DEVELOPMENT OF A DRIVER BEHAVIOR FRAMEWORK FOR MANUAL AND AUTOMATED CONTROL CONSIDERING DRIVER COGNITION

By

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ABSTRACT

As a crucial component of traffic safety, operational quality, and network performance, driver behavior has been the subject of numerous studies. However, research has focused primarily on descriptive mathematical models of the primary driving tasks (car-following, lane changing), while rarely considering the underlying human factors affecting driver behavior. This quality of existing models means that they are not generally capable of adapting to systemic changes in driving behavior.

At the same time, vehicle automation, one of the most revolutionary innovations in the history of transportation, advances at a very rapid pace. This development will result in deep systemic changes in the driver role and behavior, during the unavoidable transition period towards fully automated transportation networks, which the existing descriptive models are ill-equipped to predict. To achieve that, additional information about driver behavior derived from the field of cognitive sciences, and psychological constructs like cognitive workload and situational awareness, need to be integrated into driving behavior models in order to describe the driver state under various levels of automation.

This research aims to fill that gap by proposing a robust driver behavior framework that takes into account human factors and can be applied to both traditional manual driving, as well as driving of vehicles with varied automation capabilities. Based on a comprehensive literature review, the study proposed an experimental methodology, and a data collection and analysis plan that can validate the behavioral framework for use in future transportation applications.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1 - INTRODUCTION

1.1 Problem Statement

Acknowledged as a crucial component of traffic safety, operational quality, and network performance, driver behavior has been the subject of numerous studies. However, research has focused primarily on descriptive mathematical models of car-following, lane changing, and gap acceptance, while the underlying human factors affecting driver behavior are generally ignored. In addition, even those traffic modelling algorithms are rarely data-driven. Consequently, a significant number of traffic phenomena, including breakdowns and capacity drops are not adequately captured by the existing models and per-case calibration with field data is essential to accurate replicated field conditions. This demonstrates that existing models lack wide applicability and are also not capable of adapting to systemic changes in driving behavior.

At the same time, innovations in vehicle-based technology appear at a rapid rate and the driving task is becoming automated to an ever-increasing extent. Automated vehicles and driving assistance systems are expected to reduce traffic congestion, incidents and emission levels, increase roadway capacity and improve traffic flow stability. However, it will take some time before sensors, algorithms, and data collection are sufficiently developed to completely "solve" the driving task. Even when that level of advancement is reached, a transitional user acceptance period is certain to take place. Therefore, human drivers will remain an integral part of the driving task, while their role will dynamically evolve from active actors to more passive operators monitoring the automated system as it controls anywhere from just over 0% to just under 100% of the driving task. This makes vehicle automation one of the most disruptive innovations in the history of driving and as such, existing models are ill-equipped to predict the behavioral adaptations that will occur, nor their consequences on the various aspects of driving. To achieve that, additional information about driver behavior derived from the field of cognitive sciences, and psychological constructs like cognitive workload and situational awareness, need to be integrated into driving behavior models in order to describe the driver state under various levels of automation.

1.2 Research Objectives

The objectives of this research can be summarized as follows:

1. To develop a driver behavior framework that takes into account human factors and can be applied to describe both traditional manual driving, as well as driving of vehicles with varied automation capabilities, and the transitions between the manual and the automated driving states.
2. To propose experimental processes that would capture the impact of varying levels of automation and traffic conditions on manual and automated driving preferences of demographically diverse test subjects (drivers with different individual static characteristics) via measurable changes in their workload and situational awareness under purposefully designed scenarios.
3. To describe how the findings of the suggested experiments can be incorporated into a known car-following model (e.g. the Intelligent Driver Model - IDM), as well as how the suggested improvements to the model can then be evaluated and validated through a case study involving actual drivers conducted with the use of a driving simulator.

CHAPTER 2 - LITERATURE REVIEW

This chapter provides a comprehensive review of past research regarding driver car-following behavior, human psychology and cognition during the driving task, and how these established concepts may require adjustments to account for recent technological advancements in the field of connected and automated vehicles. The first section describes the existing car-following models, with an emphasis on those that take into account human factors. Advantages and limitations of the most prominent car-following models, especially with regards to modeling interaction with automated systems, are also considered. The next section discusses psychological factors and cognitive concepts that have been developed in order to explain human driving behavior. Finally, vehicle automation classification systems are presented, followed by a review of studies that investigate how car-following behavior and driving-related cognitive concepts are impacted by the introduction of automated vehicles.

2.1 Car-following Models

Car-following is one of the earliest research topics related to driver behavior and has consequently been one of the most extensively studied subjects. It was first proposed more than half a century ago by Pipes (1953) and Reuschel (1950) and in the decades since both transportation engineers and traffic psychologists have added their contributions to the growing body of knowledge surrounding this topic. The fundamental assumption of car-following models is that drivers adjust their behavior according to that of the leading vehicle (van Wageningen-Kessels et al., 2015). Car-following models are microscopic, since they describe the longitudinal behavior of individual vehicles. The standard notation involves numbering the vehicles as shown in Figure 2-1, with the vehicle under consideration being vehicle “n”, its leading vehicle “n-1” and its follower “n+1”. Then, one or more of the following three parameters in combination are used to model the trajectory of the vehicle: its longitudinal position (usually the front of the vehicle) x, its velocity $v = dx/dt$, and its acceleration $a = dv/dt \; = \; d^2x/dt^2$.

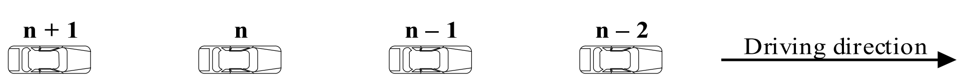


Figure 2-1: Conventional vehicle numbering in car-following models

Thus, the following basic notations are used for the majority of the car-following models, with additional terms specific to particular models defined as needed:

a_n	Acceleration (applied by the driver) of vehicle *n* (subject vehicle)
$\tilde{a}_n$	Desired acceleration of the driver of vehicle *n*
a_{max}	Maximum acceleration
a_{comf}	Comfortable acceleration
b_n	Deceleration of vehicle *n*
b_{n-1}	Deceleration of vehicle *n-1* (leading / preceding vehicle)
$\tilde{b}_n$	Desired deceleration of the driver of vehicle *n*
b_{max}	Maximum deceleration
b_{comf}	Comfortable deceleration
V_n	Speed of vehicle *n*
$\tilde{V}_n$	Desired speed of the driver of vehicle *n*
V_{max}	Maximum velocity
ΔV_n	Speed difference between the subject vehicle and the preceding vehicle ($V_{n-1} - V_n$)
x_n	Position of vehicle *n*
Δx_n	Space headway between the subject vehicle and the preceding vehicle ($x_{n-1} - x_n$)
$\widetilde{\Delta x}_n$	Desired space headway (following distance) of the driver of vehicle *n*
L_{n-1}	Length of the preceding vehicle
S_n	Spacing between the subject vehicle and the preceding vehicle ($\Delta x_n - L_{n-1}$)
$\tilde{S}_n$	Desired vehicle spacing of the driver of vehicle *n*
S_{jam}	Spacing between the subject vehicle and the preceding vehicle at standstill
s_{n-1}	Effective length of the preceding vehicle ($L_{n-1} + S_{jam}$)
t	Time
τ_n	Reaction time of the driver of vehicle *n*
T_n	Time headway between the subject vehicle and the preceding vehicle
$\tilde{T}_n$	Desired time headway of the driver of vehicle *n*

2.1.1 Safety distance or collision-avoidance models

Safety distance or collision-avoidance (CA) models are based on the fundamental assumptions that the driver of the subject vehicle *n* aims to always maintain a safe following distance to the preceding vehicle *n-1* (Olstam & Tapani, 2004). Pipes (1953) was the first to propose a safety distance car-following model by defining the position of the subject vehicle as a function of the position of the leading vehicle, as shown in Equation (2.1):

$$x_n = x_{n-1} - S_{jam} - L_{n-1} - S(v_n) \qquad (2.1)$$

where $S(v_n)$ is Pipes' interpretation of the "legal distance" between the two vehicles (van Wageningen-Kessels et al., 2015), also known as Pipe's rule: "*a good rule for following another vehicle at a safe distance is to allow yourself at least the length of a car between you and the vehicle ahead for every ten miles of hour speed at which you are travelling.*" (Olstam and Tapani, 2004).

However, the first instance of a safety-distance model that used Newtonian equations of motion to more specifically define safe distance was proposed by Kometani and Sasaki (1959). In their model, safe distance is the distance necessary to avoid a collision if the vehicle in front would act in an "unpredictable" manner, such as suddenly decelerating heavily. Compared to Pipes' model they introduce more velocity-related terms as well as a time delay term τ_n that represents the reaction time of the drive, as shown in Equation (2.2):

$$\Delta x_n(t - \tau_n) = \alpha V^2{}_{n-1}(t - \tau_n) + \beta V^2{}_n(t) + \gamma V_n(t) + d \qquad (2.2)$$

where α, β, γ are parameters that require calibration, and d is a constant representing the minimum space headway required to avoid a collision between the two vehicles.

In 1961, Newell modified that model by expressing the speed of the subject vehicle $V_n(t)$ as a non-linear function of the space headway to the lead vehicle, according to Equation (2.3):

$$V_n(t) = V_{max}[1 - e^{\left(\frac{-\lambda(\Delta x_n(t-\tau_n)+d)}{V_{\max}}\right)}] \qquad (2.3)$$

where λ is another calibration parameter.

The most impactful enhancement of the safety-distance model was proposed by Gipps (1981), as it became one of the most popular car-following models (Saifuzzaman & Zheng, 2014) and has been extensively used in simulation (Brackstone & McDonald, 1999), such as the micro-simulation software package AIMSUN (Barceló & Casas, 2005). In his model, Gipps used the desired deceleration rate instead of the maximum one, among other mitigating factors, to further reduce the possibility of collision under any circumstances. The model also introduced the concept of multiple regimes. In particular, it assumed two driving modes: one that takes place during free-flow conditions, and one during car-following. In the first mode, velocity is limited only by the desired velocity of the driver, while in the second mode it is determined by maintaining a safe distance from the preceding vehicle. The formulation of Gipps' model is shown in Equation (2.4):

$$V_n(t-\tau_n) = \min \begin{cases} V_n(t) + 2.5\tilde{a}_n\tau_n\left(1-\dfrac{V_n(t)}{\tilde{V}_n}\right)\sqrt{0.025+\dfrac{V_n(t)}{\tilde{V}_n}} \\ \tilde{b}_n\tau_n + \sqrt{(\tilde{b}_n\tau_n)^2 - \tilde{b}_n\left[2(\Delta x_n(t) - s_{n-1}) - V_n(t)\tau_n - \dfrac{V_{n-1}^2(t)}{\hat{b}_{n-1}}\right]} \end{cases} \tag{2.4}$$

where $\hat{b}_{n-1}$ represents an estimate of the leading vehicle's deceleration. Two options for that estimation are provided in the AIMSUN version 4.1 user manual (TSS, 2002): the first assumes that the estimation corresponds perfectly with the actual deceleration of the preceding vehicle and thus $\hat{b}_{n-1} = b_{n-1}$, while the second option introduces an estimation error by calculating the deceleration as the average of the leading vehicle's deceleration and the follower's desired deceleration: $\hat{b}_{n-1} = \frac{\tilde{b}_n + b_{n-1}}{2}$.

The transition between the two regimes is usually smooth, but there are two exceptions: when the preceding vehicle decelerates much faster than estimated ($b_{n-1} > \hat{b}_{n-1}$), or when a lane-changing event occurs in front of the subject vehicle, with either the leading vehicle moving to another lane or a third vehicle from an adjacent lane moving between the subject and the formerly leading vehicle. (Saifuzzaman & Zheng 2014).

Gipps' model provides a number of advantages that account for its popularity (Brackstone & McDonald, 1999). It considers human factors by including behavioral parameters such as the desired speed, acceleration and deceleration of the subject driver, along with their reaction time and their estimation of the braking rate of the leading vehicle. Many of these parameters (for example, reaction time) can also be calibrated by assuming "common sense" or "realistic" values derived from previous driver behavior studies, or by performing simple experiments in order to estimate the driver's desired kinematic parameters. Gipps himself used simulation along with assumed "realistic" values for these parameters, and showed that the model produced results regarding the propagation of disturbances which corresponded to empirical data.

On the other hand, the model exhibits a number of problems: a) it is difficult to define what constitutes a "safe headway"; b) determining how a driver estimates the deceleration of the preceding vehicle is especially difficult, while the model ignores that drivers tend to consider multiple downstream vehicles in order to anticipate the preceding vehicle's reaction; and c) it produces unrealistic speed discontinuities when the distance between the subject vehicle and the preceding vehicle changes abruptly, such us when lane-changing or hard-breaking events occur.

The most recent development in the safety-distance car-following models is Newell's simplified car-following model (Newell, 2002). As shown in Equation (2.5), the assumption of this model is that in congested conditions (second regime) the vehicle follows the time-space trajectory of the leading vehicle with space and time shifts corresponding to the jam spacing and the time headway between the two vehicles:

$$x_n(t + T_n) = min\begin{cases} x_n(t) + V_n T_n \\ x_{n-1}(t) - S_{jam,n} \end{cases} \qquad (2.5)$$

According to Newell, the values of T_n and $S_{jam,n}$ should be sampled independently from a joint probability distribution and thus exhibit variation between the various vehicles of a traffic stream.

The simplicity of Newell's model appeals to researchers (Saifuzzaman & Zheng 2014), and so does its equivalence (Leclercq, 2007) to the macroscopic traffic flow LWR model (Lighthill & Whitham, 1955; Richards, 1956), which is considered the prototype kinematic wave model (van Wageningen-Kessels et al., 2015). Thus, it has resulted in the creation of hybrid (microscopic and macroscopic) models and has also allowed researchers to approach complex topics, such as the study of traffic oscillations (Zheng et al., 2011a; Zheng et al., 2011b; Chen et al., 2012a; Chen et al., 2012b; Chen et al., 2014) or the effect of lane-changing maneuvers (Zheng et al., 2013) using a simple car-following model as their foundation. Finally, Laval and Leclercq (2010) introduced a modified version of Newell's model, where the time shift T_n is time-dependent and able to capture the difference between "timid" and "aggressive" drivers (or the switch between the two behaviors is some drivers due to stop-and-go traffic). Equation (2.6) shows the formulation of their model:

$$x_n(t) = min\begin{cases} x_n(t - T_n) + min\{V_n T_n, \tilde{x}_n(t)\} \\ x_{n-1}(t - \eta_n(t)T_n) - \eta_n(t)S_{jam,n} \end{cases} \tag{2.6}$$

where $\tilde{x}_n(t)$ is the desired distance that vehicle *n* travels during a time period equal to T_n and $\eta_n(t)$ serves as a dimensionless variable that reflects the deviation of the vehicle's spacing from its equilibrium spacing calculated by Newell's original model (Equation 2.5).

However, despite the extensions and refinements to Newell's model that have been proposed, human factors are either not sufficiently included or some of the proposed behavioral variables, such as the desired distance $\tilde{x}_n(t)$ under free-flow conditions, are not easy to measure or calibrate.

2.1.2 Stimulus-response models

One of the most populous category of car-following models follow the stimulus-response framework that is the product of research by General Motors researchers in the late fifties and early sixties (Chandler, Herman, & Montroll, 1958, Gazis, Herman, & Rothery, 1961). The primary assumption of the framework is that drivers adjust their acceleration in accordance to external stimuli and their own sensitivity to each of them. Thus, response (acceleration) = sensitivity × stimulus. A variety of factors have been proposed for the role of explanatory stimuli, but three are the most prominent ones:

1. Current speed of subject vehicle *n*: V_n
2. Spacing between the subject vehicle *n* and the preceding vehicle *n-1*: S_n
3. Speed difference between the subject vehicle *n* and the preceding vehicle *n-1*: ΔV_n

2.1.2.1 Gazis-Herman-Rothery (GHR) family models

The GHR model is considered as the most well-known and most studied car-following model. Its earliest expressions were simple linear models (Chandler et al., 1958; Herman et al., 1959), as the one shown in Equation (2.7):

$$a_n(t) = \lambda \Delta V_n(t - \tau_n) \qquad (2.7)$$

where λ is a sensitivity parameter with many potential functional forms (Saifuzzaman & Zheng, 2014):

a) $\lambda = C,$ Constant

b) $\lambda = \begin{matrix} C_1, \Delta x_n \leq \Delta x_{cr} \\ C_2, \Delta x_n > \Delta x_{cr} \end{matrix}$ Step function

c) $\lambda = C/\Delta x_n$ Reciprocal spacing

d) $\lambda = C \cdot V_n/\Delta x_n$ Edie's (1961) model

e) $\lambda = C/\Delta x^2{}_n$ Greenshields et al. (1935) macroscopic flow-density relationship

where Δx_{cr} is a threshold that depends on the model developer, and C, C_1, C_2 are constants. Eventually, the last three expressions (c,d, and e) where consolidated into the non-linear GHR car-following model by Gazis et al. (1961), presented in Equation (2.8):

$$a_n(t) = \alpha \cdot {V_n}^{\beta}(t) \cdot \frac{\Delta V_n(t - \tau_n)}{{\Delta x_n}^{\gamma}(t - \tau_n)} \qquad (2.8)$$

where $\alpha > 0, \beta, \gamma$ are parameters calibrated to fit the model to field data.

Brackstone and McDonald (1999) reported a plethora of studies in the following decades that attempted to calibrate and validate the GHR model. However, the results of these were often contradictory with regards to the values of the calibration parameters. This uncertainty in successfully calibrating the GHR model was considered its greatest disadvantage by Brackstone and McDonald (1999). Saifuzzaman and Zheng (2014) acknowledged the simplicity of the GHR model as its primary advantage but also identified a number of limitations, and pointed that the model's inherent assumptions contrast with observations of driver behavior:

- Inter-driver heterogeneity is not accounted for, since identical reaction time for all drivers is assumed.
- The model overestimates the ability of human drivers to perceive any small changes in spacing and relative speed with accuracy.
- Situational behavioral differences are not considered, as the estimates of the model parameters have a single value for all circumstances. Thus, there is no distinction between acceleration and deceleration, nor between free-flow and congested conditions.
- Driver awareness is limited to only the preceding vehicle and only at the current time step, without accounting for the behavior of vehicles further downstream or for the past behavior of the preceding vehicle.

Aiming to counteract the above limitations, many researchers have proposed extensions and modifications to the GHR model.

Regarding the GHR model's assumption of symmetrical acceleration and deceleration, Herman and Rothery (1965) suggested that personal vehicles tend to have a greater deceleration than acceleration capacity. Their hypothesis was validated in studies by Subramanian (1996) and Siuhi and Kaseko (2010) who observed greater driver sensitivity to deceleration than to acceleration under congested conditions. Yang and Koutsopoulos (1996) developed an asymmetrical GHR model that is shown in Equation (2.9):

$$a_n = \alpha^{\pm} \cdot {V_n}^{\beta^{\pm}}(t) \cdot \frac{\Delta V_n}{{S_n}^{\gamma^{\pm}}} \qquad (2.9)$$

where the parameters $\alpha^+, \beta^+, \gamma^+$are used if $\Delta V_n \geq 0$ and $\alpha^-, \beta^-, \gamma^-$are used if $\Delta V_n < 0$.

Their asymmetrical GHR was also a part of a three-regime car-following model used in the micro-simulation software MITSIM (Olstam & Tapani, 2004). That model distinguished between its three regimes (free driving, following, emergency) via time headway thresholds:

$$regime = \begin{cases} free\ driving, & if\ T_n > T_{upper} \\ following, & if\ T_{lower} \leq T_n \leq T_{upper} \\ emergency, & if\ T_n < T_{lower} \end{cases}$$

where the behavior in the following regime is described by Equation (2.9), in the free driving regime by Equation (2.10) and in the emergency regime by Equation (2.11).

$$a_n = \begin{cases} \tilde{a}_n, & if\ V_n < \tilde{V}_n \\ 0, & if\ V_n = \tilde{V}_n \\ \tilde{b}_n, & if\ V_n > \tilde{V}_n \end{cases} \quad (2.10)$$

$$b_n = \begin{cases} min\left[\tilde{b}_n, \left(a_{n-1} - \frac{0.5\Delta V_n^{\ 2}}{S_n}\right)\right], & if\ \Delta V_n < 0 \\ min\left[\tilde{b}_n, \left(a_{n-1} + 0.25\tilde{b}_n\right)\right], & if\ \Delta V_n \geq 0 \end{cases} \quad (2.11)$$

Ahmed (1999) developed another asymmetric GHR model, where he also accounts for driver heterogeneity with regards to reaction time. This model uses two regimes (free-flow and car-following), which are determined by comparing the headway Δx_n to a critical headway $\Delta x_{n,cr}$ which is itself obtained from a two-side truncated normal distribution (Equation 2.12) and thus varies for each driver.

$$f(\Delta x_{n,cr}) = \begin{cases} \dfrac{\frac{1}{\sigma_{\Delta x}} \varphi\left(\frac{\Delta x_{n,cr} - \mu_{\Delta x}}{\sigma_{\Delta x}}\right)}{\Phi\left(\frac{\Delta x_{max} - \mu_{\Delta x}}{\sigma_{\Delta x}}\right) - \Phi\left(\frac{\Delta x_{min} - \mu_{\Delta x}}{\sigma_{\Delta x}}\right)}, & if\ \Delta x_{min} \leq \Delta x_{n,cr} \leq \Delta x_{max} \\ 0\ , & otherwise \end{cases} \quad (2.12)$$

where $\mu_{\Delta x}$, $\sigma_{\Delta x}$ represent the mean and standard deviation of the untruncated distribution,

$\Delta x_{min}, \Delta x_{max}$ are boundaries of $\Delta x_{n,cr}$ that need to be estimated,

$\varphi(\cdot)$ is the probability density function of a standard normal variable, and

$\Phi(\cdot)$ is the cumulative distribution function of a standard normal variable.

Therefore, when $\Delta x_n(t - \tau_n) \leq \Delta x_{n,cr}$, the vehicle belongs in the car-following regime and follows the modified GHR equation shown in Equation (2.13), or otherwise it is in the free-flow regime and follows Equation (2.14):

$$a_n(t) = \alpha \frac{V_n^{\ \beta}(t - \ \xi\tau_n)}{\Delta x_n^{\ \gamma}(t - \ \xi\tau_n)}\ k_n^{\ \delta}(t - \ \xi\tau_n)\Delta V_n^{\ \rho}(t - \ \xi\tau_n) + \varepsilon_n^{\ cf}(t) \quad (2.13)$$

$$a_n(t) = \lambda[\tilde{V}_n(t - \tau_n) - V_n(t - \tau_n) + \varepsilon_n^{\ ff}(t)] \quad (2.14)$$

where $\alpha, \beta, \gamma, \delta, \rho$ are calibration parameters,

$k_n^{\ \delta}(t - \ \xi\tau_n)$ is the visible traffic density downstream of the subject vehicle,

$\xi \in [0,1]$ is a sensitivity lag parameter,

λ is the constant sensitivity, and

${\varepsilon_n}^{cf}(t), {\varepsilon_n}^{ff}(t)$ are normally distributed error terms for their respective regimes.

To account for drivers reacting to stimuli from additional downstream vehicles than just the first one, a multiple-vehicle interaction extension to the linear GHR model was proposed by Bexelius (1968), as shown in Equation (2.15):

$$a_n(t) = \sum_{i=1}^{m} \lambda_i \Delta {V_n}^i(t - \tau_n) \qquad (2.15)$$

where λ_i $(i = 1,2, \dots, m)$ are sensitivity parameters for the next *m* vehicles downstream, and

$\Delta {V_n}^i(t - \tau_n)$ is the speed difference between the subject vehicle and the *i^th^* vehicle ahead: $V_{n-i} - V_n$.

