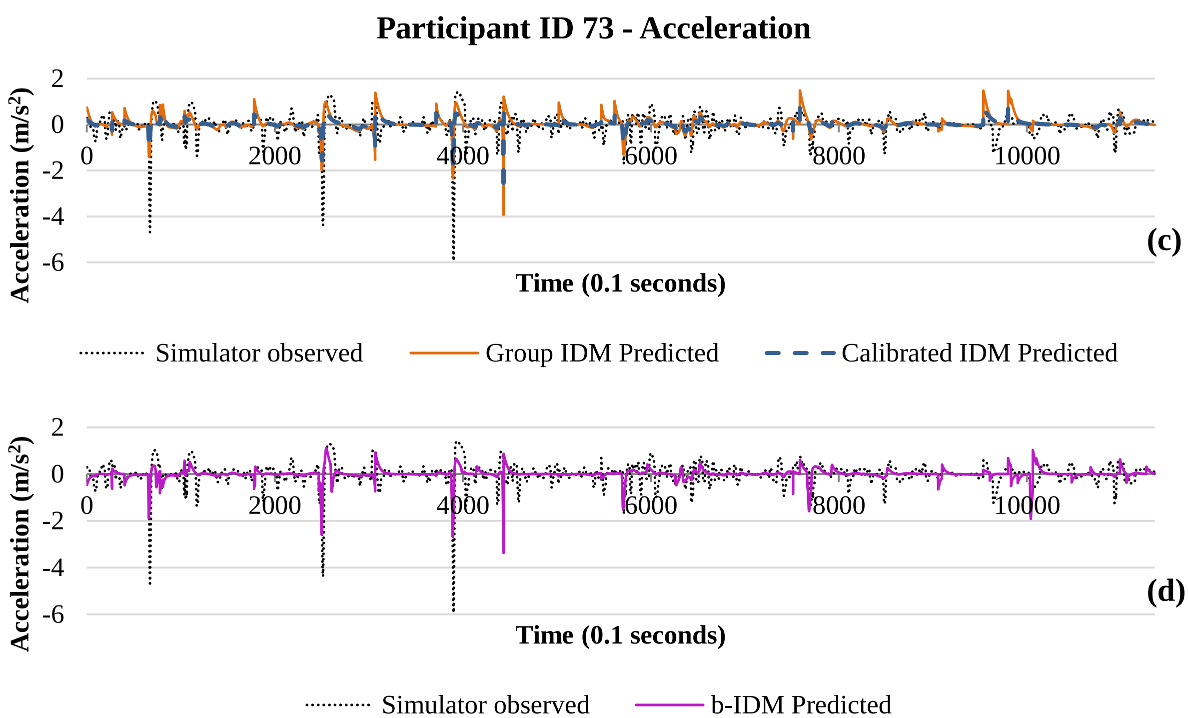


Figure H.15 Comparison plots for participant 70 showing (a) Calibrated and group IDM predicted speed, (b) b-IDM predicted speed, (c) Calibrated and group IDM predicted acceleration, (d) b-IDM predicted acceleration, (e) Calibrated and group IDM predicted trajectories, and (f) b-IDM predicted trajectories


Participant ID 73 - Speed
Speed (m/s)
45
35
25
15
0
2000
4000
6000
8000
10000
Time (0.1 seconds)
(a)
Simulator observed
Group IDM Predicted
Calibrated IDM Predicted
Speed (m/s)
45
35
25
15
0
2000
4000
6000
8000
10000
Time (0.1 seconds)
(b)
Simulator observed
b-IDM Predicted


Participant ID 73 - Acceleration
Acceleration (m/s^2)
2
0
-2
-4
-6
0
2000
4000
6000
8000
10000
Time (0.1 seconds)
(c)
Simulator observed
Group IDM Predicted
Calibrated IDM Predicted
Acceleration (m/s^2)
2
0
-2
-4
-6
0
2000
4000
6000
8000
10000
Time (0.1 seconds)
(d)
Simulator observed
b-IDM Predicted