Hoogendoorn, Ossen, and Schreuder (2006) suggested the following modification (Equation 2.16) to eliminate the inconvenient additive function of Bexelius' equation:

$$a_n(t) = \min_{1 \le i \le m} \lambda_i \Delta {V_n}^i(t - \tau_n) \qquad (2.16)$$

To address the assumption that a driver reacts not only to the instantaneous relative speed of the leading vehicle but rather to its overall speed history over a period of time, Lee (1966) extended the linear GHR model with the addition of a memory function, as seen in Equation 2.17:

$$a_n(t) = \int_0^t M(t - \acute{t}) \Delta V_n(\acute{t}) d\acute{t} \qquad (2.17)$$

where *M* is a memory function representing the information regarding the preceding vehicle that the driver of the subject vehicle has accumulated over the driving period. Lee (1996) suggests a number of alternative expressions for that memory function, such as a Dirac-Delta function: $M(t) = \lambda \delta(t - \tau_n)$, which corresponds to the instantaneous (no memory) model, or a decaying exponential function: $M(t) = \mu k e^{-kt}$ ($\mu, k > 0$ are parameters), among other forms, which represent a more realistic "weighted response over a finite interval of past history". Saifuzzaman and Zheng (2014) noted that although the introduction of a memory function results in a smoother acceleration profile, without unrealistic peaks that were previously present, the complexity of the model increases significantly, since each vehicle's past trajectory must be stored and included in the model's calculations at every step.

Finally, a more recent attempt to extend the GHR model in order to account for driver uncertainty and perception inaccuracy is the use of fuzzy-logic models, where parameters such as the time headway are defined by overlapping fuzzy sets. Such models were suggested by Kikuchi and Chakroborty (1992), as well as Wu, Brackstone, and McDonald (2000). However, fuzzy sets remain notoriously difficult to define, calibrate and validate (Ross, 2010), and therefore applications of these models are not common.

2.1.2.2 Desired measures models

The stimulus-response car-following models of the previous subsection considered as stimuli only the current speed of the subject vehicle and its speed difference with the vehicles ahead of it. However, this assumption inevitably results in the following incongruous conclusion: that when two vehicles travel at the same speed, any distance between them, no matter how unrealistic, is possible – and acceptable by the drivers – since the spacing between the vehicles is not a factor taken into account by the model (when $\Delta V_n = 0$). To avoid this, desired measures models fundamentally suggest that each driver has a desired space (or time) headway, and that they attempt to maintain that headway, while also minimizing the speed difference with the leading vehicle (Saifuzzaman & Zheng, 2014).

The first model of this class is attributed to Helly (1959), relies on the concept of the desired space headway ($\widetilde{\Delta x}_n$), and is formulated as shown in Equation (2.18):

$$\begin{gathered} a_n(t) = \alpha_1 \Delta V_n(t - \tau_n) + \alpha_2\left[\Delta x_n(t - \tau_n) - \widetilde{\Delta x}_n(t)\right], \\ \widetilde{\Delta x}_n(t) = \beta_1 + \beta_2 V_n(t - \tau_n) + \beta_3 a_n(t - \tau_n) \end{gathered} \tag{2.18}$$

where $\alpha_1, \alpha_2, \beta_1, \beta_2, \beta_3$ are calibration parameters.

Helly's initial calibration of the model resulted in the following average values for these parameters: $\alpha_1 \sim 0.5,\ \alpha_2 \sim 0.125,\ \beta_1 \sim 20,\ \beta_2 \sim 1$, but – most importantly – $\beta_3 \sim 0$, meaning that the desired space headway for the driver of the subject vehicle did not appear to be affected by its acceleration, but only by its speed.

In 1995, Xing developed a complex non-linear model by incorporating elements of both Helly's linear model and the non-linear GHR model, as presented in Equation (2.19). It consists of four terms which correspond to (i) "standard" driving, (ii) accelerating from a standing queue, (iii) the effect of a gradient, and (iv) free-flow conditions (when the first term tends to zero), respectively:

$$a_n(t) = \alpha_1 \frac{\Delta V_n(t-\tau_1)}{\Delta {x_n}^l(t-\tau_1)} + \alpha_2 \frac{\left[\Delta x_n(t-\tau_2) - \widetilde{\Delta x}_n(t)\right]}{\Delta {x_n}^m(t-\tau_2)} - \gamma sin\theta + \lambda[\tilde{V}_n - V_n(t-\tau_3)],$$
$$\widetilde{\Delta x}_n(t) = \beta_0 + \beta_1 V_n(t-\tau_n) + \beta_2 {V_n}^2(t-\tau_n) + \beta_3 {V_n}^3(t-\tau_n) \quad (2.19)$$

where $\alpha_1, \alpha_2, \alpha_3, \beta_0, \beta_1, \beta_2, \beta_3, \gamma, \lambda, l, m, \tau_1, \tau_2, \tau_3$ are calibration parameters, with the last three representing different time lags for each driving condition, and θ is the gradient difference. Similar to Helly's findings when calibrating his linear model, the desired following distance $\widetilde{\Delta x}_n(t)$ is only determined by the speed of the vehicle and not its acceleration, though the relationship suggested by Xing is more complicated. Calibration of Xing's model showed that $l{\sim}m{\sim}\beta_2{\sim}\beta_3{\sim}0$ which reduces the model back to a linear form. Comparing the results of the model with trajectories obtained from actual vehicles showed an exceptionally good fit, but Brackstone and McDonald (1999) noted that the distributions of the significant (non-zero) calibrated parameters exhibited high standard deviations, and thus caution should be exercised with regards to the validity of Xing's model.

One of the most recent and most commonly used desired measures model, is the Intelligent Driver Model (IDM), proposed by Treiber, Hennecke, and Helbing in 2000. As shown in Equation (2.20), it factors both the desired speed and the desired space headway (as a function of the desired time headway) and applies to both car-following and free-flow situations (when the spacing between the vehicles tends to infinite and thus the last term of the equation tends to zero):

$$a_n(t) = a_{max,n}\left[1 - \left(\frac{V_n(t)}{\tilde{V}_n(t)}\right)^{\delta} - \left(\frac{\tilde{S}_n(t)}{S_n(t)}\right)^2\right],$$
$$\tilde{S}_n(t) = S_{jam,n} + S_{1,n}\sqrt{\frac{V_n(t)}{\tilde{V}_n(t)}} + V_n(t)\tilde{T}_n(t) - \frac{V_n(t)\Delta V_n(t)}{2\sqrt{a_{max,n} \cdot b_{comf,n}}} \quad (2.20)$$

where $\delta \sim 4$ is a parameter representing the sensitivity to deviation from the desired speed, and $S_{1,n} \sim 0$ quantifies the effect of this deviation in the desired vehicle spacing. However, since the typical value of this parameter is usually zero, the entire second term of the desired spacing equation is omitted in most applications of the model, though a non-zero $S_{1,n}$ may be required in order to better match field data, especially in less common cases such as when the collected empirical data produces a flow-density relationship with inflection points (Treiber et al., 2000).

Eventually, to simplify the model for the purpose of studying its properties more easily, as well as allowing for added complexity in other areas and for the subsequent development of more focused and less generalized model extensions, the assumption of identical vehicles, where $a_{max,n} = a_{max}$, $b_{comf,n} = b_{comf}$, $S_{jam,n} = S_{jam}$, $S_{1,n} = S_1$, $\tilde{V}_n(t) = \tilde{V}$, $\tilde{T}_n(t) = \tilde{T}$ was adopted by Treiber et al. (2000), along with the use of standard values, such as $\tilde{T} = 1.6s$, $\delta = 4$, and $S_1 = 0$. The latter evidently results to the omission of the related term. Thus, the IDM model formulation upon which most future models are based on is the one shown in Equation (2.21):

$$
\begin{aligned}
a_n(t) &= a_{max}\left[1 - \left(\frac{V_n(t)}{\tilde{V}}\right)^{\delta} - \left(\frac{\tilde{S}_n(t)}{S_n(t)}\right)^2\right], \\
\tilde{S}_n(t) &= S_{jam} + V_n(t)\tilde{T} - \frac{V_n(t)\Delta V_n(t)}{2\sqrt{a_{max} \cdot b_{comf}}}
\end{aligned}
\qquad (2.21)
$$

In 2003, Treiber and Helbing proposed a memory function extension to the IDM, which they called IDMM (IDM with memory). Their basic assumption is that drivers adapt to the surrounding conditions (such as congested traffic) by changing their desired time headway within a range bounded by the following parameters: $T_0 = \tilde{T}$ (for free-flowing traffic) and $T_{jam} = \beta_T T_0$ (for congested traffic), where $\beta_T \sim 1.8$ is an adaptation factor. This is achieved by substituting the $\tilde{T}$ term in Equation (2.21) with $T\{\lambda(t)\}$, where $\lambda(t)$ is the "subjective level of service", which can assume values from 0 (in congested conditions) to 1 (in free-flow conditions), and is calculated as the exponential moving average of the "instantaneous level of service" $\lambda_0(V_n)$ during the adaptation time τ (usually 600 seconds), according to Equation (2.22):

$$
\begin{aligned}
T\{\lambda(t)\} &= \lambda(t)T_0 + [1 - \lambda(t)]T_{jam} = \tilde{T}[\beta_T + \lambda(t)(1 - \beta_T)], \\
\lambda(t) &= \int_0^t \lambda_0\big(V_n(\acute{t})\big)\, e^{-\frac{t-\acute{t}}{\tau}} d\acute{t}
\end{aligned}
\qquad (2.22)
$$

The instantaneous level of service $\lambda_0(V_n)$ is in turn a monotonically increasing function of the actual speed V_n, with $\lambda_0(0) = 0$ (worse level of service at standstill) and $\lambda_0(\tilde{V}) = 1$ (best level of service, since the desired speed is reached). For example, the $\lambda_0(V_n)$ function could have the following form: $\lambda_0(V_n) = V_n/\tilde{V}$. Treiber and Helbing (2003) demonstrated through simulation that the adaptation effect included in IDMM succeeds in reproducing observed traffic instabilities, oscillations, and the wide scattering in flow-density data during congested traffic, despite using only identical vehicles, on a single lane, following a simple deterministic model, and without the need of other destabilizing factors, such as stochastic and heterogeneous multi-lane traffic.

Another refinement of the (non-memory) IDM was incorporated into the model by Treiber and Kesting (2010) in their German-language book "Verkehrsdynamik und -simulationen" and its English-translated version (2013): "Traffic flow dynamics: Data, models and simulation", after acknowledging (Treiber, Kesting, & Helbing, 2010) that IDM is fundamentally a two-regime model. The refinement involves adding a maximum condition to the second part of Equation (2.21) as shown in Equation (2.23):

$$\tilde{S}_n(t) = S_{jam} + max\left(0, V_n(t)\tilde{T} - \frac{V_n(t)\Delta V_n(t)}{2\sqrt{a_{max} \cdot b_{comf}}}\right) \qquad (2.23)$$

This addition is relevant in two situations: (i) when the speed of the preceding vehicle is significantly greater and (ii) in stop-and-go traffic when the vehicle in the queue begins to accelerate again from zero speed. The most likely scenario for the occurrence of the first state is when a faster vehicle enters the lane in front of the subject vehicle, but since the actual spacing $S_n(t)$ is likely to be much greater than S_{jam} it is not expected to cause a significant discontinuity in the acceleration function. In the second situation, not allowing the latter part of the equation to assume negative terms produces a more realistic, though still discontinuous, acceleration profile and averts an unreasonably low acceleration rate when starting from a stopped state. However, despite its empirically demonstrated necessity, the addition of this maximum condition does contradict a previously fundamental property of the IDM: that its acceleration function $a_n(t)$ is continuous and its time derivate is always finite, while ensures smooth regime transitions.

In assessing the IDM's positive aspects, Treiber and Kesting (2013) point favorably to the model's simplicity, where the number of calibration parameters remains low and each of them is associated with or explains only one specific driving behavior element, allowing for easier and intuitive model calibration. They also consider the IDM's intelligent breaking strategy as one of its greatest innovations and advantages over other models. This strategy is captured by the term $[V_n(t)\Delta V_n(t)]/\left(2\sqrt{a_{max} \cdot b_{comf}}\right)$ of the desired spacing $\tilde{S}_n(t)$, and Treiber and Kesting (2013) demonstrate how this breaking strategy is "dynamically self-regulating", with the deceleration always heading in the direction the comfortable deceleration b_{comf}.

On the other hand, though, Treiber and Kesting (2013) also acknowledge a number of deficiencies and limitations inherent in IDM. In particular, the model's equations result in: (i) unrealistically abrupt deceleration when the speed of the subject vehicle exceeds the desired speed ($V_n > \tilde{V}_n$), which can occur when encountering a reduced speed limit area, (ii) greater vehicle dispersion than what is observed in the field, when a platoon of vehicles ($\Delta V = 0$) are driving close to the desired speed ($V_n \lesssim \tilde{V}_n$), because the spacing S_n at equilibrium ($a_n = 0$) ends up being significantly larger than the desired spacing $\left(\tilde{S}_n = S_{jam} + V_n\tilde{T}\ \right)$ of the IDM formulation, as shown in Equation (2.24), (iii) exaggerated breaking reaction when the actual spacing becomes abruptly smaller than the desired spacing ($S_n \ll \tilde{S}_n$), a situation that can arise when a changing-lane vehicle enters the subject vehicle's lane. Finally, they recognize that the model's continuous acceleration function and its lack of a factor that captures the reaction time of the driver, make IDM more suited for use in describing the behavior of semi-automated vehicles under adaptive cruise control (ACC) than the behavior of human drivers.

$$S_n(t) = \frac{S_{jam} + V_n(t)\tilde{T}}{\sqrt{1 - \left(\frac{V_n(t)}{\tilde{V}}\right)^{\delta}}} = \tilde{S}_n(t) \cdot \frac{1}{\sqrt{1 - \left(\frac{V_n(t)}{\tilde{V}}\right)^{\delta}}} \qquad (2.24)$$

with Equation (2.24) derived by solving Equation (2.21) for $S_n(t)$ when $a_n(t) = \Delta V_n(t) = 0$, and as $V_n(t) \rightarrow \tilde{V} \Rightarrow S_n(t) \gg \tilde{S}_n(t)$.

To address the first three shortcomings of the model, Treiber and Kesting (2013) developed the Improved Intelligent Driver Model (IIDM), while also emphasizing its applicability for semi-automated driving behavior. In contrast to the automation-focused IIDM, the Human Driver

Model (HDM) was introduced (Treiber, Kesting, & Helbing, 2006; Treiber and Kesting, 2013) to better model human driving behavior and account for the lack of human factors in the base IDM, such as reaction time, but also temporal and multi-vehicle anticipation, and estimation and driving errors. Thus, the HDM, though still a desired measures stimulus-response model, can best be classified as a psycho-physical model and is described in depth in subsection 2.1.3 (Psycho-physical models).

The latest contribution of Treiber and Kesting (2017) to the IDM was to introduce stochasticity, in the form of white acceleration noise $\xi_n(t)$ added to the acceleration function a_n. $\xi_n(t)$ has an expected value of zero, lacks any correlation with time and between vehicles, and has intensity Q, which is a parameter than can be calibrated. Mathematically, this is expressed in Equation (2.25):

$$\dot{a}_n(t) = a_n(t) + \xi_n(t), E[\xi_n(t)] = 0, E[\xi_n(t)\xi_m(\acute{t})] = Q\delta_{nm}\delta(t - \acute{t}) \quad (2.25)$$

where $\dot{a}_n(t)$ is the stochastic acceleration, $E[\cdot]$ represents the expected value, δ_{nm} is the Kronecker delta function, where $\delta_{nm} = 1$ for $n = m$ and zero if $n \neq m$, while $\delta(t - \acute{t})$ is the Dirac delta distribution.

In addition to the stochastic noise, Treiber and Kesting (2017) incorporated the concept of indifference regions, used primarily in psycho-physical models, where the drivers update their acceleration only at discrete "action points", when the difference between the actual acceleration and the acceleration of the car-following model exceeds a certain value $\Delta\alpha$. In this case, that value is also stochastic, obtained from a uniform distribution: $\Delta\alpha \sim U(0, \Delta\alpha_{\max})$.

The IDM has been the subject of study by many researchers, besides its originators, though most extensions to the model also attempt to introduce psycho-physical elements to the IDM, so they are addressed in more detail in that section. The two most prominent models belong to Saifuzzaman et al. (2015a; 2017), who introduced TDIDM, incorporating a task difficulty factor $TD_n(t)$ into IDM which affects the desired vehicle spacing $\tilde{S}_n$ (Equation 2.26), and Hoogendoorn et al. (2013), who – based on Fuller's (2005) task capability interface (TCI) – added task demand and driver capability in the IDM in the form of compensation $m_d(t)$ and performance $m_p(t)$ adaptation effects (Equation 2.27).

$$a_n(t+\acute{\tau}_n) = a_{max}\left[1-\left(\frac{V_n(t)}{\tilde{V}(t)}\right)^{\delta}-\left(\frac{\tilde{S}_n(t)\cdot TD_n(t+\acute{\tau}_n)}{S_n(t)}\right)^2\right],$$
$$\tilde{S}_n(t) = S_{jam}+V_n(t)\tilde{T}-\frac{V_n(t)\Delta V_n(t)}{2\sqrt{a_{max}\cdot b_{comf}}} \quad (2.26)$$

where $\acute{\tau}_n$ represents reaction time, but modified due to human factor parameters.

$$a_n(t) = a_{max}\left(1-m_p(t)\right)\left(1-m_d^3(t)\right)\left[1-\left(\frac{V_n(t)}{\tilde{V}(t)\left(1-m_d^3(t)\right)}\right)^{\delta}-\left(\frac{\tilde{S}_n(t)}{S_n(t)}\right)^2\right],$$
$$\tilde{S}_n(t) = S_{jam}+V_n(t)\tilde{T}_n\left(1+m_d^3(t)\right)-\frac{V_n(t)\Delta V_n(t)}{2\sqrt{a_{max}\left(1-m_d^3(t)\right)\cdot b_{comf}\left(1-m_d^3(t)\right)}} \quad (2.27)$$

Concluding this subsection, it must be pointed that while the desired measures model resolve many of the issues of previous stimuli-response models, they also introduce additional complications. Their greatest disadvantage is that the desired measures themselves (e.g. desired speed, desired time or spacing headway) are not directly measurable in the field and thus must be estimated indirectly (Saifuzzaman & Zheng, 2014). This is also the reason why validation of most of these models was performed through simulation and not through actual data obtained from real drivers.

2.1.2.3 Optimal Velocity (OV) family models

In optimal velocity models, the acceleration of the subject vehicle depends on the difference between its current speed V_n and its optimal (or safe) velocity ${V_n}^*$, which is in turn a function of the space headway Δx_n. Therefore, unlike all the previous subcategories of stimulus-response models, the speed difference ΔV_n is ignored as a potential stimulus.

The originators of the optimal velocity model were Bando et al. (1995), which proposed the following Equation (2.28):

$$a_n(t) = \gamma\left[{V_n}^*\left(\Delta x_n(t)\right)-V_n(t)\right],$$
$${V_n}^*\left(\Delta x_n(t)\right) = V_0\left[tanh\left(\frac{\Delta x_n - L_{n-1}}{b}-C_1\right)+C_2\right] \quad (2.28)$$

where γ is a sensitivity constant, b the length scale, and V_0, C_1, C_2 calibration parameters.

In 1998, Bando et al. updated the OV model to include driver reaction (Equation 2.29):

$$a_n(t) = \gamma\left[V_n^{*}\left(\Delta x_n(t-\tau_n)\right) - V_n(t-\tau_n)\right] \quad (2.29)$$

Comparisons of the results of the optimal velocity model with field data demonstrated that it produced unrealistic results, specifically high accelerations and decelerations (Saifuzzaman & Zheng, 2014). Treiber and Kesting (2013) also identified that the base OV model has not only quantitative deficiencies, but also qualitative, as its outcome depends heavily on the calibration of its parameters, and thus it does not exhibit robustness. This result is the product of not considering the speed difference between the subject and the leading vehicle, while still being affected by the traffic stream density through the space headway. For this reason, the Generalized Force (GF) model, an extension of the OV that includes speed difference, was developed by Helbing and Tilch (1998), as shown in Equation (2.30):

$$a_n(t) = \gamma\left[V_n^{*}\left(\Delta x_n(t)\right) - V_n(t)\right] + \lambda(\Delta V_n(t)) \cdot H\left(-\Delta V_n(t)\right) \quad (2.30)$$

where λ is a sensitivity coefficient, and H is the Heaviside step function, that takes a value of 1 when $\Delta V_n(t) = V_{n-1} - V_n$ is negative (the leading vehicle is slower than the subject vehicle), and zero otherwise. However, the GF model still does not avoid unrealistic results.

An alternative solution, based on the GF model, was proposed by Jiang, Wu, and Zhu (2001), where they explicitly considered the speed difference (either negative or positive) as an additional linear stimulus, deriving the Full Velocity Difference (FVD) model (Equation 2.31):

$$a_n(t) = \gamma\left[V_n^{*}\left(\Delta x_n(t)\right) - V_n(t)\right] + \lambda(\Delta V_n(t)) \quad (2.31)$$

Treiber and Kesting (2013) considered the above model “incomplete” because the second term of Equation (2.31), which describes the sensitivity to the speed difference is itself independent of the vehicle spacing. Thus, they suggested the Improved Full Velocity Difference (IFVD) model of Equation (2.32):

$$a_n(t) = \gamma\left[V_n^{*}\left(\Delta x_n(t)\right) - V_n(t)\right] + \frac{\lambda(\Delta V_n(t))}{max[1, S_n/V_o T]} \quad (2.32)$$

where $V_o T$ is the “interaction length”.

This model produces more realistic acceleration, but still lacks sufficient robustness.

Another disadvantage of the FVD model is that it treats acceleration and deceleration in the same manner, using a single sensitivity parameter, for both. However, field observations have shown that this does not reflect actual driver behavior. For this reason, Gong, Liu, and Wang (2008) developed the asymmetric full velocity difference (AFVD) model (Equation 2.33):

$$a_n(t) = \gamma\left[V_n^*\left(\Delta x_n(t)\right) - V_n(t)\right] + \lambda_1(\Delta V_n(t)) \cdot H\left(-\Delta V_n(t)\right) + \lambda_2\left(\Delta V_n(t)\right) \cdot H\left(\Delta V_n(t)\right) \quad (2.33)$$

where λ_1, λ_2 are sensitivity parameters for deceleration and acceleration respectively.

The AFVD exhibits more realistic results, but also requires a longer time period to stabilize.

A multi-vehicle interaction extension of the OVM was proposed by Lenz, Wagner, and Sollacher (1999), as shown in Equation (2.34):

$$a_n(t) = \sum_{i=1}^{m} \gamma_i \left[V_n^*\left(\frac{\Delta x_{n,n-1}(t)}{i}\right) - V_n(t)\right] \quad (2.34)$$

where $\Delta x_{n,n-1}(t)$ is the space headway to the nearest i^{th} leading vehicle. V_n^* is calculated by the same equation as in the original OVM (Equation 2.28). The multi-vehicle interaction extension exhibits higher stability than the base model.

Finally, Davis (2003) used simulation to prove that the updated OVM (Equation 2.29) which considers reaction time (Bando et al., 1998), is extremely sensitive to the latter, and that longer reaction times resulted in unstable flow and unavoidable collisions. His solution, shown in Equation (2.35), produces a stable, collision-free flow. However, Davis does not provide any justification, behavioral or otherwise, for why the speed of the subject vehicle is calculated at time (t), while the space headway and the speed difference are calculated at time $(t - \tau_n)$.

$$a_n(t) = \gamma\left[V_n^*\left(\Delta x_n(t - \tau_n)\right) + \tau_n \Delta V_n(t - \tau_n) - V_n(t)\right] \quad (2.35)$$

2.1.3 Psycho-physical models

Psycho-physical models were developed in order to address the apparent inability of all previous car-following models to "provide a psychologically plausible characterization of how humans think about, and address, the driving problem" (Saifuzzaman & Zheng, 2014). Indeed, as Boer

(1999) points out, the aforementioned models are often based on unrealistic assumptions, such as that: (i) drivers always optimize their driving performance, (ii) drivers react to inputs that they shouldn't be able to perceive, and (iii) the same rules apply for each driver and driving style. Finally, the previous models are largely descriptive, thus any inaccuracies or inexplicable results are attributed to noise, while little research effort directed towards investigating if they are the product of an underlying, and unaccounted for, behavioral factor.

On the other hand, psycho-physical models emerge from challenging the above assumptions and they approach car-following by trying to understand and model the fundamental psychological causes that result in the various observed behavioral phenomena. Thus they "combine physiological restriction (reaction times, estimation errors, perception thresholds) and psychological aspects (anticipation, heuristic, context, sensitivity, driving strategy in general)" (Treiber & Kesting, 2013), from which their name is derived. Non-psycho-physical models often include some of these physiological and psychological factors, but in a limited capacity and without dealing with their fundamental causes, but only as parameters that can be calibrated.

There are various categories of psycho-physical models, that are presented in the following subsections. The biggest distinction can be made between Action Point models, which question the assumption that drivers react in a continuous manner, especially in cases where they shouldn't be able to perceive a change in their current situation (use of perceptual thresholds), and continuous models. Action point models are the most known and more widely applicable psycho-physical models; Continuous models are more diverse, but also more speculative in general and thus they have not been adopted by practitioner to a significant extent. They include "driving by visual angle" models, based on the observation that humans do not accurately estimate distances, speeds and accelerations, but can estimate time-to-collision (TTC) according to the rate of change of the visual angle of the lead vehicle; risk-taking, distraction and error models focus on driver decision-making as a function of their perceived – and acceptable – levels of risk-taking, modified by human factors; or the previously mentioned Human Driver Model (Treiber et al., 2006; Treiber & Kesting, 2013), the Task Difficulty IDM (TDIDM) by Saifuzzaman et al. (2015a; 2017), and the extension of the IDM developed by Hoogendoorn et al. (2013), based on Fuller's (2005) task capability interface (TCI).

2.1.3.1 Action Point (AP) psycho-physical models

Wiedemann (1974) was among the first who attempted to address the issue of drivers having limits to their perception and therefore are stimulated and react only when certain "perceptual thresholds" are exceeded. These driver reactions can also be called "Action Points". As shown in Figure 2-2 there are six main thresholds in the Wiedemann model that are defined as follows:

- AX: The desired space headway between two vehicles in standstill
- BX: The desired minimum following distance, which is a function of AX, the safety distance, and speed
- SDV: The action point where a driver consciously perceives that he/she is approaching a slower leading vehicle; SDV increases with increasing speed difference
- CLDV: Closing delta velocity (CLDV) is an additional threshold that accounts for additional deceleration by the application of brakes
- OPDV: The action point where a driver notices that he/she is slower than the leading vehicle and starts to accelerate again
- SDX: A perception threshold to model the maximum following distance, which is approximately 1.5–2.5 times BX

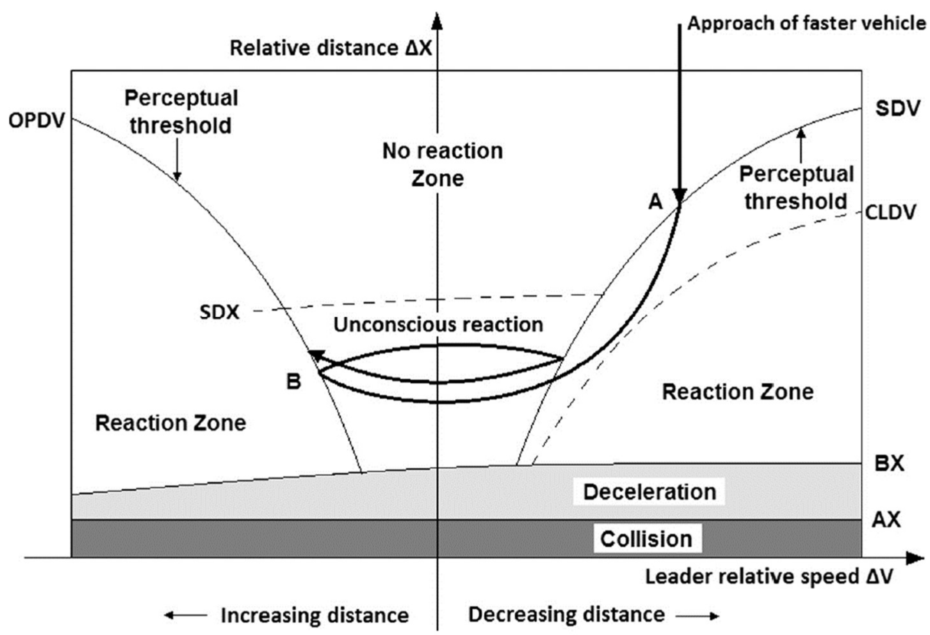


Figure 2-2: Wiedemann car-following model ΔV-ΔX diagram (Wiedemann 1974)

A modified version of the original Wiedemann car-following model (known as "Wiedemann 99") is used in the commercial microsimulation software VISSIM. The thresholds definitions of that model are not publicly known, but the developers of VISSIM refer to Wiedemann and Reiter (1992) for a comprehensive listing of the parameters used.

In 1998, Fancher and Bareket, suggested an extension of the Wiedemann 74 model by introducing the concept of a "comfort zone", when a driver is with ±12% of their desired spacing. Drivers inside the comfort zone, unable to perceive a speed difference with the preceding vehicle, will attempt to maintain their current speed.

A similar Action Point car-following model was developed by Fritzsche (1994), which uses six thresholds to divide the space of the ΔV-ΔX diagram into five regions, as shown in Figure 2-3. The six thresholds are:

- PTN: Perception of negative speed difference ($\Delta V_n < 0$)
- PTP: Perception of positive speed difference ($\Delta V_n > 0$)
- AD: Desired distance threshold ($AD = S_{jam} + \tilde{T}_n V_n$)
- AR: Risky distance threshold, when spacing is too small for comfortable driving, ($AR = S_{jam} + T_f V_{n-1}$), where $T_f \sim 0.5s$ is a fixed time headway.
- AS: Safety distance threshold, when the subject vehicle decelerates too much and achieves a safe distance with a positive speed difference ($\Delta V_n > 0$) and has to accelerate to match the speed of the preceding vehicle. $AS = S_{jam} + T_s V_n$), where $T_s \sim 1.0s$ is the safe time headway. The model requires that $\tilde{T}_n > T_s > T_f$.
- AB: Breaking distance threshold, applied to avoid collisions that might occur at high speeds.

The five resulting regions are:

- Free Driving
- Danger
- Following I
- Following II
- Closing in

The model assumes that the subject vehicle will decelerate only in either the "Danger" or "Closing in" regions.

The greatest advantage of both Action Point models is the use of perception thresholds, an important human factor that specifies minimum values for the stimuli that drivers will react to. These thresholds are expressed as functions of the relative speed and spacing and are even different for acceleration and deceleration decisions. Finally, they define several decision zones, where driver behavior is significantly different, and the transitions between them. On the other hand, obtaining values for these perception thresholds based on field data is a difficult task, and thus most models simply adopt default values for them human factors literature instead (Saifuzzaman & Zheng 2014).

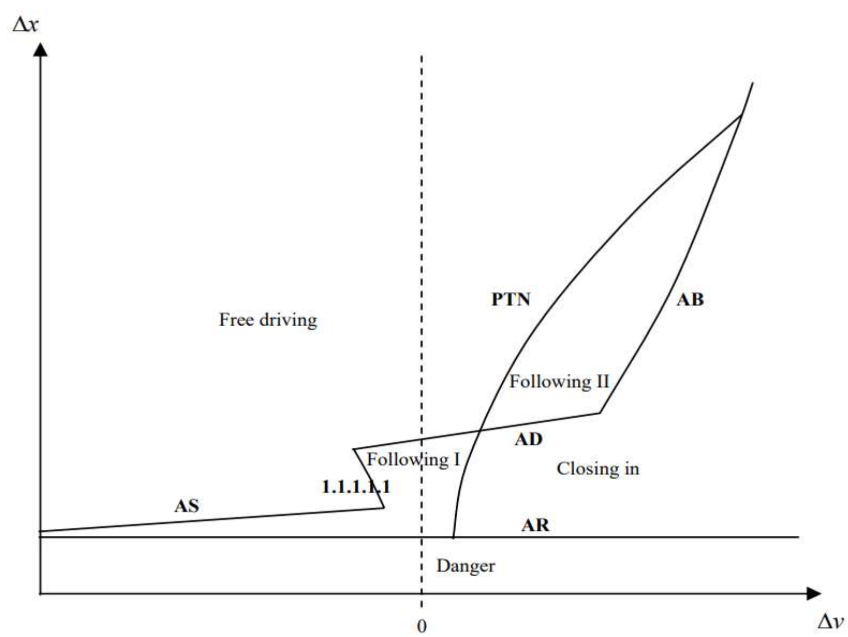


Figure 2-3: Fritzsche car-following model ΔV-ΔX diagram (Olstam & Tapani 2004)

2.1.3.2 Continuous psycho-physical models

Michaels (1963) first stated that when drivers are approaching a vehicle in front, they perceive the situation from the changes in the apparent size of the vehicle. More specifically, the relative speed is estimated through the changes in the visual angle subtended by the leading vehicle. Gray and Regan (1998) confirmed that assumption by showing that human drivers are not well-suited to estimate longitudinal distances, absolute speeds, and accelerations of other objects, but they are capable of accurately estimating time to collision (TTC) based on visual angles (in this case, visual angle divided by the rate of change of the visual angle). The visual angle (θ_n) is calculated in Equation (2.36), while the angular velocity (by differentiating Equation 2.25 with respect to time) is calculated in Equation (2.37):

$$\theta_n(t) = 2arctan\left(\frac{W}{2S_n(t)}\right) \approx \frac{W}{S_n(t)} \quad (2.36)$$

$$\frac{d}{dt}\theta_n(t) = -W\frac{\Delta V_n(t)}{\left(S_n(t)\right)^2} \quad (2.37)$$

where W is the width of the leading vehicle.

Thus visual angle is used to replace relative spacing from the leading vehicle, and angular velocity is used to replace speed difference in existing models. Andersen and Sauer (2007) modified Helly's (1959) model accordingly and developed the "Driving by Visual Angle" (DVA) model, shown in Equation 2.38.

$$a_n(t) = \alpha\left(\frac{1}{\theta_n(t)} - \frac{1}{\widetilde{\theta_n}(t)}\right) + \frac{d}{dt}\,\theta_n(t) \quad (2.38)$$

where $\widetilde{\theta_n}(t)$ is the desired visual angle of the leading vehicle.

Visual angle models accurately reflect the capability of human drivers to accurately estimate time to collision (TTC) as well as the method they use (visual angles). They are also able to produce similar speed and acceleration profiles that are observed in data obtained from real driving situations. However, they do not incorporate reaction time, nor driver heterogeneity (Saifuzzaman & Zheng 2014).

Hamdar et al. (2008) developed a driver behavior model that aims to better model risk-taking behavior. To do so, they used Kahneman and Tverksy's (1979) prospect theory, which has been shown to be better suited for driver decision-making processes compared to the expected utility theory (Neumann & Morgenstern, 1949), as it produces more realistic results when risky outcomes are possible (Saifuzzaman & Zheng 2014). In the Prospect Theory model, the subjective probability $(p_{n,i})$ of a rear-end crash with the leading vehicle is calculated, based on spacing S_n, speed difference ΔV_n and acceleration a_n, as shown in Equation (2.39):

$$p_{n,i} \approx p_n(t + \hat{\tau}_n) = \phi\left(\frac{\Delta V_n(t)\hat{\tau}_n + 0.5a_n(\hat{\tau}_n)^2 - S_n(t)}{\sigma(V_{n-1})\hat{\tau}_n}\right) \quad (2.39)$$

where $\hat{\tau}_n$ is the anticipation time span, and $\phi(z)$ is the cumulative distribution function of the standardized Gaussian.

Then the value function U_{PT}, which defines gains (or losses) as related to increase (or decrease, respectively), in speed from the previous time step is given by Equation (2.40):

$$U_{PT}(a_n) = \frac{a_n}{a_0}\left[w + 0.5(1 - w)(\tanh\left(\frac{a_n}{a_0}\right) + 1\right]\left[1 + \left(\frac{a_n}{a_0}\right)^2\right]^{0.5(\gamma-1)} \quad (2.40)$$

where a_0 is an acceleration normalizing factor, γ is a non-negative sensitivity parameter, and w is the weight assigned to negative acceleration. The gains and losses of Equation (2.40) are constrained by the maximum desired speed of the driver, and non-negative speed.

Finally, the driver assesses prospective accelerations and selects the one resulting in the highest probability, according to Equation (2.41):

$$U(a_n) = \left(1 - p_{n,i}\right)U_{PT}(a_n) - p_{n,i}w_c k(V_n, \Delta V_n) \quad (2.41)$$

where the first term indicates the losses or gains in a non-collision situations, while the second term considers the losses of a possible collision through two parameters: the seriousness factor $k(V_n, \Delta V_n)$, which reflects the expected consequences of a crash, and the weighting term w_c, which is related to driver behavior, with higher values indicating conservative drivers and lower values aggressive drivers respectively.

The model can also incorporate the stochasticity observed in driver responses, by selecting the acceleration via the probability density function of Equation (2.42):

$$f(a_n) = \begin{cases} \dfrac{e^{[\beta \cdot U(a_n)]}}{\int_{a_{min}}^{a_{max}} e^{[\beta \cdot U(\acute{a})]}\, d\acute{a}}, & if\ a_{min} \leq a_n \leq a_{max} \\ 0, & otherwise \end{cases} \quad (2.42)$$

where $\beta > 0$ is a parameter that defines the driver's sensitivity to the utility $U(a_n)$, but can also be related to driver experience, with more experienced drivers being more sensitive (higher β values) than less experienced ones, by evaluating risk with more accuracy.

In 2011, Talebpour, Mahmassani, and Hamdar (2011) proposed an extension to the model which considers traffic conditions. He assumed that a driver's preferences are different depending on the situation, as for example, in congested traffic, higher speed and acceleration would not be as desirable, and would not be assigned high gains in the utility function $U_{PT}(a_n)$, compared to free-flow conditions, where the opposite would be true. This two-regime model is described in Equation 2.43:

$$U_{PT}(a_n) = P(C) \cdot U_{PT}^{C}(a_n) + \big(1 - P(C)\big) \cdot U_{PT}^{UC}(a_n) \quad (2.43)$$

where $P(C)$ is the probability of driving under congested conditions, and $U_{PT}^{C}(a_n)$ and $U_{PT}^{FF}(a_n)$ are respectively the two different utility functions under congested and congested and free-flow conditions. A calibration of the two-regime model by Alexiadis et al. (2004) using the Next-Generation Simulation (NGSIM) data, showed consistency with field observations of driver behavior, including that higher density (lower spacing) results in lower probability of high acceleration values, or that drivers in congested traffic tend to match their speed to the average speed of the surrounding vehicles to reduce the possibility of a collision.

The main advantages of the Prospect Theory model are that it allows for the possibility of crashes to occur (unlike most models that assume a crash-free traffic stream), as well as incorporating the driver's subjective risk (both their sensitivity to the probability of risk and the value they associate with negative consequences) even when the preceding vehicle's behavior is uncertain.

Another model that incorporates driver risk, alongside other human factors, is the Task-Difficulty Intelligent Driver Model (TDIDM) developed by Saifuzzaman et al. (2015a). Based on Fuller's (2005) Task-Capacity interface model, a task difficulty car-following (TDCF) framework (Figure 2-4) was established, leading to a formulation that calculates perceived driver task difficulty at time t, $TD_n(t)$, as shown in Equation 2.44.

$$TD_n(t) = \left(\frac{V_n(t - \acute{\tau}_n)\tilde{T}_n}{(1 - \delta_n) S_n(t - \acute{\tau}_n)} \right)^{\gamma} \quad (2.44)$$

where $\delta_n < 1$ is a risk parameter associated with human factors, with positive values indicating that the driver perceives the risk of driving under reduced capability, while negative values correspond to aggressive (or impaired) drivers that underestimate the risk, γ is a sensitivity parameter with regards to the task difficulty, and $\acute{\tau}_n = \tau_n + \varphi_n$ is the modified reaction time, expressed as the standard reaction time τ_n plus the additional reaction time increase φ_n which can be attributed to impairment or other human factors.

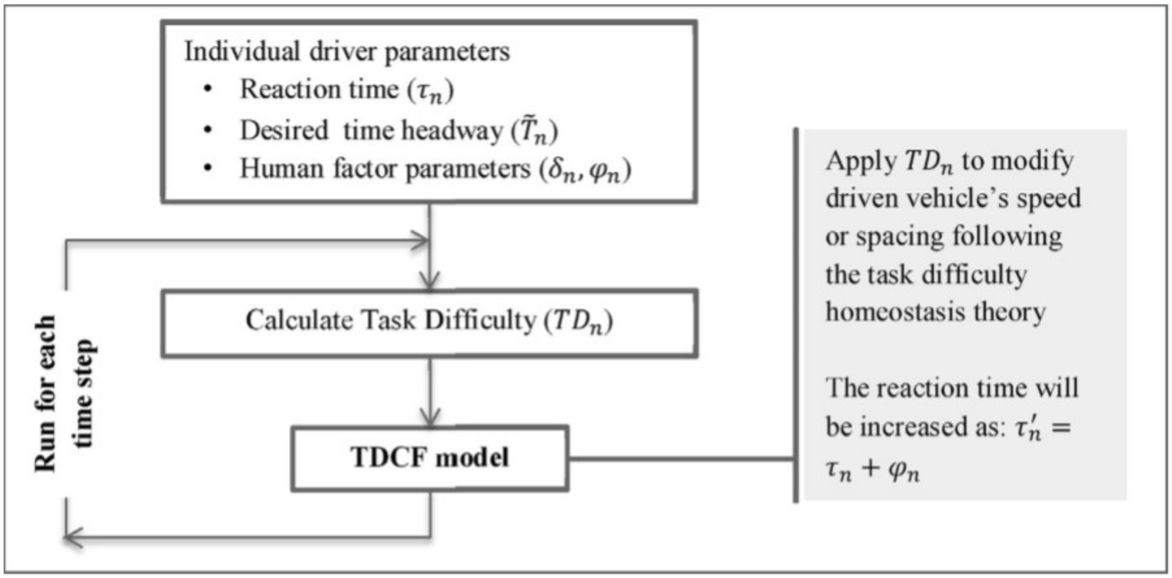


Figure 2-4: Task difficulty car-following (TDCF) framework (Saifuzzaman et al., 2015a)

Saifuzzaman et al. (2015a) then proceeded to apply the TDCF framework into the IDM, producing the TDIDM formulation shown in Equation 2.45:

$$a_n(t + \acute{\tau}_n) = a_{max,n}\left[1 - \left(\frac{V_n(t)}{\tilde{V}_n}\right)^{\delta} - \left(\frac{\tilde{S}_n(t) \cdot TD_n(t + \acute{\tau}_n)}{S_n(t)}\right)^2\right] \quad (2.45)$$

The TDIDM model was calibrated and validated through a driver simulator experiment, where vehicle trajectory data along with human factor information was collected. In particular, 32 participants, with ages from 18 to 26 years old drove the simulator vehicle under three scenarios with increased task difficulty and cognitive load: (i) baseline (no distractions), (ii) while in a conversation with a hands-free device, and (iii) while in a conversation with a handheld device. The phone conversations were of a cognitive nature, meaning that processing and storage of information was required from the participants. Various scripted traffic events that required driver reaction also took place during all three scenarios. Using genetic algorithms, the IDM model parameters (and reaction time) were calibrated first for the baseline scenario, and then then human factors added in the TDIDM (δ_n, φ_n) were similarly calibrated for the “distracted” scenarios. Only 20 of the 32 trajectories were used for calibration, while the rest were used to validate the model.

Saifuzzaman et al. (2015a) concluded that the model “outperformed” the standard IDM model and exhibited higher robustness (less sensitivity regarding changes in the calibrated parameters). They also stated the advantage of including driver reaction time into the IDM, especially one which can be modified according to the condition of the driver. Thus, capacity drop, traffic hysteresis, and stop-and-go oscillation phenomena were more realistically modeled, while modelling risk perception reflected aggressive and conservative driver behavior as seen in the literature. However, they also noted that a more comprehensive sensitivity analysis in necessary before these results can be more widely applied.

In 2013, Hoogendoorn et al. suggested another adaptation of the IDM which takes into account risk and other behavioral factors. Their theoretical framework is also derived from Fuller’s (2005) Task-Capacity interface model, but in this case the difference between task demand and driver capability is used to derive driver adaptation effects in longitudinal driving behavior. Adaptation effects include compensation effects, which are conscious adaptations performed by the drivers in order to reduce or increase the difficulty of the driving task (task demand), and performance effects, which are subconscious effects emerging from an imbalance between task demand and driver capability. Examples of compensation effects include altering the desired spacing, the desired speed or the acceleration. Examples of performance effects can be changes in perceptual thresholds, reaction time increases, or alterations in the sensitivity of acceleration and spacing. Hoogendoorn et al. (2013) suggest that $m_d(t)$ is the difference between task demand $m_t(t)$ and driver capability $m_c(t)$ at time *t*, as shown in Equation 2.46:

$$m_d(t) = m_t(t) - m_c(t) \qquad (2.46)$$

Assuming that $0 < m_t(t) < 1$ and $0 < m_c(t) < 1$, then $-1 < m_d(t) < 1$, and the value of $m_d(t)$ raised to the cube is used to quantify driver compensation effects, by affecting behavior elements they have direct control over. If, however, the imbalance between driver capability and task demands is not resolved through compensation efforts, performance effects $m_p(t)$ will also occur. Based on Brookhuis, de Vries, and de Waard (1991), Hoogendoorn et al. (2013) assume that the performance effects are related to the difference between task demands and driver capability with an inverted U-shaped function (Equation 2.47):

$$m_p(t) = -(\alpha m_d^2 + \beta m_d + \gamma\,) \qquad (2.47)$$

where α, β, γ are calibration parameters.