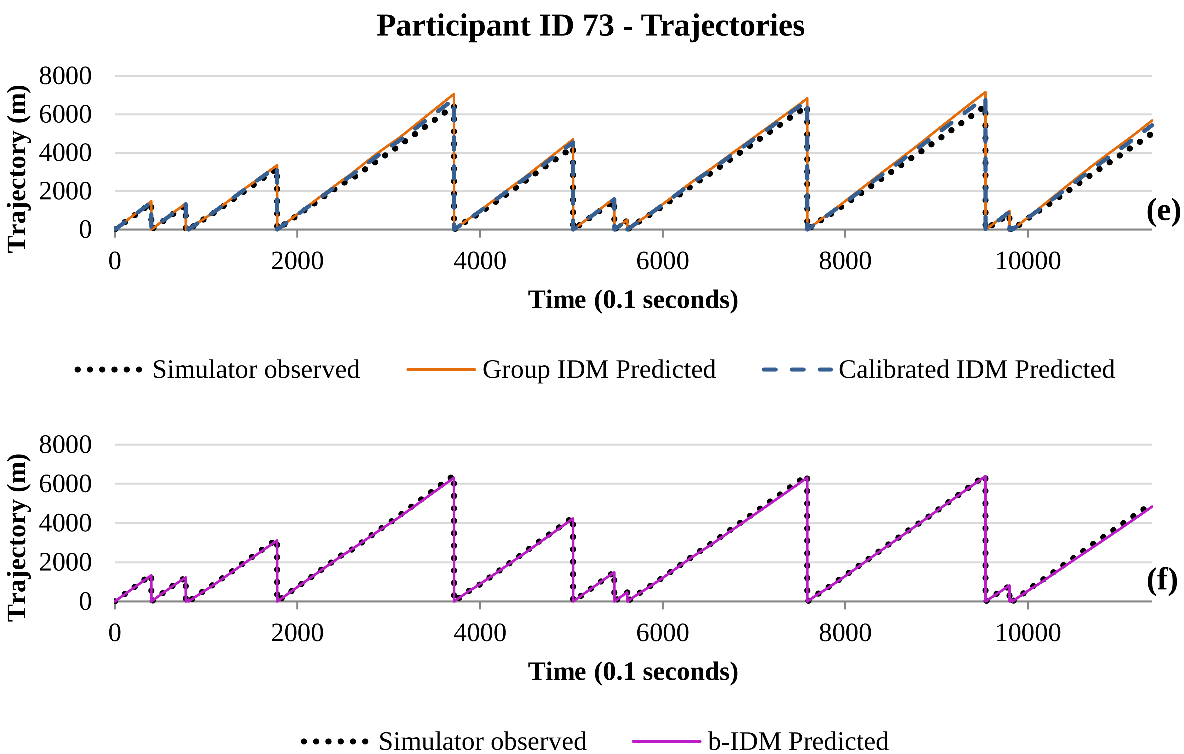
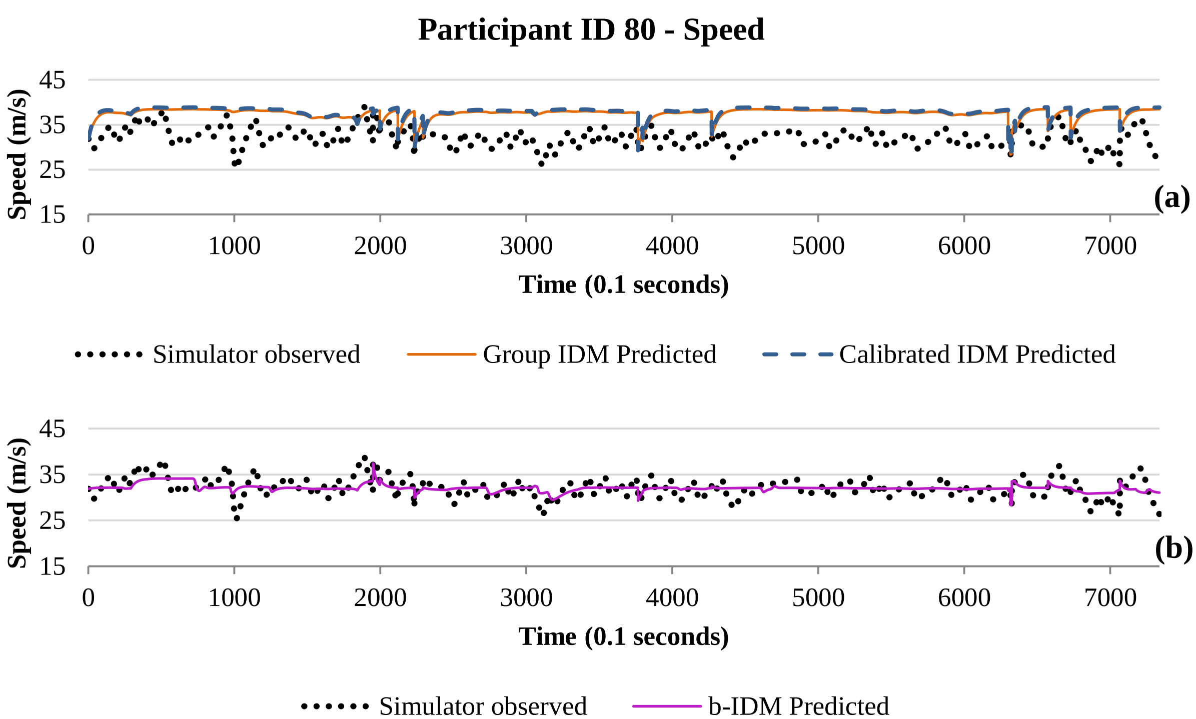