Including both compensation and performance effects in the IDM, Hoogendoorn et al. (2013) obtained the model described in Equation 2.48:

$$\begin{aligned} a_n(t) &= a_{max}\left(1 - m_p(t)\right)\left(1 - m_d^3(t)\right)\left[1 - \left(\frac{V_n(t)}{\tilde{V}(t)\left(1 - m_d^3(t)\right)}\right)^{\delta} - \left(\frac{\tilde{S}_n(t)}{S_n(t)}\right)^2\right], \\ \tilde{S}_n(t) &= S_{jam} + V_n(t)\tilde{T}_n\left(1 + m_d^3(t)\right) - \frac{V_n(t)\Delta V_n(t)}{2\sqrt{a_{max}\left(1 - m_d^3(t)\right)\cdot b_{comf}\left(1 - m_d^3(t)\right)}} \end{aligned} \qquad (2.48)$$

Finally, in 2006, Treiber et al. developed the Human Driver Model (HDM) by extending the IDM to consider four behavioral aspects: (i) finite reaction times, (ii) estimation errors, (iii) spatial anticipation (looking several vehicles ahead), and (iv) temporal anticipation:

- For reaction times, they consider the effective reaction time τ_{eff} to be equal to the "proper" reaction time of attentive drivers $\tau_r = 1s$ plus the effect of the attention span Δt, as follows: $\tau_{eff} = \tau_r + \Delta t/2$
- For estimation errors arising from imperfect estimation capabilities of human drivers, they include:
  - Estimation error of the spacing. The error of the logarithm of the gap is essentially constant: $lnS_{est} - lnS_n = V_s w_s(t)$, where V_s is the relative standard deviation from the real spacing S_n with typical values around 10%, and $w_s(t)$ is a normally distributed variable with values from 0 to 1.The spacing error is assumed to have no bias.
  - Estimation error of the speed of the preceding vehicle. This is based on the driver's estimation of the relative speed difference between the two vehicles via the change of the visual angle of the leading vehicle, and is also inversely related to the time-to-collision $\tau_{TTC} = \Delta V_n / S_n$. Experiments showed that the error of the relative angular

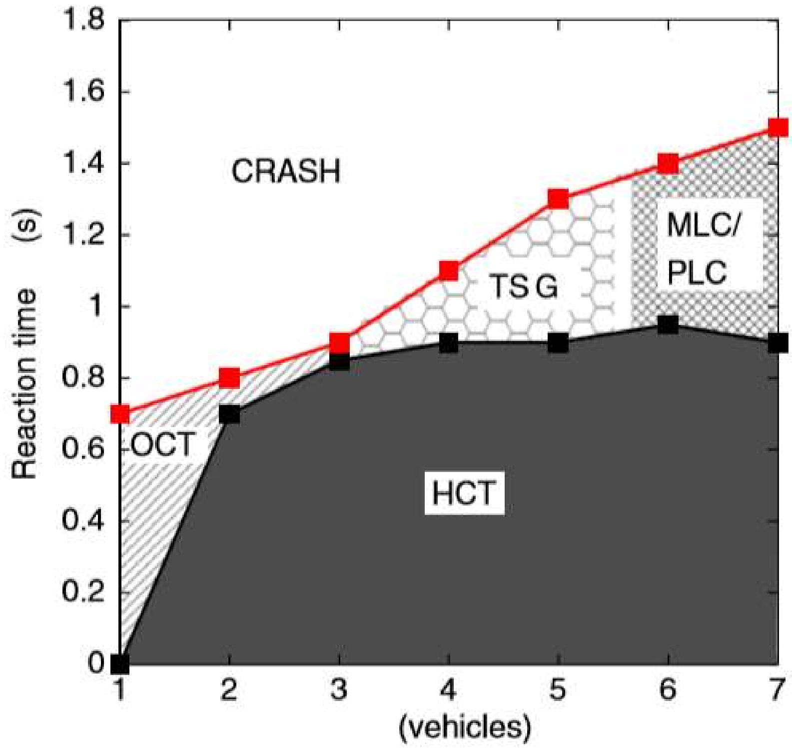
change is constant, and with the assumption that the standard deviation σ_r of the speed difference ΔV is also constant, the following is obtained: $V_{n-1}^{est} - V_{n-1} = -(\Delta V_n^{est} - \Delta V_n) = -S(1/\tau_{TTC}^{est} - 1/\tau_{TTC}) = -S\sigma_r w_{\Delta V}(t)$, where $w_{\Delta V}(t)$ is a normally distributed variable with values from 0 to 1.

- For spatial, or multi-vehicle anticipation, the acceleration function a_n is divided into a free-flow acceleration a_{free} and an interaction acceleration a_{int} and for $k \geq 1$ leading vehicles $n-1, \ldots n-k$, it is given by the following function: $a_n = a_{free}(V_n) + c\sum_{\beta=n-k}^{n-1} a_{int}\ (S_{n\beta,} V_n, V_k)$.
- For temporal anticipation, two simple heuristic models are used:
  - For the speed of the subject vehicle, the constant-acceleration heuristic is used: $V_n^{prog}(t) = V_n(t-\tau_n) + \tau_n a_n(t-\tau_n)$
  - For the speed of the leading vehicle, a constant-speed heuristic is applied, which can be expanded to include multiple vehicles: $V_{n-1}^{prog}(t) = V_{n-1}^{est}(t-\tau_n)$

Finally, all of the above functions combined with the IDM model produce the Human Driving Model, as shown in Equation 2.49:

$$a_n = a_{free}^{IDM}(V_n) + c_{IDM}\sum_{\beta=n-k}^{n-1} a_{int}^{IDM}\ (\mathrm{S}_{n\beta}^{prog}, \mathrm{V}_n^{prog}, \mathrm{V}_\beta^{prog}) \qquad (2.49)$$

The most impactful additions to the model are spatial (or multi-vehicle) anticipation and the effective reaction time, as demonstrated in Figure 2-5. This is a phase diagram of the following congested traffic regimes: (i) homogeneous congested traffic (HCT), (ii) oscillating congested traffic (OCT), (iii) triggered stop-and-go traffic (TSG), (iv) pinned localized clusters (MLC/PLC), and (v) a crash regime, obtained from simulation tests on a single-lane road section. The diagram shows that the number of vehicles anticipated and the reaction time are crucial in defining the type of traffic observed and also the possibility of crashes. Specifically, it can be seen that as the number of vehicles anticipated increases, the more time drivers have to react in order to avoid a crash.



.Figure 2-5: Phase diagram of congested traffic states of the HDM (Treiber et al., 2006)

2.1.4 Summary

Car-following models have a long history and thus exhibit a great variety of approaches, assumptions and levels of complexity. The most popular and well-studied of these models, such as Gipps' safety distance (or collision-avoidance) model (Gipps, 1981), the non-linear GHR stimulus-response model (Gazies et al., 1961), Helly's desired-measures model (Helly, 1959), the Intelligent Driver Model (Treiber et al., 2000), the Optimal Velocity model (Bando et al., 1995,) and the Full Velocity Difference model (Jiang et al., 2001) are primarily descriptive of driver behavior, rather than explanatory, containing parameters that reflect the drivers' physical signals (such as speed, acceleration, headway) which can be directly measured and calibrated (Saifuzzaman & Zheng 2014), and in general they do not consider human factors beyond driver reaction time. Some of the extensions of these model selective include some additional simplistic human factors, such as risk sensitivity, or distraction, but only as parameters to be calibrated to fit the observed data without considering why the relationships between these variables are specified in this manner (van Winsum, 1999). While their applicability (thanks to their simplicity) and their adequate approximation of traffic trajectories, when properly calibrated for local conditions, has served the transportation community well over the years, their lack of underlying explanatory factors means that these models are not well-equipped to handle fundamental changes in the long-established assumptions regarding the driving task.

In contrast with these models, several psycho-physical models, focusing on the drivers' psychological reactions, motivations and decision-making, have been proposed, including Wiedemann's (1974) and Fritzsche's (1994) action point (or perception threshold) models, Andersen and Sauer's (2007) "driving by visual angle" model, Hamdar et al.'s (2008) risk-assessing model using prospect theory, Saifuzzaman et al.'s (2015a) task difficulty car-following framework (and extension to the IDM, called TDIDM), Hoogendoorn et al.'s (2013) behavioral adaptation framework and IDM extension based on Fuller's (2005) Task-Capacity interface model, and Treiber et al.'s (2006) Human Driver Model. The primary limitations of the psycho-physical models are a significant increase in model complexity, a narrower scope and higher sensitivity to driver variance. This additional complexity and sensitivity often result in increased computational requirements, reduced applicability, and cause their calibration and validation processes to be much more difficult. The latter is especially compounded by the fact that most of their human factor variables are much harder or even impossible to measure directly, though this is a critique that can also apply to the "desired measures" variables as well. For this reason, much less studies, with conclusive results derived from real driver data, have been performed for these models, and a widely-accepted and empirically verified driver behavior theory has not yet been established.

Because vehicle automation is one of the most disruptive innovations in the history of driving, it is essential that a detailed driver behavior framework that takes into account complex human factors and can be applied to describe both traditional manual driving, as well as driving of vehicles with varied automation capabilities, and the transitions between the two driving states, must developed. This model incorporates the most relevant components of both descriptive and psycho-physical car-following model with the substantial psychological literature on driving behavior and (more generally) machine operation, including advanced cognitive constructs, in order to identify the more crucial elements (and their relationships) that are required to understand human driving behavior in the transitional era between manual and fully autonomous driving.

2.2 Human Factors in Driving Behavior

Driver behavior has been commonly studied by researchers in the fields of human factors and psychology. Michon (1985) defined driving as a hierarchical process that includes strategic, maneuvering and control levels, which are in turn based on the driver's information, adherence to a set of rules, and skills respectively (Figure 2-6).

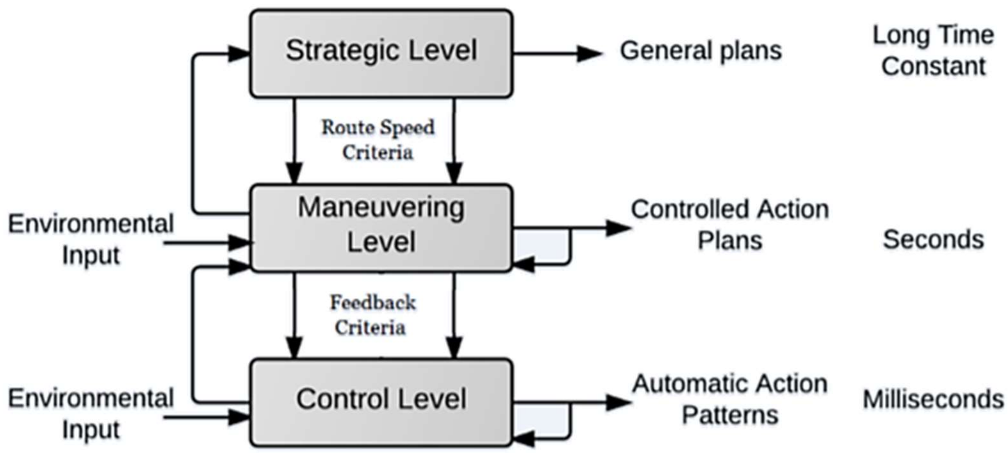


Figure 2-6: The hierarchical model of the driving task (Michon, 1985)

The strategic level involves long-term decision making and thus contributes negligibly to car-following behavior. The control level, on the other hand, operates on a very short-term scale that includes immediate and automatic decisions, like emergency breaking, and does not involve conscious control or use of cognitive resources, such as driver attention. It is thus the maneuvering level, which involves conscious control, driver attention and cognitive resources to perform tasks such as obstacle avoidance, gap acceptance, turning, speed and acceleration selection, etc., which matters the most with regards to car-following models.

A non-hierarchical but also more comprehensive approach, in terms of the affecting factors included to describing driver behavior, was proposed by Bekiaris, Amditis, and Panou (2003). In that study, the concept of "Drivability" was introduced as the "combination of permanent and temporary factors that affect a driver's performance". Figure 2-7 depicts the type of relationships that the drivability framework proposes. However, this model lacks any objective quantitative methods and instead relies on subjectively graded indices for each factor, which are then weighted accordingly to produce the Drivability index.

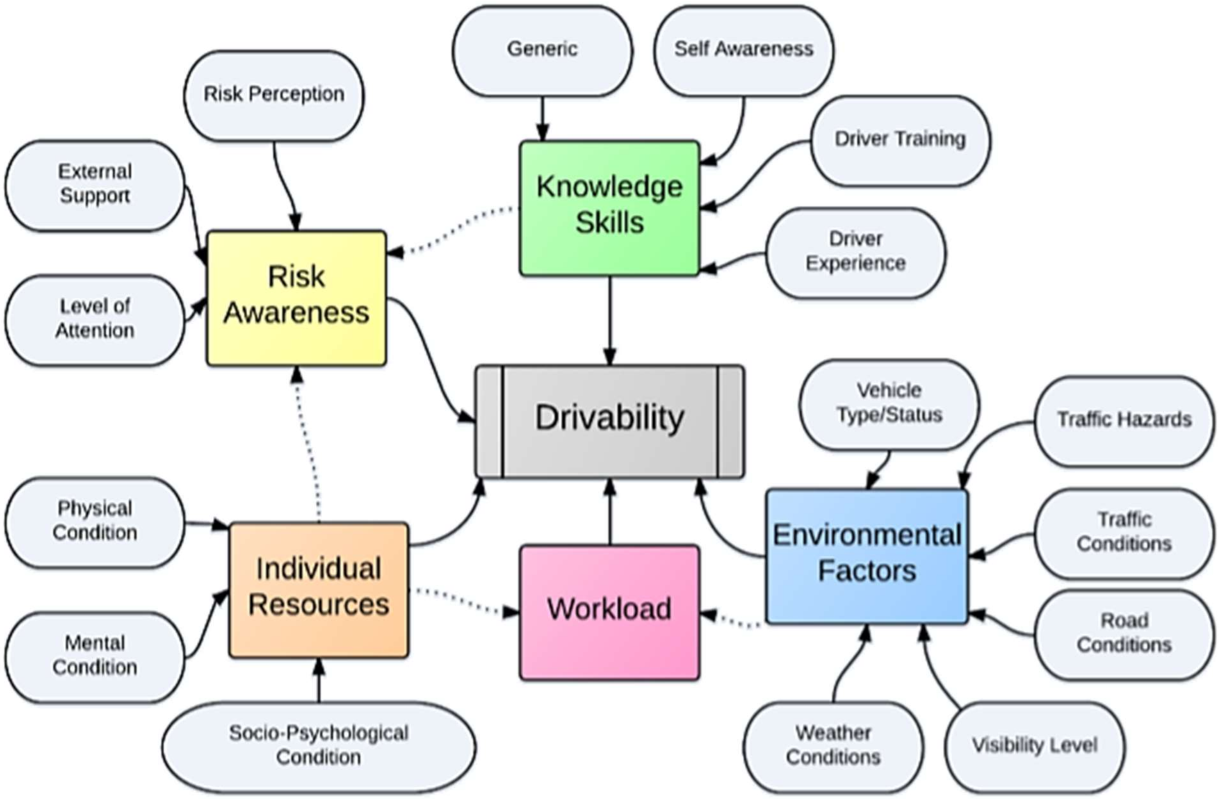


Figure 2-7: Drivability and the factors affecting it (Bekiaris et al., 2003)

Fuller (2000; 2005), examined the impact of task demand on risk-taking and described when and how loss of vehicle control and collisions (or near-collisions) take place, by introducing the task-capability interface model (TCI). According to Fuller (2005), the TCI model "describes the dynamic interaction between the determinants of task demand and driver capability. It is this interaction which produces different levels of task difficulty", as depicted in Figure 2-8.

Fuller (2005) also identified the inversely proportional relationship of task difficulty and the difference between task demand and driver capability, closely related the concepts of task difficulty and workload, and pointed that task difficulty also impacts situational awareness. These last three fundamental psychological concepts affecting driving behavior are examined in more detail in the following subsections.

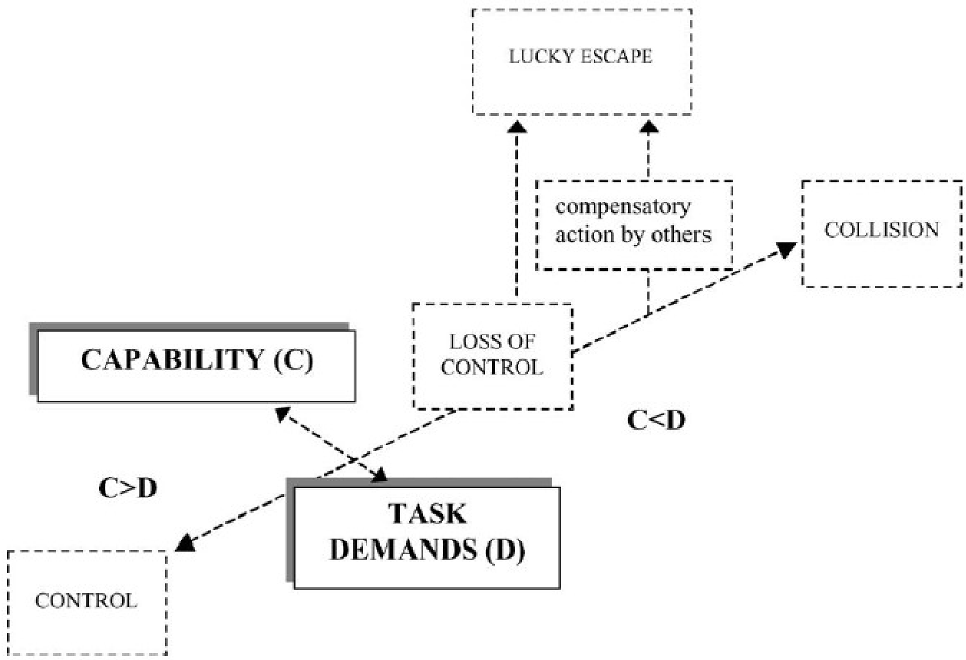


Figure 2-8: Outcomes of the dynamic interface between task demand and capability (Fuller 2005)

2.2.1 Driving Task Difficulty (Objective and Perceived)

Fuller (2000), defines task demand as "the objective complexity of the task" that "arises out of a combination of features of the environment, the behavior of other road users, control and performance characteristics of the vehicle" (Figure 2-9). He also defined driver competence as the driver's "range of skills broadly described as roadcraft, which includes control skills, ability to read the road (hazard detection and recognition), and anticipatory and defensive driving skills". So, according to that definition, as well as the work of previous authors (Evans, 1991), competence serves as a ceiling (or an upper limit) on capability but human factors (such as fatigue, drowsiness, distraction, stress and other emotions, or alcohol impairment) can reduce the driver's momentary roadcraft skills. That final result is driver capability (Figure 2-9). As mentioned above, The TCI model then defines task difficulty in a mostly objective manner, as the difference (or the ratio) between Capability and Task Demand.

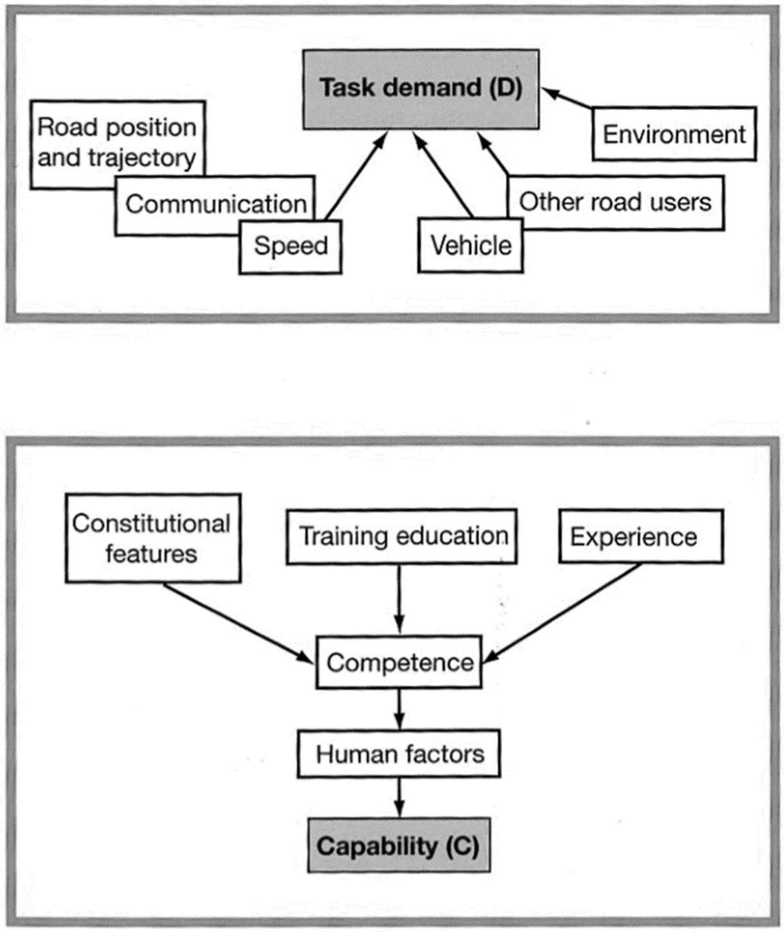


Figure 2-9: Determinants of driver capability and task demand. (Fuller, 2000)

However, driver behavioral reactions do not necessarily correspond to the objective driving task difficulty of Fuller. For this reason, Saifuzzaman et al. (2015a), developed his task-difficulty car-following framework (TDCF), described in the previous section (Figure 2-4), where he proposed the concept of the Perceived Driving Task Difficulty (Equation 2.44), by expanding Fuller's definition to include a risk parameter that captures how drivers perceive risk, and a sensitivity parameter towards the task difficulty. These factors can account for heterogeneity in driver behavior based on subjective psychological factors, such as the aggressiveness of the driver, or human factors that interfere with the driver's risk or task difficulty assessment.

Another aspect of Saifuzzaman et al.'s (2015a) formulation of Perceived Driving Task Difficulty is the way that Driver Capability and Task Demand were quantified. Driver capability is not easily measurable, as it is a factor of many abstract and unobservable variables, such as the constitutional features or the effect of the human factors on driver competence. However, several studies have indicated a correlation between driver capability and desired time headway selection: Johansson and Rumar (1971) found a relationship between headway and human factors such motivation or alertness; Heino, Molen, and Wilde (1992) showed that aggressiveness levels – or “sensation seeking/avoiding drivers” – affect time headways; Ranney et al. (2004) showed that mentally demanding tasks, such a phone conversation, also resulted in higher time headways, and finally Saifuzzaman et al. (2015b) proved that there is negative correlation between driving experience and time headway selection. For these reasons, the assumption that actual driver capability is inversely proportional to a driver’s desired time headway selection was proposed. Task Demand was also quantified in a more simple manner than Fuller’s model, using only a positive correlation with the vehicle’s speed and a negative correlation with the vehicle’s spacing from its preceding vehicle.

2.2.2 Cognitive Workload

The concept of cognitive workload, is one of the most widely used concepts in ergonomics research and practice (Young et al., 2015). Since the 1980s (Hancock & Meshkati, 1988; Moray, 1979) it has been the focus of many studies that attempted to define it, measure it or apply it to describe the performance of operators interacting with mechanical equipment, often partially automated.

Defining cognitive workload appears to be intuitively appealing, as “the allocation of attention based on the mental resources available for information processing” (Patten et al. 2006) or “the total amount of mental effort (i.e., the amount of information-processing resources used per time unit) to meet the level of performance required” (van Lint et al., 2016) for the task (driving, in this case). Teh et al. (2014) also equate workload to information-processing resources the driver dynamically allocates to the driving task. Stanton and Young (2005) suggest that cognitive workload “reflects the level of attentional resources required to meet both objective and subjective performance criteria, which may be mediated by task demands, external support, and past experience.”, a definition which assumes finite mental and attentional resources. However, investing mental resources is a voluntary, though effortful, activity. In other words, it is possible to increase the available resources by exerting more effort, in order to maintain specific performance criteria. (Young et al., 2015). This malleability of attentional resources is highlighted by Young and Stanton (2002) who posit that attentional capacity can change size in response to changes in task demands. In this way, reduced performance effects can also be the result of mental underload, as the cognitive capacity of the drivers is reduced due to the low difficulty – and thus low stimulation – of the driving task. In conclusion, according to the above definitions, suboptimal workload can mean either overload or underload (Brookhuis and de Waard, 2001). This exposes one of the major disadvantages of defining cognitive workload as an absolute value, that currently no method exist to measure or strictly quantify the absolute amount of mental resources used by an individual.

In contrast, de Waard (1996), defined mental workload as a relative concept, and specifically the ratio of demand to allocated resources. With this definition, mental workload is unit-less and also corresponds more closely to both task performance and physiological reactions, both of which allow for the development of objective workload-measuring techniques. Even subjective, self-reporting measuring methods benefit by this definition, as it bounds workload between a minimum (zero percentages of resources allocated) and a maximum value (all available resources are allocated) that have an intuitive interpretation. Thus defined, workload is also not just task-specific, but also person-specific (Rouse, Edwards, & Hammer, 1993). Task complexity (external task demand) is a significant contributing factor, but so are the individual's reaction to that demand, as well as their desired performance goals. Driver capability is crucial, but so is their motivation, mood, and operator state, as well the strategies applied in task performance.

In workload measurement, not only processing effort or resource allocation (Norman & Bobrow, 1975) are of primary importance, the term effort is also used for the mobilization of additional resources as a compensatory process (Aasman et al., 1987; Mulder, 1980; Vicente et al., 1987). Effort reflects the operator's reaction to demand and the amount of effort being expended is considered by many to be one of the most important components of (if not equal to) mental workload. Vicente et al. (1987) mention two important reasons for this. Firstly, the effort expended by the operator is not necessarily related to input load (demand). The operator's reaction to the demand depends on internal goals and adopted criteria or strategies. Secondly, there is no simple relationship between performance and effort invested. The expended amount of effort depends very much on the structure of the task (data-limited versus resource-limited, Norman & Bobrow, 1975) and, related to this, the amount of practice and experience, and of the operator's state.

From that definition, de Waard (1996) formulates a workload model, in relation to task performance and demand (Figure 2-10). In the model, several "regions" are specified. In region D, the driver's state is affected (D stands for "deactivation"). In region A2, performance is optimal, the driver handles the task demand adequately and achieves their self-selected performance goals. In regions A1 and A3, performance remains unaffected, but the driver has to exert increasingly higher effort in order to achieve that. In region B that is no longer possible and performance declines, while in region C (minimum performance region) the driver in overloaded. The A1 and A3 regions are of increased importance, as they signify optimality thresholds for workload, and it is at these regions where drivers will initiate compensation strategies in order to avoid a decline in performance.

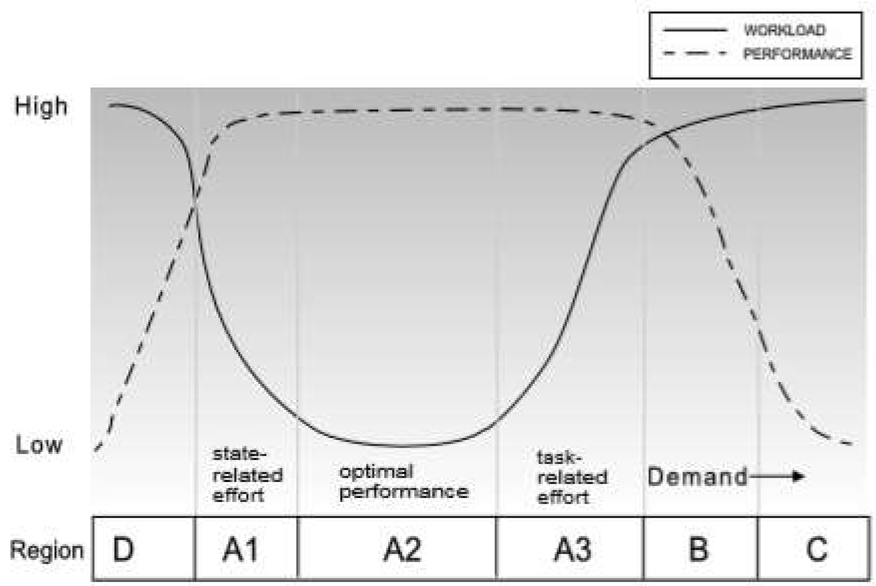


Figure 2-10: Workload-Performance Relationship in 6 regions. (de Waard, 1996)

A distinction between state-related effort and task-related effort is also necessary to be made. State-related effort is exerted in the case that the operator's state deteriorates but performance remains unaffected, while task-related effort is exerted to maintain performance in the case of increased task complexity.

Terminology in mental workload research has its roots in cognitive and physiological theories. As a result, the terms used are sometimes unclear, as different authors use the same terms with differing meanings. In this thesis, task demands are determined by goals that have to be reached by performance. Workload is the result of reaction to demand; it is the proportion of the capacity that is allocated for task performance. Effort is a voluntary mobilization process of resources. State-related effort is exerted to maintain an optimal state for task performance while task-related effort is exerted in the case of controlled information processing.

2.2.3 Situational Awareness

A general definition of Situational Awareness (SA), is "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and projection of their status in the near future" (Endsley, 1995). Figure 2-11 depicts the three levels of SA, within a dynamic decision-making environment. Endsley and Garland (2000) further analyzed these three components of SA: Perception, Comprehension, and Projection. Perception is the most fundamental SA component, as with appropriate information regarding each particular situation, the higher levels cannot successfully function. Mere perception is not sufficient either though. How the perceived information is interpreted, integrated into a more complete depiction of the environment, and how that information relates to the current performance goals is also essential. Flach (1995) also states the importance of assigning meaning and objective significance to the subjectively perceived information. Finally, projection, the highest level of SA, involves the ability to predict and anticipate future situation events and dynamics, thus involving a higher level of situational understanding that results in more timely decision making.

2.2.4 Relationships between the psychological concepts

De Waard's model (1996) proposed a relationship between workload and performance (Figure 2-10), with regards to task demand, which corresponds to driver task difficulty. In this relationship, both high and low task difficulty results in higher workloads, while the lowest workload (and best performance) is observed in a region of optimal demand. The reasons stated for this effect is that for lower task difficulty the workload is higher due to state-related effort, as the driver must exert effort to maintain their attention on the task (their cognitive resource pool is diminished), while for higher task difficulty the workload increases due to task related effort (there is higher demand for cognitive effort).

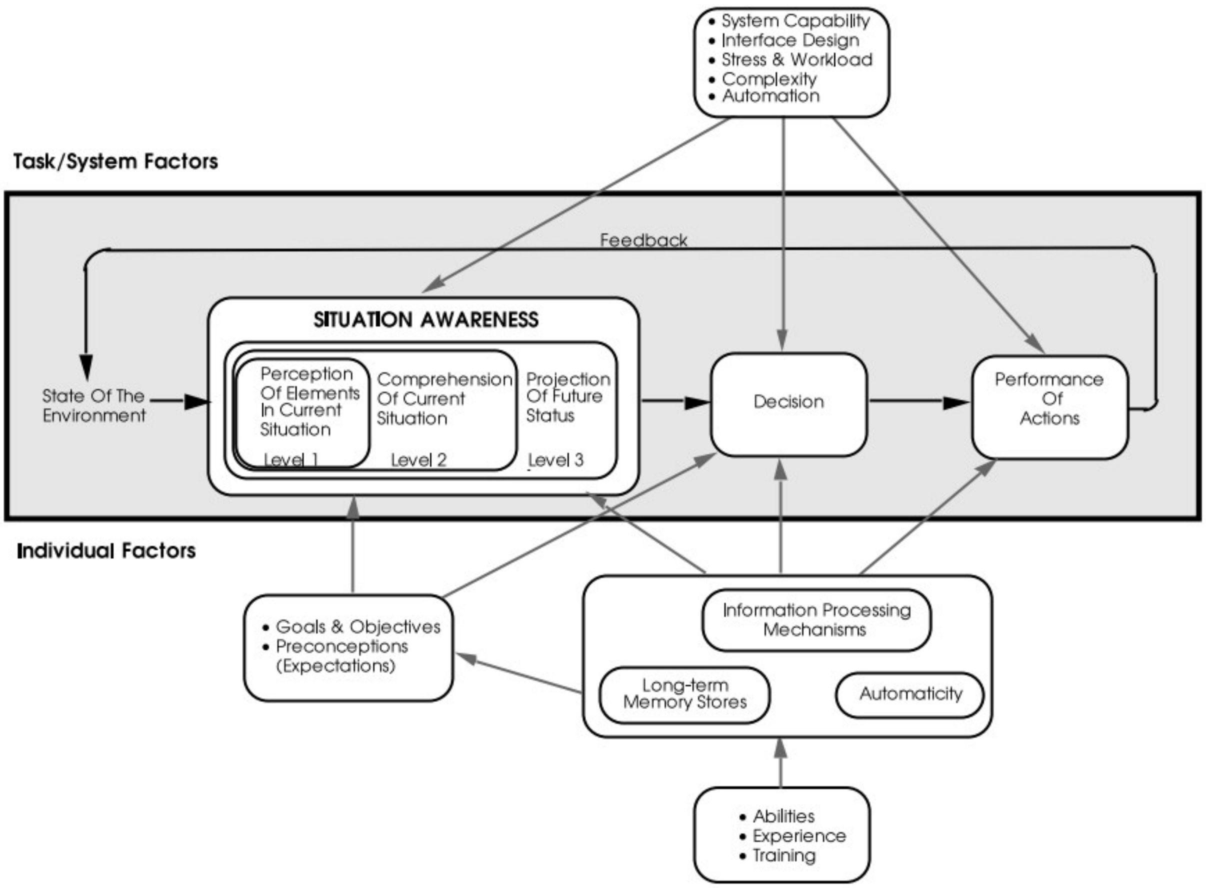


Figure 2-11: Situation Awareness Framework in Dynamic Decision Making. (Endsley, 1995)

In a similar manner, the Malleable Attentional Resources Theory (Young and Stanton, 2012) correlates task difficulty and workload with situational awareness, showing that when underload is present, situational awareness tend to decrease as well, as the overall cognitive resources pool is reduced. However, Endsley (1995), while recognizing that other cognitive constructs (like workload) can affect and interact with situational awareness, they also behave independently of each other. Hendy (1995) and Wickens (1995) also considered situational awareness and mental workload as clearly distinct concepts, while at the same time recognizing that they interact in a complex manner. This association stems from the observation that both concepts seem to be influenced by many of the same human factors (such as limited processing capacity and limited working memory) and external variables (such as task demand and automation). To depict that correlation between the two concepts, Wickens (2008) proposed three potential ways that workload and situational awareness interact with each other (Figure 2-12), each of which results in a different optimal point of performance. He used automation as the reason for the workload reaction.

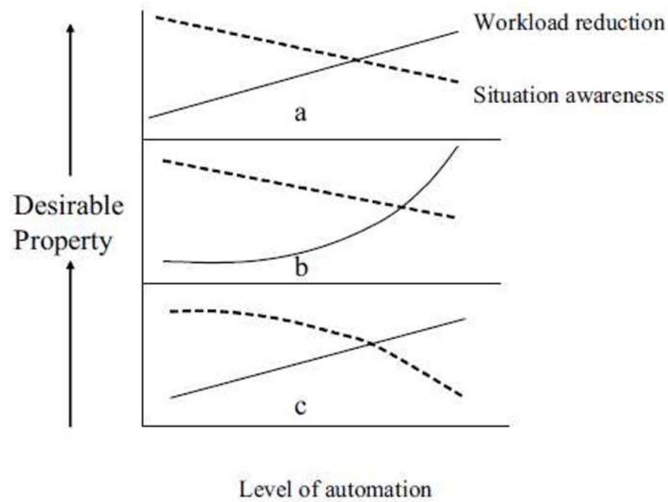


Figure 2-12: Hypothetical relationship forms between WL and SA. (Wickens, 2008)

Adapting Fuller's model, Hoogendoorn (2013) also proposed a framework that: i) associates mental workload with the difference between driver capability and task demand, iii) considers workload as a determinant of situational awareness, and iii) directly links compensation effects with task demand and performance effects with situational awareness (Figure 2-13).

In order to further distinguish the two concepts, and define their interactions, Wickens (2001), posited that "Mental Workload is fundamentally an energetic construct, in which the quantitative properties ("how much") are dominant over the qualitative properties ("what kind"), as the most important element. In contrast, situation awareness is fundamentally a cognitive concept, in which the critical issue is the operator's accuracy of ongoing understanding of the situation." In other words, workload should be determined by its amount and type, while situational awareness by its quality (scope, depth and accuracy). Both the level of workload and the quality of the SA are influenced by exogenous and endogenous factors, with the former being inherent in the situation (e.g. task demand and situation complexity), while the latter relies in a person's ability and skill (Vidulich, 2003).

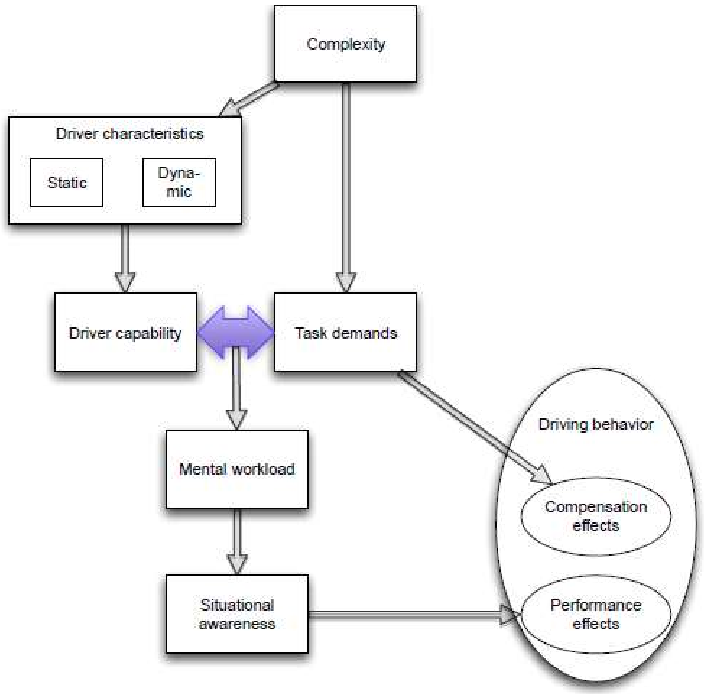


Figure 2-13: Theoretical framework of adaptation effects (Hoogendoorn 2013)

To the extent that "workload is caused by and SA supported by many of the same cognitive processes", Vidulich and Tsang (2012) argued that they are enabled by, and subject to, common limitations. Therefore, the following relationships were identified: the more demanding the task, the more complex the situation and the more effort is required to complete the task and assess the situation. Higher level of workload demands more attention for adequate task performance leaving less attentional resources for situation assessment. Thus, task performance and SA may compete for the limited attentional resource supply, and therefore a high level of workload could lead to poor SA. On the other hand, increased effort could result in improved SA, so high-level workload can be sometimes necessary to maintain a good SA. Thus, a high-level of workload could be associated with either a low or high degree of SA, while poor SA may or may not inflict higher workload levels. In the latter, the driver could simply not be allocating additional effort either by choice or by not being aware of their current lack of SA. In the former, awareness of one's lack of SA could start a course of action that increases the level of workload in the process of attaining and restoring SA. The ideal scenario is one where a high degree of SA would result in more efficient use of resources thus producing a low level of workload. In conclusion, mental workload and SA can both support each other as well as compete with each other, depending on the circumstances.

2.3 Human Factor Measurements

According to reviews of measurement methods regarding workload (Matthews et al., 2014; de Waard, 1996) and situational awareness (Nguyen et al, 2019; Salmon et al., 2006), the various metrics and assessment techniques can be evaluated according to the following criteria codified by O'Donnell and Eggemeier (1986) and Eggemeier et al. (1991):

- Sensitivity
- Diagnosticity
- Selectivity
- Reliability
- Intrusiveness
- Operator acceptance
- Implementation requirements

The first four properties determine the validity of each metric: sensitivity indicates the capacity of the process or instrument to detect changes in the measured cognitive concept; diagnosticity is the ability to distinguish between different aspects of the concept (such as the three SA levels), or identify specific causal sources (such as a specific resource demand or a specific task); selectivity ensures that the metric is only sensitive to changes of the chosen concept and not to other factors or constructs; finally, reliability reflects the consistency of the measure both within and across different tests. The remaining three properties are practical considerations, but the first two can also indirectly impact the validity of the measurement method by affecting performance: intrusiveness is an undesirable property that should be minimized, since it is the amount of disruption to the primary task performance caused by the measurement technique; operator acceptance regards the level of approval of the procedure displayed by the operators, and is related to intrusiveness, but also to their perception of validity and artificiality of the technique, all of which can potentially result in undesired, performance-altering behavior; last, implementation requirements are additional practical limitations of the measurement methodology, such as the need for specific equipment and software or training of the operators;

De Waard (1996) points that the above criteria exhibit a significant amount of interdependence. Diagnosticity is negatively correlated with sensitivity, since a highly diagnostic measurement is by definition sensitive only to distinct and limited changes of the measured concept. At the same time, selectivity is an essential prerequisite for diagnosticity, while considerably sensitive techniques generally tend to exhibit lower reliability, and intrusiveness can interfere with diagnosticity. Consequently, no measurement method can be ideal for all experimental purposes and the relative importance of the evaluation criteria should be adjusted accordingly.

Matthews et al. (2014) add that the American Educational Research Association, American Psychological Association, and National Council on Measurement in Education (AERA/APA/NCME; 1999) consider the need for additional criteria in order to ascertain test validity when cognitive concepts such as workload and SA are involved: individual differences in responses must be accounted for, there must be evidence of a consistent internal structure of the metric that corresponds to a theoretical construct, as well as evidence on correlations with other relevant variables that also assess the common latent construct (convergent evidence). However, this type of evidence is found very rarely in the workload and SA literature, and thus it is difficult to satisfy these additional criteria, but during measurement method and model selection they should also be taken into consideration.

2.3.1 Workload Measurement

Being an abstract cognitive concept primarily applicable to human-machine interaction, cognitive workload is difficult to be directly observed or measured (Matthews et al., 2014). Instead, multiple methods have been devised to deduce the level of workload, including self-reporting, psychophysiological measurements, and task performance (Hancock & Chignell, 1988; O'Donnell & Eggemeier, 1986; Vidulich & Tsang, 2012). Currently, self-reporting scales, such as the NASA Task Load Index have seen the most use, and are the most thoroughly studied and validated (NASA-TLX; Hart, 2006; Hart & Staveland, 1988; Stanton et al., 2005). Vidulich and Tsang (2012) acknowledge the pragmatic utility of self-report methods, but point to several limitations. First, responses may be susceptible to biases, such as social desirability. Second, self-reports cannot be used for continuous monitoring of workload. Third, they do not capture subconscious aspects of workload. These disadvantages can be addressed through the use of psychophysiological measurements, such as recordings of the electroencephalogram (EEG), electrocardiogram (ECG), eye tracking, and other response systems (Cain, 2007; Vidulich & Tsang, 2012; Wilson & Eggemeier, 1991) that can be obtained in real-world settings, typically without interfering with task performance (Stanton et al., 2005). However, both self-reporting and psychophysiological measurements of workload have limited practical use unless contextualized through their effect on driver performance. This effect is what task performance measures attempt to capture.

2.3.1.1 Self-report techniques

2.3.1.1.1 Rating Scale Mental Effort (RSME)

Developed by Zijlstra (1993), the RSME asks subjects to indicate how much effort they invested towards the completion of a task on a unidimensional scale of 0 to 150. This assessment is assisted by providing nine descriptive statements related to invested effort along with their location on the scale (Figure 2-14). RSME addresses only the amount of invested effort and not the more abstract aspects of mental workload, such as mental demand. Its simplicity and ease of implementation, however, qualify RSME as a good candidate for self-report workload measurement, that also shows good correlation with more complex methods (Sartang et al., 2017).

In traffic research, RSME has not seen much use. De Waard (1996) applied the method in three simulation studies where baseline ratings of effort of driving were compared with ratings of effort of driving while using a phone, a feedback system, or being under the influence of Triprolidine, respectively. In all cases, RSME was able to distinguish between the task-load situations and baseline, showing sensitivity to both task-related effort, in the first two cases, and to state-related effort, in the latter. On the other hand, the diagnosticity of RSME is low unless applied per task dimension, as proposed by Zijlstra and Meijman (1989). Selectivity is difficult to assess as the main other factor to which the scale could be sensitive, physical workload, is very restricted in driving. Reliability is high, as sensitivity to mental workload in the three different studies was high. Primary-task intrusion is low as long as the rating is asked after completion of the task. The implementation requirements are low since the measures are collected without the need for any equipment. Finally, no problems in operator acceptance have been reported, which suggests high operator acceptance (de Waard,1996).

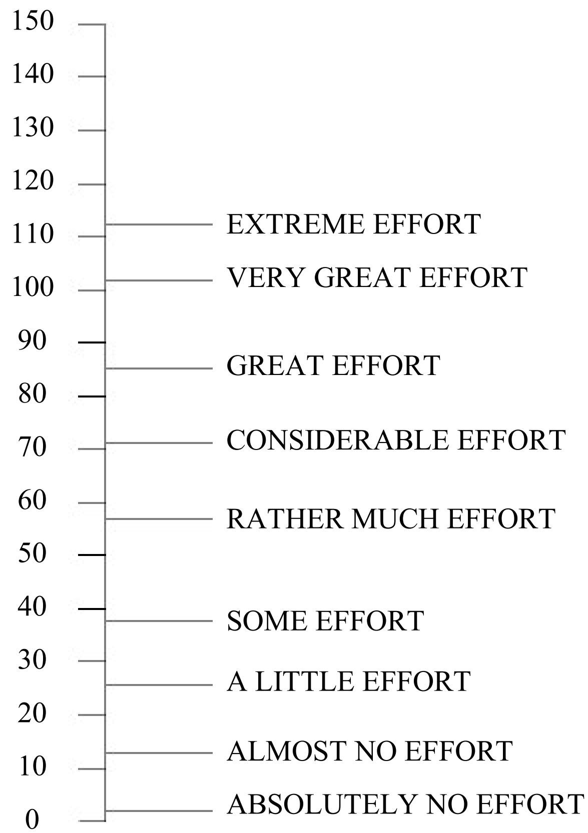


Figure 2-14: Rating Scale Mental Effort (RSME) graded and labeled axis (Zijlstra, 1993)

2.3.1.1.2 NASA Task Load Index (NASA-TLX)

Developed by Hart and Staveland (1988) at the Human Performance Group at NASA's Ames Research Center, this multidimensional workload rating technique is one of the most frequently used across a wide range of applications. The method uses six dimensions to assess mental workload: mental demand, physical demand, temporal demand, performance, effort, and frustration. The subjects evaluate each category on a twenty-step scale (Figure 2-15) and then an overall workload score is then derived based on a weighted average of the ratings on these six subscales (Rubio et al, 2004). The weights are obtained from fifteen paired comparisons between the six categories, in each of which the subject selects which workload dimension contributed more to their feeling of workload. The number of times a dimension is chosen as more relevant to the overall workload is the weighting of that dimension scale. The final workload score, ranging from 0 to 100, is obtained by multiplying that weight by the corresponding subscale score for all six categories, summing them, and dividing by 15. Like RSME, NASA-TLX is administered after task completion. In 1992, Hill et al. determined that NASA-TLX exhibited high sensitivity even outside its original application in aviation, while its multidimensional nature results in high diagnosticity as well. Stojmenova and Sodnik (2015) observed a strong influence by the last performed task to the reported ratings, and a heavy reliance on the subject's memory and recollection abilities, which is not conducive to high reliability. Like RSME, the method is non-intrusive, with no implementation requirements and high operator acceptance (Tokunaga et al., 2000). However, both methods cannot provide continuous data regarding workload variance across time.

2.3.1.1.3 Driver Activity Load Index (DALI)

Since NASA-TLX was developed for use in aviation applications, its six subscales are not specifically attuned to the dimensions that define the workload of the driving task (Pauzie & Pachiaudi, 1997; Pauzie, 2008a, Pauzie, 2008b). For example, the driving task is not considered physically demanding, thus the respective dimension had much less relevance in assessing a driver's workload. For this reason, Pauzie and Pachiaudi (1997) proposed a revision of the NASA-TLX method, where the six subscales were replaced with the following: effort of attention, visual demand, auditory demand, temporal demand, interference, and situational stress. The revised method was named the Driver Activity Load Index (DALI) and is otherwise identical in its implementation to NASA-TLX. However, although DALI was developed specifically for driving applications, NASA-TLX remains the most commonly used method for driver workload applications (Stojmenova & Sodnik, 2015).