Figure H.16 Comparison plots for participant 73 showing (a) Calibrated and group IDM predicted speed, (b) b-IDM predicted speed, (c) Calibrated and group IDM predicted acceleration, (d) b-IDM predicted acceleration, (e) Calibrated and group IDM predicted trajectories, and (f) b-IDM predicted trajectories



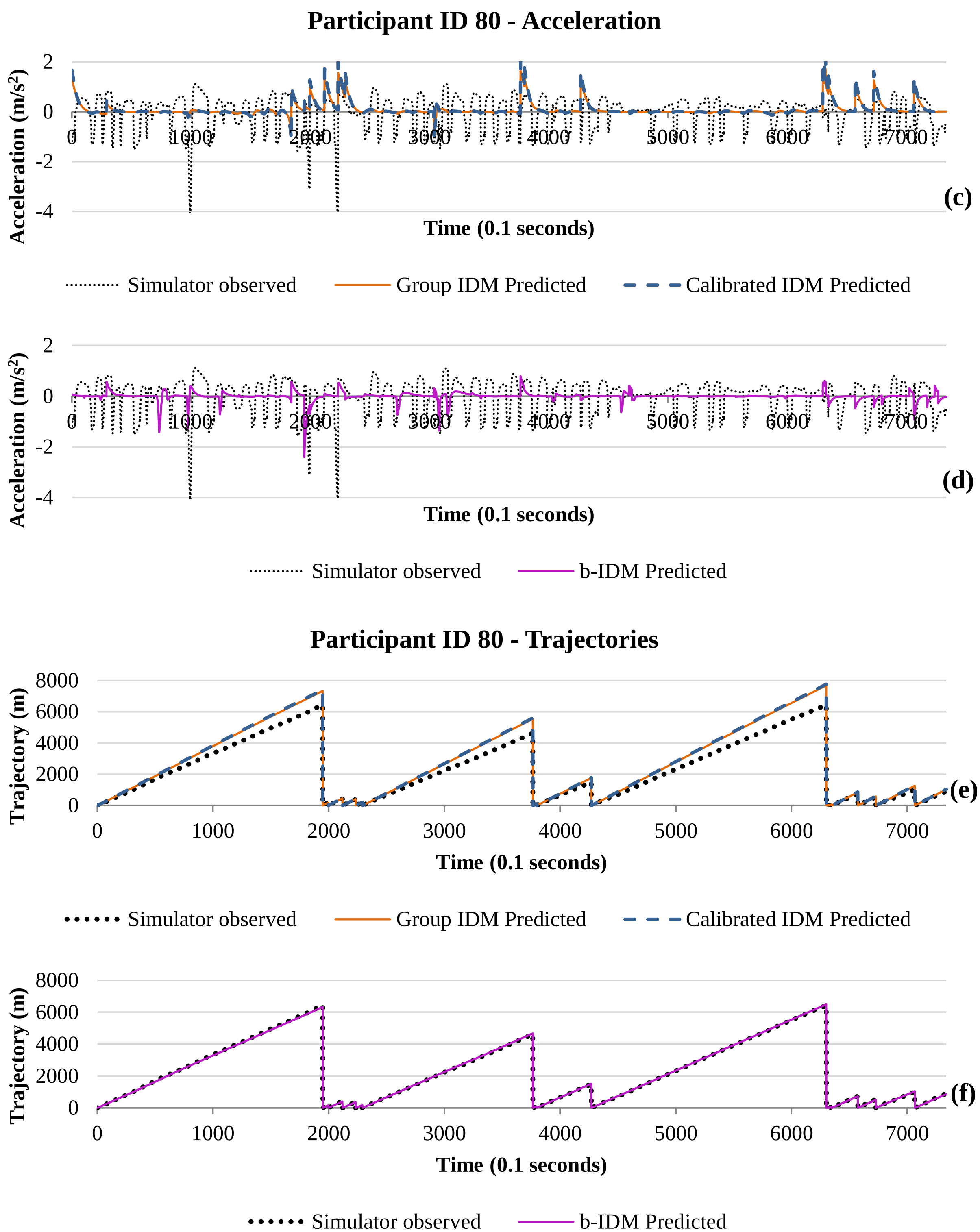


Figure H.17 Comparison plots for participant 80 showing (a) Calibrated and group IDM predicted speed, (b) b-IDM predicted speed, (c) Calibrated and group IDM predicted acceleration, (d) b-IDM predicted acceleration, (e) Calibrated and group IDM predicted trajectories, and (f) b-IDM predicted trajectories