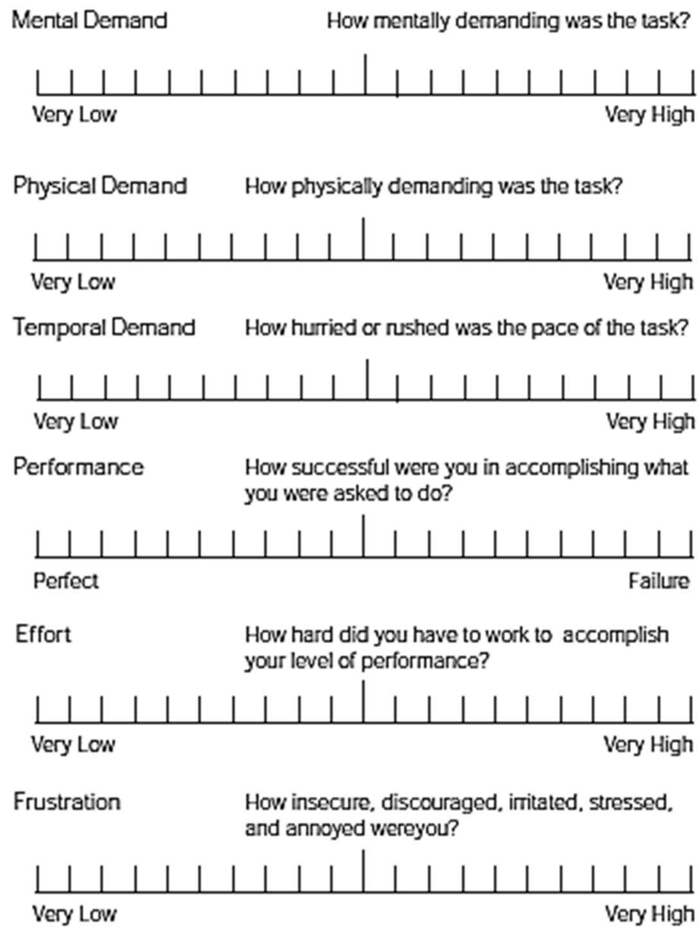


Figure 2-14: NASA Task Load Index (NASA-TLX) subscales (Hart & Staveland, 1988)

2.3.1.1.4 Subjective Workload Assessment Technique (SWAT)

Developed by Reid and Nygren (1988), SWAT uses three dimensions to assess workload: time load, mental effort load, and psychological stress load. Each category is rated on a three-level scale: (1) low, (2) medium, and (3) high, which are defined in Figure 2-15. The three ratings are eventually combined into a single, overall workload score between 0 and 100 through a scale development process. This involves the subjects being presented with 27 cards that correspond to all possible combinations of the three levels of each of the three dimensions, and tasked to rank them in an order that reflects their own perception of increasing workload. Scale development is a complex procedure involving conjoined measurement and scaling techniques which requires a significant amount of time (for the subjects) and resources (computer analysis) to implement (Rubio et al., 2004).

I. Time Load
1. Often have spare time. Interruptions or overlap among activities occur infrequently or not at all. 2. Occasionally have spare time. Interruptions or overlap among activities occur infrequently. 3. Almost never have spare time. Interruptions or overlap among activities are very frequent, or occur all the time.
II. Mental Effort Load
1. Very little conscious mental effort or concentration required. Activity is almost automatic, requiring little or no attention. 2. Moderate conscious mental effort or concentration required. Complexity of activity is moderately high due to uncertainly, unpredictability, or unfamiliarity. Considerable attention required. 3. Extensive mental effort and concentration are necessary. Very complex activity requiring total attention.
III. Psychological Stress Load
1. Little confusion, risk, frustration, or anxiety exists and can be easily accommodated. 2. Moderate stress due to confusion, frustration, or anxiety noticeably adds to workload. Significant compensation is required to maintain adequate performance. 3. High to very intense stress due to confusion, frustration, or anxiety. High extreme determination and self-control required.

Figure 2-15: Subjective Workload Assessment Technique (SWAT) rating scale definitions (Reid and Nygren, 1988)

The SWAT technique exhibits good sensitivity in a variety of tasks, (manual control tasks, display monitoring), but is less sensitive in low workload conditions. It has the advantage of being non-intrusive, but high levels of statistical expertise required to apply and interpret conjoint measurement for the scale development process, and is also less suitable for persons unfamiliar with running psychometric tests. It has also limited applications in driving applications (Janssen, Kuiken, & Verwey, 1994; Verwey & Veltman, 1995).

2.3.1.1.5 Instantaneous self-assessment (ISA)

ISA is a technique that was developed to provide immediate subjective ratings of workload demand during the performance of primary work tasks (Jordan & Brennen, 1992). ISA involves subjects self-rating their workload during a task (normally every two minutes) on a scale of 1 (low) to 5 (high). Typically, the assessment is performed through a color-coded keypad which flashes when a workload rating is required and the participant simply pushes the button that corresponds to their perceived workload rating. Girard et al. (2005) adapted the ISA method by adding a 5-level “relative” scale to the original 5-level “absolute” scale, based on the assumption that drivers can better gauge changes in their workload than evaluate their actual workload level. Using an auditory - instead of a visual - stimuli, to indicate when a rating is required, they first asked the subjects to assess their workload on the absolute ISA scale, and then on the relative scale, that takes the following values : (-2) “the load is much lower than the last assessment”, (-1) “the load is lower than the last assessment”, (0) “the load is the same as the last assessment”, (1) “the load is higher than the last assessment”, (+2) “the load is much higher than the last assessment”. In a 2016 driving simulation study, Jansen et al. used the original absolute ISA scale to assess driver workload, but further adapted the technique’s interface by not only using an auditory prompt but also evoking a verbal numeric response in order to “minimize interference with the visual/manual driving task”. In contrast to the previous self-report techniques, ISA produces a temporal workload profile of each driving task, thus allowing for higher diagnosticity. It is also a simple method, with few implementation requirements and high operator acceptance. The method is intrusive to the primary task, but not to a high degree, and several alternative protocols (auditory trigger, verbal reply) have been developed to further mitigate that disadvantage. However, despite its extensive use in many applications, only limited validation evidence for ISA has been available (Jordan & Brennen, 1992) as on-line self-reporting of cognitive states has often been shown to be less accurate. Thus, to ensure comprehensiveness, ISA has often been used in combination with other self-reporting techniques, like NASA-TLX.

2.3.1.1.6 Continuous Subjective Ratings (CSR).

Schießl (2009), while acknowledging the high sensitivity of previous self-report measurements, pointed that neither post-task (NASA-TLX, SWAT) nor discrete event-, time-, or spatial-triggered (ISA) workload assessment techniques are ideal for capturing the effects of dynamically changing load factors over time. Thus, a continuous subjective rating method (CSR) was developed, where subjects rated their experienced load during the drive using a 15-point rating scale (Figure 2-16), giving a new rating whenever they perceived a change of their subjective workload, instead of at specific trigger points. Both online (while driving) and offline (post-hoc, using video recordings of the drive) ratings were tested, where the first is more intrusive, while the second depends on memory skills. The results were comparable for both approaches, and Schießl (2009) concluded that the choice can depend the specific requirements and goals of each experiment. Finally, noticing biased clustering of the results, Teh et al. (2014)

suggested a simpler 10-point rating scale, representing low (1-3), medium (5-6), and high (8-10) workload, instead.

very little strenuous			little strenuous			moderate			strenuous			very strenuous		
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Figure 2-16: Continuous Subjective Ratings (CSR) scale (Schießl, 2009)

2.3.1.2 Psychophysiological measurements

2.3.1.2.1 Cardiac activity measures

The electrocardiogram (ECG) is a technique that monitors electrical activity in the heart in a continuous manner. Metrics such as heart rate (HR), heart rate variability (HRV), and Inter-Beat-Interval (IBI) can be used for workload assessment (de Waard, 1996). It is considered an intrusive technique since electrodes or contact points must be placed on the subjects as part of the ECG equipment and heart rate monitors. In the absence of physical effort and intense emotional factors (i.e. fear), comparing heart rate (HR) during task performance with a baseline, is a sufficiently accurate measure of workload. Thus, the method has high sensitivity, but low selectivity. Heart rate variability (HRV) is also a good measure of cognitive workload, with HRV decrease shown to be more sensitive to increases in workload than HR, though combining the two metrics provides increased diagnosticity. For example, Lee and Park (1990) showed that an increase in physical load decreased HRV and increased HR, while an increase in mental load reduced HRV with minimal effect on HR.

2.3.1.2.2 Brain activity measures

The background Electroencephalogram (EEG) detects changes in electrical potential arising from the activity in the brain cells. The EEG provides two main ways of determining workload: using raw EEG data synchronized to the driving task timeline and using event-related potentials (ERP) (Kincses et al., 2008). EEG is a highly intrusive technique, as the device uses electrodes attached to the scalp of the subject.

The raw EEG signal is typically partitioned into five frequency bands: delta (0.5-4Hz), theta (4-8Hz), alpha (8-13Hz), beta (13-40Hz), gamma (>40Hz). Studies have shown that the power of alpha band increases the more relaxed the driver state is, while an increase in the beta band power is correlated with tension and cognition (Kim et al., 2014). A decrease in alpha band activity with a simultaneous increase in theta band activity is usually associated with increased workload (de Waard, 1996, Kramer, 1991). The ability to combine the results of multiple frequency bands in order to distinguish between the different driver states and conditions, produces a method with high diagnosticity.

An event-related potential (ERP) is the electrophysiological brain response directly accompanying a specific sensory, cognitive, or motor event. ERP captures coordinated neural activity by analyzing electrical shifts temporally relate to a task. Several studies apply this analysis to detect changes in workload (Prinzel et al., 2001). More specifically, observed peaks of around 300ms (the P300 amplitude) correlate with cognitive load and processing (Light et al., 2010). However, because "ERP signals are relatively small and ensemble averaging across many stimuli is necessary for meaningful interpretation", the sensitivity of this method is not always sufficient (Vidulich & Tsang, 2012).

2.3.1.2.3 Ocular activity measures

A variety of measures related to eye activity had been used as estimates of the cognitive workload of drivers, including blinks, fixations, and pupil dilation (Marquart & de Winter, 2015).

Blink rate analysis performed by Kramer (1991) initially showed mixed results with regards to workload. Recarte et al. (2008) settled the apparent discrepancies by observing that "visual and mental workload produce opposite effects: blink inhibition for higher visual demand and increased blink rate for higher mental workload", which means that the method has low selectivity, with the results being highly affected by visually demanding tasks. Blink rate changes have also been observed in studies regarding highly automated driving. Specifically, it was found that blink rate increases during highly automated driving in comparison to manual driving, despite the assumed decrease in mental workload that is derived from automation (Merat et al., 2012). Blink duration was also studied by Kramer (1991), who found that increasing task demand resulted in shorter blink durations.

Fixation duration has been the subject of several workload studies. Underwood, Crundall, and Chapman (2011) reviewed several studies that correlated eye fixation duration with high mental load, in attentionally demanding situations.

Pupillometry, the measurement of pupil diameter, is also a promising method of assessing the cognitive workload of the driver. Pupil dilation is associated with changes in workload levels through what is called task-evoked pupillary responses (TEPR) (Strayer et al., 2013, Devos et al., 2017). Several studies have shown that cognitive workload and pupil diameter tend to increase together (Kahneman et al., 1969; Klingner, 2010; Szulewski et al., 2014). However, pupil diameter is also affected by other factors, with the most important being the presence or absence of light. For this reason, the Index of Cognitive Activity (ICA) a was developed (Marshall, 2002) in order to measure pupil changes that are caused by mental effort, while factoring out the light reflexes. This is achieved by distinguishing between the two sets of muscles that control the pupil: the circular set which reacts to light, and the radial set that only reacts to mental effort. The ICA has been incorporated into most modern eye-tracking devices, allowing for real-time automatic and non-disruptive cognitive workload assessment.

2.3.1.3 Performance measures

2.3.1.3.1 Primary Task Performance

De Waard (1996) showed that several performance aspects of the primary task (driving), including speed control, car-following ability and lane-keeping ability, were related to workload levels. Thus, performance measures such as speed instability, distance headway instability, and the standard deviation of the lateral position (SDLP) or the standard deviation of the steering wheel movements (SDSTW) can be a useful measure of task workload. Of the above, the two lateral deviation measures (SDLP, SDSTW) showed higher sensitivity and reliability (Brookhuis, Louwerens, & Hanlon, 1985; Brookhuis et al., 1991) in assessing driver workload. However, studies summarized by de Waard (1996) produced conflicting results between the lateral deviation metrics and workload (presumably due to unknown interfering factors), demonstrating that these measures exhibit low selectivity. The diagnosticity of these performance measures is also low. On the other hand, though, they are non-intrusive and with high operator acceptance.

2.3.1.3.2 Secondary Task Performance.

These methods assess workload by requiring the subjects to react to a visual or sensory stimulus and measuring their performance in that secondary task under the assumption that high cognitive workload will result in less mental resources being allocated towards the secondary task, reducing the performance. Common measures include the peripheral detection task (PDT) and the detection response task (DRT). The PDT procedure measures the detection ability and response time of the subjects to multiple stimuli (typically visual) presented during the driving task (Patten et al., 2006). The response is usually signified by pressing a button on the steering wheel after a stimulus has been detected. The DRT evolved from the PDT, incorporating controls to eliminate sources of unwanted variability in the DRT metrics and conflicts between the visual demands of the primary (driving) and secondary task (Ranney et al., 2014). Thus, PDT and DRT differing primarily in the method of target presentation, with the most prominent version between that of the tactile DRT (TDRT) which uses an electrical vibrator taped on the subject's shoulder to deliver the stimulus. In this way, the TDRT also eliminates all potential visual conflicts. The DRT assesses performance by measuring response time, hit rate, and miss rate (ISO 17488, 2016). Manjunatha and Elefteriadou (2018) proposed a single performance assessment measure that combines both miss rates and reaction times. Reaction "cut-off" times were assumed (2 seconds for the lower cut-off point and 3 seconds for the higher cut-off point), and responses higher than 3 seconds were considered "complete misses" (maximum workload), less than 2 seconds were "complete hits" (minimum workload), while the workload for responses between 2 and 3 seconds was assumed to be linearly increasing with the reaction time (Figure 2-17).

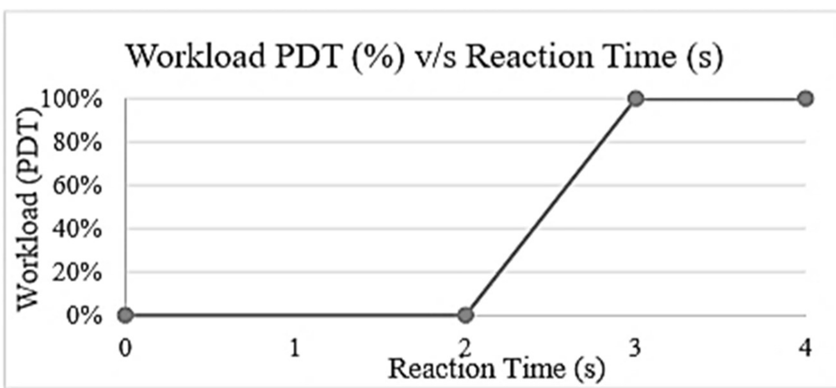


Figure 2-17: Proposed relationship between Reaction Time (RT) and Workload (PDT) (Manjunatha & Elefteriadou, 2018)

2.3.1.4 Summary

Table 2-1 comparatively summarizes the characteristics, as well as the advantages and disadvantages of the workload measurement techniques presented in this chapter.

Table 2-1. A summary and comparison of workload measurement techniques

Method	Type of Method	Equipment	Advantages	Disadvantages
RSME (Zijlstra, 1993)	Self-report (post-hoc)	Pen & Paper	• Simplicity (unidimensional) • Ease of Implementation • High Sensitivity • High Reliability • Low Intrusiveness	• Low Diagnosticity (unidimensional) • Addresses only invested effort • Reliance on Memory • No continuous data across time
NASA-TLX (Hart & Staveland, 1988)	Self-report (post-hoc)	Pen & Paper	• High Diagnosticity (multidimensional) • High Sensitivity • High Selectivity • Low Intrusiveness	• More Complex Implementation • Reliance on Memory • Average Reliability • No continuous data across time
DALI (Pauzie, 1997)	Self-report (post-hoc)	Pen & Paper	• Developed Specifically for driving applications (NASA-TLX variant)	• Not as validated as NASA-TLX
SWAT (Reid & Nygren, 1988)	Self-report (post-hoc)	Pen & Paper, Ranking Cards, Computer Analysis	• High Diagnosticity (multidimensional) • High Sensitivity • High Selectivity • Low Intrusiveness	• Complex Implementation • High Requirements (Time and Resources) • Reliance on Memory • No continuous data across time
ISA (Jordan & Brennen, 1992)	Self-report (on-line)	Stimuli and Input Devices	• Simplicity (unidimensional) • Ease of Implementation • High Temporal Diagnosticity	• Mild Intrusiveness • Low Reliability
CSR (Schießl, 2009)	Self-report (post-hoc or on-line)	Recording Device	• Simplicity (unidimensional) • Ease of Implementation • High Temporal Diagnosticity	• Reliance on Memory (if post-hoc) • High Intrusiveness (if on-line) • Low Reliability
ECG (e.g., Lee & Park, 1990)	Psychophysiological	Electrocardiogram Equipment	• High Sensitivity • Continuous Measurements	• High Intrusiveness • Low Selectivity
EEG (e.g., Kramer, 1991)	Psychophysiological	Electroencephalogram Equipment	• High Diagnosticity • Continuous Measurements	• High Intrusiveness • Average Sensitivity
ICA (Marshall, 2002)	Psychophysiological	Eye-Tracking Equipment and Software	• Low Intrusiveness • Automatic Results • Continuous Measurements	• Low Diagnosticity • Low Selectivity
SDLP/SDSTW (e.g., Brookhuis et al., 1985)	Primary Performance	Trajectory tracking / Steering-wheel tracking	• High Sensitivity • High Reliability • Low Intrusiveness • Continuous Measurements	• Low Diagnosticity • Low Selectivity
PDT/DRT (e.g., Patten et al., 2006)	Secondary Performance	Stimuli and Input Devices	• High Diagnosticity • Continuous Measurements	• High Intrusiveness • Low Selectivity

2.3.2 SA Measurement

Measurement of actual SA levels is troublesome because SA is an inferred cognitive state that only indirectly relates to decision making and performance. In addition, the lack of a universally accepted model of SA results in measurement techniques that capture different aspects of the concept. Some deal with the processes used in achieving and maintaining SA, while others capture SA as the end result of these processes (Stanton et al., 2005). Therefore, there are a number of different SA assessment approaches available to researchers. 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.

2.3.2.1 Freeze-probe techniques

Applicable only to simulation experiments, freeze-probe techniques involve randomly pausing the task and evaluating the subject's perception of the current situation via queries. The main advantage of the freeze-probe techniques is that they provide a simple and direct way to quantitatively assess the subject's overall SA (Salmon et al., 2006). They are also free from issues associated with post-hoc data collection, such as performance bias or insufficient recall (Stanton et al., 2005) However, they are also highly intrusive on the primary task performance, as they interrupt the natural flow of the task. Sensitivity is low, and the importance of all queried topics is assumed to be equal, while the subject's memory capabilities are introduced as an additional complicating factor. Finally, freeze-probe methods cannot be applied in the field or in real time, but require expensive equipment under a simulated environment that has pausing capabilities (Salmon et al., 2006), and significant preparation is also require for the analysis (Stanton et al., 2005). The Situational Awareness Global Assessment Technique (SAGAT) developed by Endsley (2000) is the most common freeze-probe technique. The SAGAT queries are designed to assess all three levels of situational awareness (perception, comprehension, and projection). The validity of the method has been confirmed by multiple studies.

2.3.2.2 Real-time probe techniques

These methods are similar to freeze-probe techniques but the subjects are queried "on-line", without freezing the simulation. Both the accuracy of the answer and the response latency are considered for assessing the subject's situational awareness. The primary advantage of the real-time probe techniques is that they retain the objectivity of freeze-probe methods but reduce the level of intrusion on task performance by avoiding task freezes. However, real-time probe queries may also function as distractions, drawing the attention of the participant, and thus introducing a different kind of bias, so the intrusiveness of these techniques is not minimal. The situation present assessment method (SPAM) is the most common real-time probe technique and was developed by Durso et al. (1998) to assess the situational awareness of air traffic controller. Unlike SAGAT, SPAM measures the ability of the subject to locate information in the environment as an indicator of SA, rather than the recall of specific information regarding the current situation. SPAM queries are typically administered and answered verbally. SPAM is quick and easy to use, requiring minimal training, and its real-time nature allows it to be used even in non-simulated applications.

2.3.2.3 Self-rating techniques

Similar to self-reporting workload measurements, self-rating techniques involve questionnaires that the subjects reply to after the completion of the task. The Situation Awareness Rating Technique (SART) is a multidimensional scaling technique developed by Taylor (1990) that consists of ten subscales each rated from one (low) to seven (high). The subscales include: instability of situation, variability of situation, complexity of the situation, arousal, spare mental capacity, concentration, division of attention, information quantity, information quality, and familiarity (Figure 2-18).

These ten subscales are categorized in three domains: attentional demand (D), attentional supply (S), and understanding (U). A composite SART score is calculated using the following formula: SA = U – (D – S), where: U is summed understanding, D is summed demand, and S is summed supply (Selcon & Taylor, 1989). The quicker and simpler method, 3-D SART, uses a 100-point scale from 0 (low) to 100 (high), directly for each of the three domains (demand on attentional resources, supply of attentional resources and understanding of the situation). Then the overall SART score is calculated similar to above: SA = Understanding – (Demand – Supply).

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 straightforward (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 within the situation? Are there a 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 focussed on only one (Low)?

1 2 3 4 5 6 7

Division of Attention
How much is your attention divided in the situation? Are you concentrating on many aspects of the situation (High) or focussed 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

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

Figure 2-18: SART questionnaire with rating subscales (Taylor, 1990)

Domains	Construct	Definition
Attentional demand	Instability of situation	Likeliness of situation to change suddenly
	Variability of situation	Number of variables that require attention
	Complexity of situation	Degree of complication of situation
Attentional supply	Arousal	Degree that one is ready for activity
	Spare mental capacity	Amount of mental ability available for new variables
	Concentration	Degree that one's thoughts are brought to bear on the situation
	Division of attention	Amount of division of attention in the situation
Understanding	Information quantity	Amount of knowledge received and understood
	Information quality	Degree of goodness of value of knowledge communicated
	Familiarity	Degree of acquaintance with situation experience

Figure 2-19: SART subscales, their definitions and categorical domains (Selcon & Taylor, 1989)

2.3.2.4 Process Indices

Process indices can also be used to measure SA. Process indices involve recording the processes that the participants use in order to develop SA during the task under analysis. One example of using process indices to assess SA is the measurement of participant eye movements during task performance (Smolensky, 1993). Eye-tracking measures such as gaze overlays, fixation patterns, and saccades can also be used for assessing situational awareness. For example, fixations can be used to determine how the participant's attention was allocated during the task under analysis. There are a number of disadvantages associated with the use of an eye-tracker device, including their indirect nature (how do we know the participant perceived what they looked at?), an inability to be used outside of laboratory settings, the temperamental nature of the equipment, and also the problem of the 'look but do not see' phenomenon, whereby participants may fixate upon an environmental element but do not actually perceive it. Concurrent verbal protocol analysis (VPA) involves creating a written transcript of operator behavior as they perform the task under analysis. The transcript is based upon the operator 'thinking aloud' as he conducts the task under analysis. VPA is used as a means of gaining an insight into the cognitive aspects of complex behaviors and is often used to indicate operator SA during task performance (Salmon et al., 2006).

2.3.2.4 Summary

Table 2-2 comparatively summarizes the characteristics, as well as the advantages and disadvantages of the situational awareness measurement techniques presented in this chapter.

Table 2-2. A summary and comparison of situational awareness measurement techniques

Method	**Type of Method**	**Equipment**	**Advantages**	**Disadvantages**
SAGAT (Endsley, 2000)	Freeze Probe	Driving Simulator with pause capabilities, Probe queries prepared by Subject Matter Experts (SMEs)	• Simplicity • Direct, and objective assessment • Designed to assess all 3 levels of SA • No post-hoc data collection problems (e.g., performance bias, poor recall)	• High Intrusiveness (primary task interruption) • Questionable Validity (is SA or memory assessed) • Expensive Equipment Requirements • Cannot be applied 'in-the-field'
SPAM (Durso et al., 1998)	Real-time Probe	Dynamic real-time probe queries generated administered by Subject Matter Experts (SMEs), (Optional) Driving Simulator	• Simplicity • On-line and objective assessment • Decreased intrusiveness compared to freeze probe methods (no primary task freeze/interruption) • No information recall (memory) required • Can by applied 'in-the-field'	• Average Intrusiveness (distraction by queries) • Potentially Biased (queries may direct subjects to relevant SA information) • Real-time probes generation places a great burden upon Subject Matter Experts (SMEs), and is difficult in dynamic environments
SART (Taylor, 1990)	Self-rating (post-hoc)	Pen & Paper	• Low intrusiveness (post-hoc) • Ease of implementation (easy, quick, low cost, requires little training)	• Low Sensitivity/ Subjective rating (i.e. subjects may not be able to precisely rate their poor SA as they may not realize they had inadequate SA in the first place • Post-hoc data collection problems (e.g. correlation of SA with performance, poor recall
Eye Fixation Patterns (e.g. Smolensky, 1993)	Process Indices	Eye-Tracking Equipment and Software	• Low intrusiveness • Can be used to determine which situational elements the subject fixates upon during task performance	• Indirect assessment (susceptible to the 'look but do not see' phenomenon when subjects may fixate upon an environmental element but do not accurately perceive it) • Concurrent Verbal protocols analysis (VPA) may be required, increasing intrusiveness

2.4 Vehicle Automation

2.4.1 Automation Classification

The driving task is highly complex and involves "different levels of control with different levels of temporal granularity" (Michon, 1985). Lu et al. (2016) divided it in three primary sub-tasks: lateral control, longitudinal control, and monitoring. That distinction is also used in the definitions that classify vehicle automation levels independently developed by the German Federal Highway Research Institute (BASt; Gasser & Westhoff, 2012), the Society of Automotive Engineers (SAE, 2014), and the United States National Highway Traffic Safety Administration (NHTSA, 2013). Even though the BASt, SAE and NHTSA definitions differ from each other, all three organizations use similar criteria based on how the three essential sub-tasks are distributed between the driver and the automated system.

2.4.1.1 NHTSA Definitions of Vehicle Automation Levels

The definitions below were developed by the United States National Highway Traffic Safety Administration and cover the complete range of vehicle automation, from vehicles that do not have any of their control systems automated (level 0) through fully automated vehicles (level 4) (NHTSA, 2013).

- **Level 0 – No-Automation.** The driver is in complete and sole control of the primary vehicle controls (brake, steering, throttle, and motive power) at all times, and is solely responsible for monitoring the roadway and for safe operation of all vehicle controls. Vehicles that have certain driver support/convenience systems but do not have control authority over steering, braking, or throttle would still be considered "level 0" vehicles. Examples include systems that provide only warnings (e.g., forward collision warning, lane departure warning, blind spot monitoring) as well as systems providing automated secondary controls such as wipers, headlights, turn signals, hazard lights, etc.
- **Level 1 – Function-specific Automation.** Automation at this level involves one or more specific control functions; if multiple functions are automated, they operate independently from each other. The driver has overall control, and is solely responsible for safe operation, but can choose to cede limited authority over a primary control (as in adaptive cruise control), the vehicle can automatically assume limited authority over a primary control (as

in electronic stability control), or the automated system can provide added control to aid the driver in certain normal driving or crash-imminent situations (e.g., dynamic brake support in emergencies). The vehicle may have multiple capabilities combining individual driver support and crash avoidance technologies, but it does not replace driver vigilance and does not assume driving responsibility from the driver. The vehicle's automated system may assist or augment the driver in operating one of the primary controls – either steering or braking/throttle controls (but not both). As a result, there is no combination of vehicle control systems working in unison that enables the driver to be disengaged from physically operating the vehicle by having his or her hands off the steering wheel and feet off the pedals at the same time. Examples of function specific automation systems include: cruise control, automatic braking, and lane keeping.

- **Level 2 - Combined Function Automation.** This level involves automation of at least two primary control functions designed to work in unison to relieve the driver of control of those functions. Vehicles at this level of automation can utilize shared authority when the driver cedes active primary control in certain limited driving situations. The driver is still responsible for monitoring the roadway and safe operation and is expected to be available for control at all times and on short notice. The system can relinquish control with no advance warning and the driver must be ready to control the vehicle safely. An example of combined functions enabling a Level 2 system is adaptive cruise control in combination with lane centering. The major distinction between level 1 and level 2 is that, at level 2 in the specific operating conditions for which the system is designed, an automated operating mode is enabled such that the driver is disengaged from physically operating the vehicle by having his or her hands off the steering wheel and foot off pedal at the same time.
- **Level 3 - Limited Self-Driving Automation.** Vehicles at this level of automation enable the driver to cede full control of all safety-critical functions under certain traffic or environmental conditions and in those conditions to rely heavily on the vehicle to monitor for changes in those conditions requiring transition back to driver control. The driver is expected to be available for occasional control, but with sufficiently comfortable transition time. The vehicle is designed to ensure safe operation during the automated driving mode. An example would be an automated or self-driving car that can determine when the system is no longer able to support automation, such as from an oncoming construction area, and

then signals to the driver to reengage in the driving task, providing the driver with an appropriate amount of transition time to safely regain manual control. The major distinction between level 2 and level 3 is that at level 3, the vehicle is designed so that the driver is not expected to constantly monitor the roadway while driving.

- **Level 4 - Full Self-Driving Automation.** The vehicle is designed to perform all safety-critical driving functions and monitor roadway conditions for an entire trip. Such a design anticipates that the driver will provide destination or navigation input, but is not expected to be available for control at any time during the trip. This includes both occupied and unoccupied vehicles. By design, safe operation rests solely on the automated vehicle system.

2.4.1.2 BASt Definitions of Vehicle Automation Levels

The German Federal Highway Research Institute (BASt; Gasser & Westhoff, 2012) defines the following five vehicle automation categories, from lower to higher degree of automation:

- **Driver Only.** Human driver executes manual driving task.
- **Driver Assisted.** The driver permanently controls either longitudinal or lateral control. The other task can be automated to a certain extent by the assistance system.
- **Partially Automated.** The system takes over longitudinal and lateral control, the driver shall permanently monitor the system and shall be prepared to take over control at any time.
- **Highly Automated.** The system takes over longitudinal and lateral control; the driver is no longer required to permanently monitor the system. In case of a take-over request, the driver must take-over control with a certain time buffer.
- **Fully Automated.** The system takes over longitudinal and lateral control completely and permanently. In case of a take-over request that is not followed, the system will return to the minimal risk condition by itself.

Table 2-3 describes each automation level in more detail, according to the tasks assigned to the driver or the automated systems, and also provides examples of said systems.

Table 2-3. Categorization and description of automated driving functions (BASt; Gasser & Westhoff, 2012).

Nomenclature	Description of automation level according to driver and system task distribution	Exemplary Systems
Driver Only	The driver continuously (throughout the complete trip) accomplishes longitudinal (accelerating /braking) and lateral (steering) control.	No (driver-assistance) system active that intervenes into longitudinal and lateral control
Assisted	The driver continuously accomplishes either lateral or longitudinal control. The other/ remaining task is accomplished by the automating system to a certain level only. • The driver must permanently monitor the system • The driver must at any time be prepared to take over complete control of the vehicle	Adaptive Cruise Control: • Longitudinal control with adaptive distance and speed control Parking assistance: • Lateral control (automatic steering into a parking space)
Partially Automated	The system takes over lateral and longitudinal control (for a certain amount of time and/ or in specific situations). • The driver must permanently monitor the system • The driver must at any time be prepared to take over complete control of the vehicle	Motorway assistant: • Automatic longitudinal and lateral control • On motorways up to an upper speed limit • The driver must permanently monitor and take over immediately in case of takeover request by the system
Highly Automated	The system takes over lateral and longitudinal control for a certain amount of time in specific situations. • The driver needs not permanently monitor the system as long as it is active • If necessary, the driver is requested to take over control by the system with a certain time buffer. • All system limits are detected by the system. The system is not capable of re-establishing the minimal risk condition from every initial state	Motorway chauffeur: • Automatic longitudinal and lateral control • On motorways up to an upper speed limit • The driver need not permanently monitor • In case of a take-over request, the driver must react with a certain time buffer
Fully Automated	The system takes over lateral and longitudinal control completely within the individual specification of the application. • The driver need not monitor the system • Before the specified limits of the application are reached, the system requests the driver to take over with sufficient time buffer • In absence of a takeover, the system will return to the minimal risk condition by itself • All system limits are detected by the system, the system is capable to return to the minimum risk condition in all situations	Motorway pilot: • Automatic longitudinal and lateral control • On motorways up to an upper speed limit • The driver need not monitor • In case the driver does not react to a take-over request, the system will brake down to standstill

2.4.1.3 SAE Definitions of Vehicle Automation Levels

The Society of Automotive Engineers (SAE, 2014) defines six levels (0 to 5) of driving automation, covering the full spectrum from no automation to full automation, and grouped into two categories:

- Human driver monitors driving environment:
  - Level 0 - No Automation
  - Level 1 - Driver Assistance
  - Level 2 - Partial Automation
- Automated driving system monitors driving environment:
  - Level 3 - Conditional Automation
  - Level 4 - High Automation
  - Level 5 - Full Automation

Tables 2-4 and 2-5 provide descriptions of the six levels with regards to the role (if any) of a human driver and the dynamic driving task. These roles describe technical capability and not legality. Levels of driving automation are descriptive rather than normative and technical rather than legal. Elements indicate minimum rather than maximum capabilities for each level.

Table 2-4. Description of automation levels where the human driver monitors driving environment (SAE, 2014).

Automation Level	Role of Human Driver	Role of System
Level 0 - No Automation	• Monitors driving environment • Executes the dynamic driving task (steering, accelerating, braking)	• No active automation (but may provide warnings)
Level 1 - Driver Assistance	• Monitors driving environment • Executes either longitudinal (accelerating, braking) or lateral (steering) dynamic driving task • Constantly supervises dynamic driving task executed by driver assistance system • Determines when activation or deactivation of driver assistance system is appropriate, except for systems that automatically intervene in an emergency • Takes over immediately when required	• Executes portions of the dynamic driving task not executed by the human driver (either longitudinal or lateral) when activated • Can deactivate immediately with request for immediate takeover by the human driver
Level 2 - Partial Automation	• Monitors driving environment • Constantly supervises dynamic driving task executed by partial automation system • Determines when activation or deactivation of partial automation system is appropriate, except for systems that automatically intervene in an emergency • Takes over immediately when required	• Executes longitudinal (accelerating, braking) and lateral (steering) dynamic driving task when activated • Can deactivate immediately with request for immediate takeover by the human driver

Table 2-5. Description of automation levels where the automated driving system monitors driving environment (SAE, 2014).

Automation Level	Role of Human Driver	Role of System
Level 3 - Conditional Automation	• Determines when activation of automated driving system is appropriate • Takes over upon request within lead time • May request deactivation of automated driving system	• Monitors driving environment when activated • Permits activation only under conditions (use cases) for which it was designed • Executes longitudinal (accelerating, braking) and lateral (steering) portions of the dynamic driving task when activated • Deactivates only after requesting driver takeover with a sufficient lead time • May, under certain, limited circumstances, transition to minimal risk condition if human driver does not take over • May momentarily delay deactivation when immediate human takeover could compromise safety
Level 4 - High Automation	• Determines when activation of automated driving system is appropriate • Takes over within lead time, if requested • May request deactivation of automated driving system • Some applications in this category may not entail a human driver.	• Monitors driving environment when activated • Permits activation only under conditions (use cases) for which it was designed • Executes longitudinal (accelerating, braking) and lateral (steering) portions of the dynamic driving task when activated • Initiates deactivation when design conditions are no longer met • Deactivates only after human driver takes over • Transitions to minimal risk condition if human driver does not take over • May momentarily delay deactivation when immediate human takeover could compromise safety
Level 5 - Full Automation	• May activate automated driving system • May request deactivation of automated driving system • This category may not entail a human driver.	• Monitors driving environment when activated • Executes longitudinal (accelerating, braking) and lateral (steering) portions of the dynamic driving task when activated • Deactivates only after human driver takes over or vehicle reaches its destination • Transitions to minimal risk condition as necessary if failure in the automated driving system occurs • May momentarily delay deactivation when immediate human driver takeover could compromise safety

Table 2-6 summarizes the previous descriptions, provides a breakdown of each driving task alongside whether it is assigned to a human driver or to the automated system, and compares the SAE definitions with those of BASt and NHTSA, while Table 2-7 presents the approximate alignment among SAE, BASt and NHTSA more explicitly.

Table 2-6. SAE automation level definitions, task breakdown, and comparison to BASt and NHTSA automation levels (SAE, 2014).

SAE level	SAE name	SAE narrative definition	Execution of steering and acceleration/ deceleration	Monitoring of driving environment	Fallback performance of *dynamic driving task*	System capability (*driving modes*)	BASt level	NHTSA level
***Human driver* monitors the driving environment**								
0	**No Automation**	the full-time performance by the *human driver* of all aspects of the *dynamic driving task*, even when enhanced by warning or intervention systems	Human driver	Human driver	Human driver	n/a	Driver only	0
1	**Driver Assistance**	the *driving mode*-specific execution by a driver assistance system of either steering or acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	Human driver and system	Human driver	Human driver	Some driving modes	Assisted	1
2	**Partial Automation**	the *driving mode*-specific execution by one or more driver assistance systems of both steering and acceleration/deceleration using information about the driving environment and with the expectation that the *human driver* perform all remaining aspects of the *dynamic driving task*	**System**	Human driver	Human driver	Some driving modes	Partially automated	2
***Automated driving system* ("system") monitors the driving environment**								
3	**Conditional Automation**	the *driving mode*-specific performance by an *automated driving system* of all aspects of the *dynamic driving task* with the expectation that the *human driver* will respond appropriately to a *request to intervene*	System	**System**	Human driver	Some driving modes	Highly automated	3
4	**High Automation**	the *driving mode*-specific performance by an *automated driving system* of all aspects of the *dynamic driving task*, even if a *human driver* does not respond appropriately to a *request to intervene*	System	System	**System**	Some driving modes	Fully automated	3/4
5	**Full Automation**	the full-time performance by an *automated driving system* of all aspects of the *dynamic driving task* under all roadway and environmental conditions that can be managed by a *human driver*	System	System	System	**All driving modes**		

Table 2-7. Approximate alignment among SAE, BASt, and NHTSA levels (SAE, 2014).

SAE	No Automation (Level 0)	Driver Assistance (Level 1)	Partial Automation (Level 2)	Conditional Automation (Level 3)	High Automation (Level 4)	Full Automation (Level 5)
BASt	Driver Only	Assisted	Partly Automated	Highly Automated	Fully Automated	[not addressed]
NHTSA	No Automation (Level 0)	Functions Specific Automation (Level 1)	Combined Function Automation (Level 2)	Limited Self-Driving Automation (Level 3)	Full Self-Driving Automation (Level 4)	

In considering the differences between the SAE and NHTSA levels, it is helpful to bear in mind that NHTSA's level 4 encompasses SAE levels 4-5 in a manner that is not as simple as BASt's decision to omit "full" automation. For example, certain automated driving systems that are geographically or environmentally limited are included in NHTSA's level 4 rating because they do not require the presence of a human driver, while SAE level 5 excludes such systems, because they are not capable of delivering the same degree of on-road mobility as a conventional vehicle driven by a human (SAE, 2014).

2.4.2 Human Factors and Automated Driving

The interaction between the human driver and automated vehicles has been the subject of multiple studies (e.g. Nilsson, 1995). Originally, automation technologies were expected to provide significant benefits, such as the reduction of driver workload (Boer & Hoedemaeker, 1998) and safety improvements through minimizing driving errors associated with individual driving styles (Goodrich & Boer, 2003). However, further studies also demonstrated that high levels of vehicle automation can result in unwanted behavioral changes in drivers (Jamson et al., 2013), such as reduced situation awareness (de Winter et al., 2014), mental underload (Young & Stanton, 2002; Stapel et al., 2017) and eventually impaired performance (Engström et al., 2017). These behavioral adaptations can be mainly attributed to automation systems altering driver's role from an active operator to a more passive observer and system supervisor (Merat et al., 2012; Martens & van den Beukel, 2013) in an increasing function correlated to the levels of automation. This can give rise to the "out-of-the-loop performance problem" (Endsley & Kiris, 1995) which in turn results into overreliance in automation, erratic mental workload, skill degradation, reduced situation awareness and increased reaction times.

2.4.2.1 Workload and Automation

A meta-analysis of studies that investigated the effects of adaptive cruise control (ACC) and highly automated driving (HAD) systems on driver workload was performed by de Winter et al. (2014). Studies that relied on post-hoc self-reporting workload levels showed that ACC resulted in a relatively small workload reduction (about 9% on average), while HAD resulted in a much larger reduction (45%), compared to manual driving. On-line secondary-task studies showed a 12% increase in secondary tasks performed under ACC and a 150% increase under HAD, again hinting a significant workload reduction compared to non-automated driving. Physiological measure studies also generally found lower mean heart rates for ACC and HAD, but the results were not as consistent as before. When workload was measured via the drivers' reaction to visual stimuli (PDT), ACC showed quicker reactions than manual drivers, but for HAD the reaction times were slower, potentially capturing the effects of mental underload. Similar results were obtained from gaze-focusing eye-tracking techniques where ACC and manual driving were statistically similar, but HAD drivers where much less likely (by 33%) to direct their gaze towards the roadway, indicating both reduced workload and reduced situational awareness (Llaneras et al., 2013).

In summary, ACC is shown to contribute to small reductions in self-reported workload and small performance improvements on self-paced secondary tasks, while HAD results in large reductions in self-reported workload and large performance improvements, when compared to manual driving. Therefore, the evidence strongly suggests that automation reduces workload, especially as it takes over more of the driving sub-tasks. However, physiological measurements, such as heart rate, were less conclusive, and reaction times initially decreased on low automation levels, but subsequently became greater than manual driving for high automation levels.

2.4.2.2 Situational Awareness and Automation

In addition to the gaze-related studies showing a situational awareness reduction during Highly Automated Driving, freeze-probe studies using the SAGAT method found that driving with ACC assistance resulted in 20% to 50% higher situational awareness scores (Ma & Kaber, 2005; Ma, 2006). However, studies using HAD gave contradicting results, with some studies (e.g. Barnard & Lai, 2010) measuring a situational awareness decrease (18% lower SAGAT score), while others (e.g. Davis et al., 2008) showed a 20% higher detection of objects instead. The main difference between the two studies was that the first was conducted with a driving simulator, while the second was evaluating the situational awareness of the drivers of an automated military convoy, where motivation and driver discipline were different from that of civilian drivers. Therefore, it can be concluded that HAD has the potential to free up mental resources and increase situational awareness, if compared with sufficiently motivated drivers, but it also can result in lower situational awareness, due to the malleability of attentional resources (Young & Stanton, 2002), as drivers utilize a smaller percentage of what is theoretically available when less effort is seemingly required.

In summary, the effects of automation on situational awareness were varied. While some studies showed improved object detection under automated conditions, others concluded that automation tends to deteriorate the situational awareness of the drivers and induce drowsiness (Cha, 2003). Thus, the relationship between situational awareness and automation is not direct, but is affected by other human factors which regulate the attentional resources that drivers are willing to commit to the driving task (Young & Stanton, 2002). One such example is perceived task difficulty, as shown by a 2013 study by Jamson et al., where increased attentional demands imposed by heavy traffic seemingly mitigated the increased fatigue and reduced situational awareness that was observed during lighter traffic conditions.

2.4.2.3 Automation Trust

Automation may be used according to its design purposes, but instances of misuse and disuse are also prevalent (Parasuraman & Riley, 1997). One of the major factors related to both misuse and disuse is trust in automation (Lee & Moray, 1992). Low levels of trust can lead to disuse, as is often the case with automated systems that generate many false alerts (Dixon, Wickens, & McCarley, 2007; Parasuraman, Hancock, & Olofinboba, 1997). In contrast, very high levels of trust in automation can be associated with overreliance and complacency, such as neglecting to adequately monitor the situation (Parasuraman, Sheridan, & Wickens, 2008). Complacency also often results in a strategy of allocating attention away from the automated task to other concurrent tasks (Parasuraman, Molloy, & Singh, 1993).

Trust in automation is of paramount importance when studying the effects of vehicle automation on driver behavior as well, since it directly relates to defining the circumstances where drivers are willing to give up aspects of direct control of the vehicle to the automated system or refrain from doing so (Muir & Moray, 1996). Early studies showed a correlation of automation trust and vehicle headways. Specifically, de Vos et al. (1997) found that short headways under automated conditions were not comfortable for drivers, and Nilsson, Alm, and Jansson (1992) showed that drivers were reluctant to relinquish control when headways were short. However, they were more willing to do so in an emergency (Bekiaris et al., 1997). According to Endsley (2017), trust in automation has been found to be based on (a) system factors, including system validity and reliability, robustness, subjective assessments of system reliability, system understandability and predictability, timeliness, and integrity; (b) individual factors, including perceived ability to perform the task, willingness to trust, and other personal characteristics (such as age, gender, culture, and personality); and (c) situational factors, including time constraints, workload, effort required, and the need to attend to other competing tasks. (Hoff & Bashir, 2015; Schaefer et al., 2016). A meta-analysis showed that system factors (most notably, system reliability and performance) had the greatest overall impact on trust, whereas individual and situational factors had a much lower impact (Hancock et al., 2011).

2.4.3 Transitions in Automated Driving

Control Transitions in automated driving are defined as either an activation or a deactivation of an automation function (Gold et al., 2013; Miller et al., 2014), or a change from one level of automation to another (Merat et al., 2014; Varotto et al., 2015). However, these definitions do not capture all types of transitions, such as non-control transitions associated with the monitoring task, nor do they address the human factors associated with these processes. The following subchapters address these shortcomings by defining and classifying transitions, as well as investigating their relationship with human factors.

2.4.3.1 Driving States

To define transitions, it is first necessary to define the driving states of automated driving (Lu et al., 2016). Based on the automation classification criteria, driving states are also an expression of how the driver or the automated system are executing the three primary driving tasks (longitudinal control, lateral control, monitoring). When there is no transition taking place and control of a task is either performed by the driver or the automated system, the driving state is considered as “static”. Lu et al. (2016) defines the following static driving states:

- State 1 (manual driving): Longitudinal and lateral control are executed by the driver, who also is responsible for continuous monitoring of the situation.
- State 2.1 (driving assistance with longitudinal automation, such as ACC – Adaptive Cruise Control): Longitudinal control is automated, while the driver is still engaged in lateral control and (continuous) monitoring.
- State 2.2 (driving assistance with lateral automation, such as LKAS - Lane Keeping Assist System): Lateral control is automated, while the driver is still engaged in lateral control and (continuous) monitoring.

- State 3 (driving with longitudinal and lateral automation): Both longitudinal and lateral control are executed by the automation system, but the driver is still continuously monitoring in order to be able to assume control if needed.
- State 4 (high-level automated driving): Longitudinal and lateral control are still performed by the automation system, but the driver's monitoring is not continuous. As a consequence of its definition, State 4 can encompass several sub-states depending on the degree of the driver's involvement in the monitoring task.
- State 5 (fully automated driving): All three tasks (monitoring, longitudinal and lateral control) are performed by the automated system so the driver does not monitor the situation at all. In this state the driver's role is solely reduced to initiating a transition to a different state.

It should be clarified that the driving states represent what is actually taking place at any given moment during the driving task, and not the capabilities of the system or the driver. For example, the installed system may be capable of simultaneous longitudinal and lateral automation, but if the driver has only activated the latter, their driving state is 2.2, not 3. In a similar manner, in a fully automated system, where driver monitoring is not technically required, the driver state can either be 5 (no monitoring), 4 (if they choose to partially monitor the situation) or even 3 (if they continuously monitor the situation regardless of the automated monitoring that also takes place).

2.4.3.2 Classification of Transitions

Transitions are the processes that take place when the driver-automation system changes between the six driving states. Based on the definition of driving states, transitions can be distinguished in control transitions (between states 1, 2.1, 2.2, and 3 to 5) and monitoring transitions (between states 3,4 and 5). Monitoring transitions indirectly affect driving behavior, by influencing driver workload and especially situational awareness, but control transitions have the most direct impact on vehicle trajectory (speed, pathing) and the car-following task, so the latter where further classified (Lu et al., 2016) according to three criteria: (a) transition initiator, (b) transition "end point", and (c) underlying reason. The first criterion distinguishes between human-initiated and automation-initiated transitions, the second criterion determines the controller (human or automated system) of the specific driving task after the transition, and the third criterion differentiates between optional or voluntary transitions and mandatory or emergency transitions, as shown in Figure 2-20.

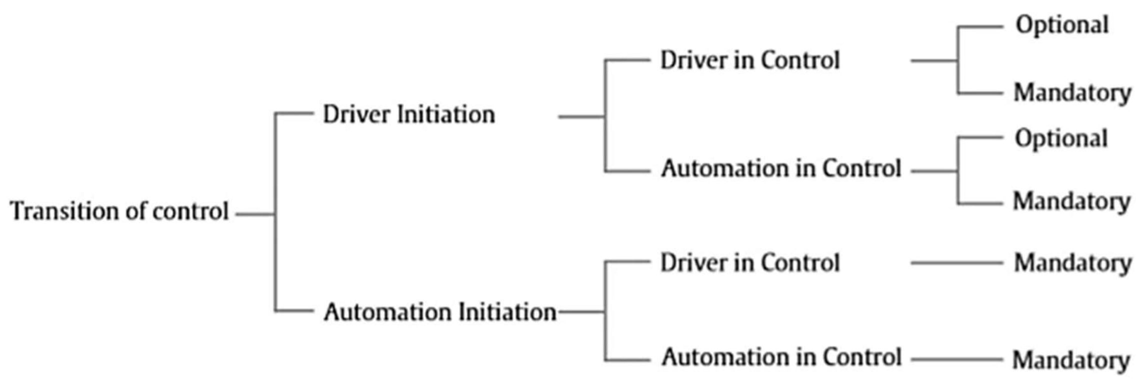


Figure 2-20: Classification Tree of Control Transitions (Lu et al., 2016)

2.4.3.3 Human Factors and Control Transitions

With regards to control transitions, human factors are only relevant in the following two cases: (a) driver-initiated, optional transitions, between driving states 2 or 3 and 1 or vice versa, and (b) transitions between states 4 or 5 and states 1, 2 or 3 (either driver- or automation-initiated, optional or mandatory). Studies involving the latter have been summarized by Lu et al. (2016) as well as de Winter et al. (2014), as presented in section 2.4.2, and show the effects of reducing driver monitoring and being "out-of-loop" to situational awareness and workload. Driver-initiated, optional transitions have also been the subject of studies on driver behavioral adaptation when using automated systems (Hoedemaeker & Brookhuis, 1998; Young & Stanton, 2007;) and studies that investigate when drivers choose to activate or deactivate their automation system (Viti et al., 2008; Pauwelussen & Feenstra, 2010; Varotto et al., 2015) though most focused on the effects of the transitions on traffic flow.

Varotto et al. (2017) performed a controlled on-road experiment in order to identify the main factors influencing drivers' choice to resume manual control from an ACC system. A discrete choice model was developed for the decision to (i) maintain the system ("Active"), (ii) to deactivate the system ("Inactive") by either pressing the break pedal or via the on-off button, or to maintain the system but temporarily override it via manual acceleration by pressing the gas pedal ("Active and accelerate"). Transitions were assumed to occur at most every 1 second, as they are driver-initiated, so the choices were modelled for every 1-second time interval and were associated with the driver behavior characteristics registered at the beginning of the interval. To predict the probabilities of transition choices a mixed logit model was applied, with a driver-specific error term assumed to be normally distributed over the sample that captures unobserved preferences which affect all choices made by the individual driver over time. The final specification was selected based on statistical significance and resulted in three utility functions: for remaining Active (A), transitioning to Inactive (I), and transitioning to Active and accelerate (AAc) for driver *n* at time *t* (Varotto et al., 2017). The study reached the following conclusions:

- Drivers are more likely to keep the system active than to transfer to manual control.
- Everything else being equal, drivers are more likely to overrule than to deactivate the system.
- The probability that drivers would resume manual control is highest in the first few seconds after the system has been activated.
- Drivers are more likely to resume manual control at higher speeds. In addition, they are more likely to intervene when their speed is higher than the target speed set in the ACC and this probability increases for larger differences.
- Drivers are more likely to overrule the system when the ACC acceleration is low.
- The time headway and the target time headway set in the ACC did not influence significantly the choice to overrule the system.
- Drivers are more likely to deactivate the system when the time headway is short for speeds higher than 30 km/h. The time headway at speeds lower than 30 km/h, the target time headway set in the ACC and the ACC acceleration did not have a significant effect on deactivations.
- Interestingly, the driver behavior characteristics of the leader have a different effect on overruling and deactivating. Drivers are more likely to deactivate the system when they are faster (negative relative speed) and accelerate more (negative relative acceleration) than the leader and to overrule the system when they are slower (positive relative speed).
- Relative accelerations had a non-significant effect on choices to overrule the system.
- Drivers are more likely to deactivate the system when they expect that a vehicle will cut in during the next 3 seconds (proactive behavior) and to overrule the system after a vehicle has cut in (reactive behavior).

- Road locations influenced significantly the choices to transfer control. Drivers are more likely to deactivate the system close to on-ramps, between two ramps (closer than 600 meters), and before exiting the freeway.
- Notably, driver characteristics have a significant effect on transition choices. Female drivers and experienced drivers are less likely to overrule the system. However, these driver characteristics did not significantly influence system deactivations.

A follow-up study (Varotto et al., 2018) investigated the association of risk feeling and task difficulty with control transitions. The results showed that the perceived level of risk feeling and task difficulty is higher when time headways are shorter, when approaching a slower leader and when expecting vehicles to cut in. Control transitions to Inactive (system deactivations) and ACC target speed decrements occurred most often in high risk feeling and task difficulty situations (short time headways, slower leader, and cut-ins expected), while control transitions to Active and accelerate (overruling actions by pressing the gas pedal) took place in low risk feeling and task difficulty situations (large time headways and faster leader). Control transitions and ACC target speed regulations were interpreted as an attempt to decrease or increase the complexity of a traffic situation. Finally, everything else being equal, some drivers have a larger acceptable range with ACC and choose smaller ACC target speed regulations.

2.4.4 Simulation of Automated Vehicles

In the case of automated driving, a simplistic adaptive cruise control algorithm based on user parameter preferences is applied by the simulation software of the National Advanced Driving Simulator (NADS), which attempts to reach and maintain the desired speed in free-flowing, non-interactive conditions, while maintaining the desired time gap from the leading vehicle instead when there is vehicle interaction.

The NADS simulator applies the following ACC algorithm (Moeckli et al., 2015):

First the ACC systems test a condition to determine whether it should be operation in free-driving or vehicle-following mode:

$$ACC\ Mode = \begin{cases} free\ driving, & if\ S_n(t) > \tilde{S}_n(t)\ or\ V_n(t) + \Delta V_n(t) > \tilde{V}_n\ (t) \\ following, & otherwise \end{cases}$$

Then the local acceleration limit is set depending on the ACC mode:

$$a_{max} = \begin{cases} A_{max}(global \max acceleration), if\ free\ driving \\ A_{min}(global \min acceleration), if\ following \end{cases}$$

Three possible values for the local deceleration limit are calculated based on different conditions. First, the limit can be varied according to the instantaneous time-to-collision (ttc) value and the time-to-collision threshold (ttc_{th}):

$$d1_{max} = \begin{cases} D_{max}(global \max deceleration), if\ ttc < ttc_{th} \\ D_{max} - (ttc - ttc_{th})\dfrac{(D_{max} - D_{min})}{4 * ttc_{th}}, if\ ttc_{th} < ttc < 5ttc_{th} \\ D_{min}(global \min deceleration), if\ 5ttc_{th} < ttc \end{cases}$$

Alternatively, it can be calculated based on how close the speed vehicle is to the desired following range:

$$d2_{max} = \begin{cases} D_{max}(global \max deceleration), if\ \dfrac{S_n(t)}{\tilde{S}_n(t)} \leq 0.2 \\ D_{max} - \left(\dfrac{S_n(t)}{\tilde{S}_n(t)} - 0.2\right)\dfrac{(D_{max} - D_{min})}{0.3}, if\ 0.2 < \dfrac{S_n(t)}{\tilde{S}_n(t)} < 0.5 \\ D_{min}(global \min deceleration), if\ 0.5 < \dfrac{S_n(t)}{\tilde{S}_n(t)} \end{cases}$$

Finally, it can be calculated using a metric that combines speed difference and time-to-collision, as an additional measure of severity:

$$d3_{max} = -\frac{\Delta V_n(t)}{ttc}$$

The final value of the local deceleration limit is chosen as the maximum of the three choices:

$$d_{max} = \max(d1_{max}, d2_{max}, d3_{max})$$

The parameters that need to be set in the model are given in Table 2-8:

Table 2-8. ACC Parameters of NADS (Moeckli et al., 2015)

Parameter	Value
ACC Velocity Increments	5 mph
ttc_{th}	3 s
A_{max}	-1 m/s
A_{max}	0.2g
A_{min}	0.1g
D_{max}	0.3g
D_{min}	0.05g

The NADS model incorporates the ACC algorithm and provides the desired functional modes of cruise control. There are four modeled cruise states: OFF, ON, SET, and WARN and eight functions: functions are: Off, On, Cancel, Resume, Set, Coast, Accel, and Ext, controlled by pressing a button in the steering column. The last is not a standard cruise function, but is a useful way to have the car track a pre-recorded velocity profile. The state transition diagram that summarizes the logic for the model is shown in Figure 2-15.

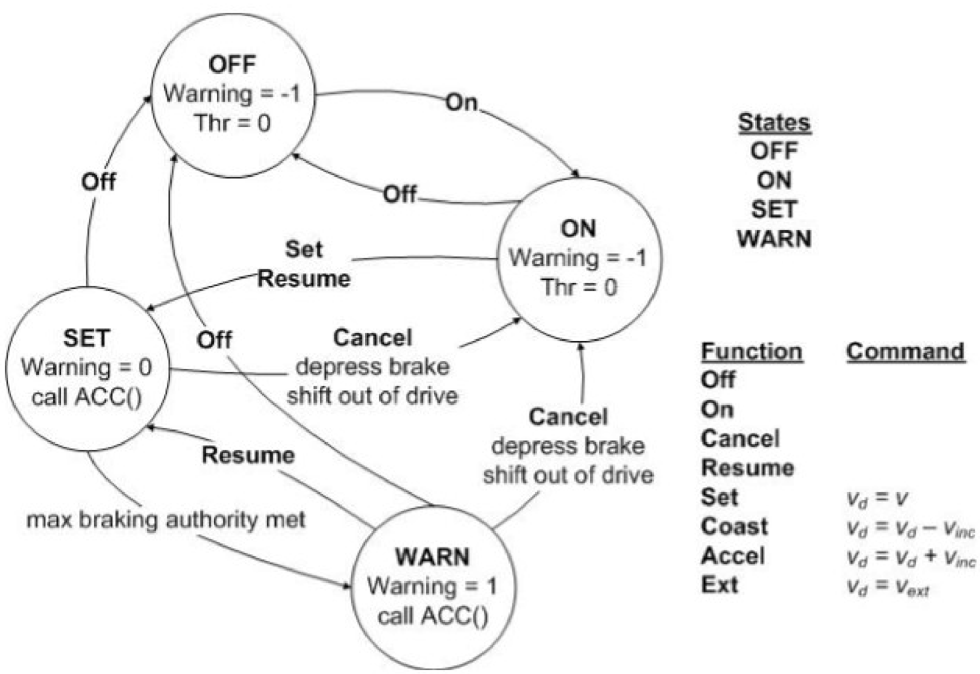


Figure 2-21: Cruise control state transition diagram (Moeckli et al., 2015)

CHAPTER 3 - METHODOLOGY

3.1 Introduction

The theoretical framework of this study (Figure 3-1) consists of a cognitive longitudinal driving behavior model, that takes into account external factors, longitudinal vehicle control factors, vehicle automation (ACC or ACC plus automated lane keeping), and a variety of human factors, with their respective interactions. The framework draws inspiration from Hoogendoorn et al. (2013), in which complexity, mental workload, situational awareness and adaptation effects are considered, and Fuller's (2000) Task-Capability Interface (TCI) Model, which is based on the interaction between driver capability and task difficulty to describe driver behavior, but introduces a number of innovative elements.

More specifically, the framework:

- Introduces an additional layer of interactions for automated driving, which runs in parallel to the interactions layer of manual driving,
- Incorporates the concept of Automation Trust (Parasuraman et al., 2008) to model driver decision to transition between automated and manual driving,
- Replaces the TCI model with the Competence-Complexity Interface (CCI) model by removing dynamic human factors and subjective assessments of task difficulty.
- Utilizes the findings of many studies (Young & Stanton, 2002; Merat et al., 2012; de Winter et al., 2014; Engström et al., 2017; Manjunatha & Elefteriadou, 2018) to define the concept of "Driver State" as a surrogate for the dynamic driver characteristics, as well as driver capability, and
- Develops a car-following model by enhancing the Intelligent Driver Model (IDM) proposed by Treiber et al. (2000), through incorporating human factors via modified versions of Saifuzzaman's Task-Difficulty framework (2015a) and Hoogendoorn's adaptation effects framework (2013), as well as discrete action points according to Treiber and Kesting (2017), and the car-following models of Wiedemann (1974) and Fritzsche (1994).

3.2 Description of Behavioral Framework

3.2.1. Model Variables

The model's input variables include:

- External Factors (Hoogendoorn, 2013) as the model's free variables:
    - Road Design (alignment; surface condition; and other factors)
    - Environmental Factors (weather conditions – visibility; and traffic conditions – traffic intensity and interaction with other users.
    - Vehicle Characteristics (breaking, acceleration, speed and steering capabilities; and in-vehicles systems, such as automation)
- Static Driver Characteristics (Hoogendoorn 2013) to account for driver behavior variability:
    - Demographics (Age, Gender)
    - Driver Experience (Experience with manual driving as well as automation)
- Longitudinal vehicle control factors at each time interval, as the model's dynamically changing inputs, derived from the car-following model of choice:
    - Speed
    - Headway
    - Acceleration/Deceleration
- Whether the automated systems are activated or not.

The free (or independent) variables of this study are a subset of the external factors, which include Traffic Conditions (both traffic intensity and interaction with other vehicles), Environmental Factors (mainly limited visibility in certain scenarios), and Vehicle Characteristics (automated features of the vehicle).

The target variables of this study, which require calibration and validation, include the Perceived Driving Task Difficulty (the driver's sensitivity to task complexity), Driver Preferences (desired speed, desired time gap) for manual driving, the User Parameter Preferences (speed, time gap) for automated driving, the effect and magnitude of Compensation Effects on either of the two aforementioned variables for both manual and automated driving, the effect and magnitude of Performance Effects on manual driving, the drivers' Trust in Automation (under

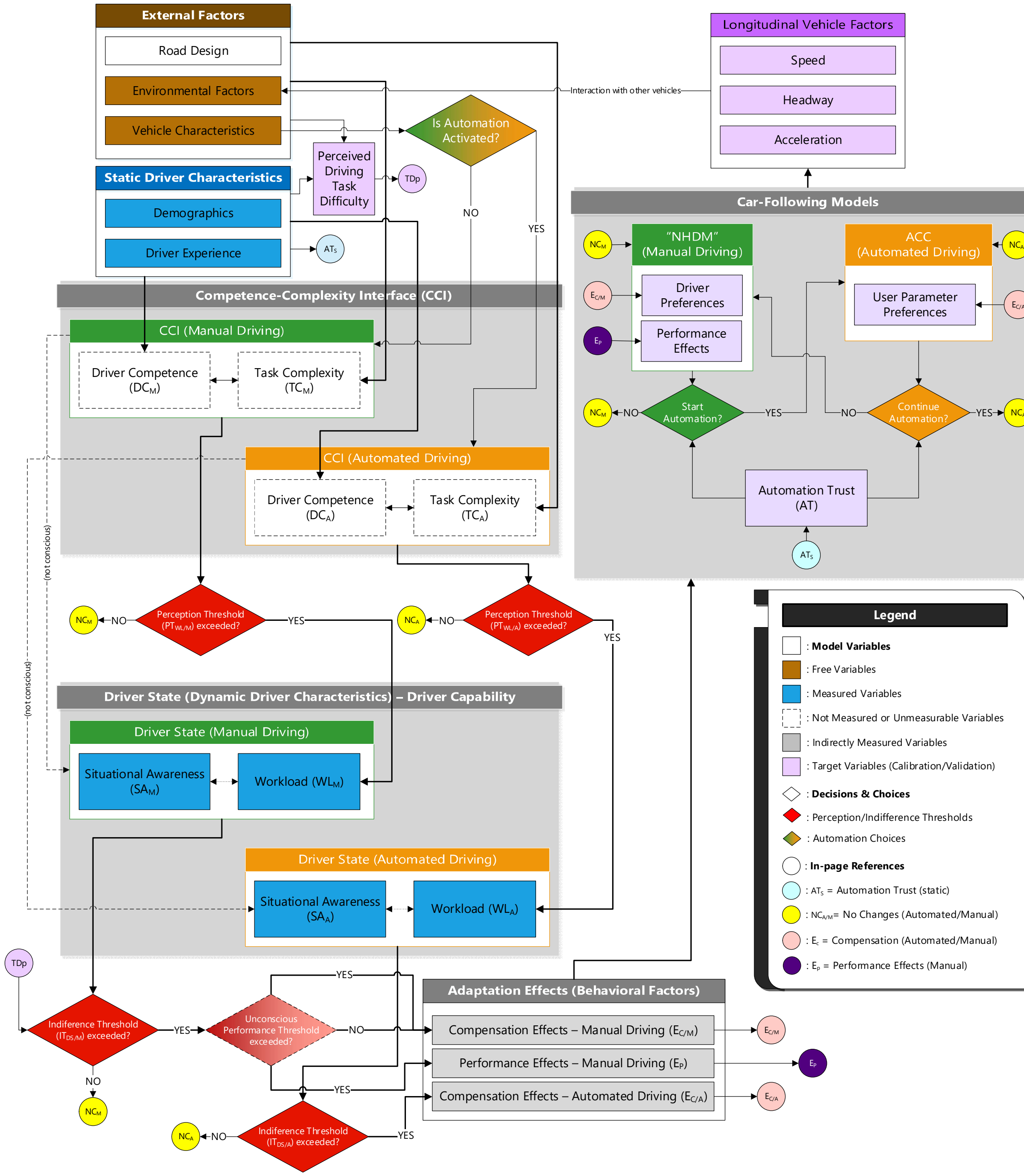


Figure 3-1: Cognitive Driving Behavior Framework

which conditions they choose to engage or disengage with the automated systems), as well as the following thresholds: perception thresholds for increase in workload, indifference thresholds for changes in driver state, the performance effects threshold, and the action points thresholds of the car-following model.

The output variables of this model (while also serving as an input since the framework has a feedback loop structure) are the longitudinal vehicle factors of the car-following models (speed, headway, acceleration) or, essentially, the vehicle trajectory. The output variables are also the calibration performance measures that can be used to validate the calibration of the target variables of the model.

3.2.2. Objective and Cognitive Constructs

The following objective (but not always measurable on the field) and subjective cognitive constructs are introduced and defined in order to study the effects on the target variables caused by respective changes of the free variables and the rest of the (static or dynamic) input variables:

- **Task Complexity (TC)** of the driving task. This model adopts Fuller's (2000) definition of task demand as the objective construct of Task Complexity (TC). The study relies on designing scenarios of varied demand and complexity by adjusting the free variables, thus TC is a dynamic factor. However, objective task complexity is not be directly measured in the data collection process but its influence on other measurable parameters serves as an indirect indication of its magnitude.
- **Driver Competence (DC)** is modelled as another objective, though non-dynamic factor, related only to static driver characteristics, and is also based on the interpretation of competence used by Fuller (2000) to define the second component of the TCI model, Driver Capability. Additionally, as with Task Complexity, no direct measurement of Driver Competence takes place but it is considered indirectly through its effects on other measurable constructs.
- **Cognitive Workload (WL)** is a dynamic cognitive construct that indicates the overall mental effort a driver exerts per unit of time in order to perform the driving task on a level of competence that meet their objective and subjective criteria (van Lint et al., 2016; Stanton & Young, 2005). Teh et al. (2014) equate workload to information-processing resources the driver dynamically allocates to the driving task. As per those sources, in this

model, Workload is also an expression of mental effort that varies with time as external or internal (human factor) conditions change and is one of the primary variables measured in the study. Workload can be considered as both a subjective or objective construct (Young et al., 2015). This study recognizes that both interpretations apply, with each having a different effect on the driving task, and endeavors to measure workload using both subjective and objective methods.

- **Situational Awareness (SA)** is another dynamically evolving mental construct which describes, in simple terms, the driver's perception, recognition and comprehension of their surrounding environment (Endsley & Garland, 2000), especially as it pertains, in this case, to the driving task (van Lint et al., 2016). Situational awareness has significant effects on decision making (Endsley, 1995) but, unlike Workload, this model assumes that the drivers are not inherently self-aware of their level of Situational Awareness, unless the researcher deliberately directs their attention to it. In addition, measuring situational awareness is also subject to complications: while the first (lowest) level (perception) can be objectively measured in a number of ways (e.g. through eye-tracking), the higher levels can only be measured subjectively. Therefore, as with workload, the study attempts to measure situational awareness through multiple means, both objective and subjective.
- **Driver State (DS)**, while pre-existing as a term in the driver behavior literature, is defined in a very specific way in this model. Acknowledging the multiple and complex ways that Workload and Situational Awareness interact with each other (Vidulich & Tsang, 2012; Manjunatha & Elefteriadou, 2018), that "SA and WL, although inter-related, are hypothesized to be essentially independent constructs" (Endsley & Garland, 2000) and that their correlation was found to be statistically insignificant (Manjunatha & Elefteriadou, 2018), it can be concluded that one cannot be derived directly from the other or be its sole causal factor. Therefore, the concept of a two-dimensional "Driver State" is introduced to encompass, describe and represent both constructs in further analysis. Based on a study by Manjunatha and Elefteriadou (2018) who arranged (and then clustered and classified) drivers on a two-dimensional plane with the two axes representing workload and situational awareness respectively, Driver State is defined as the dynamically changing position of the driver on that plane, with a qualitative assessment associated with that position (higher situational awareness and lower mental workload describing a "good" driving state and

vice versa). Workload actually is somewhat more complicated in that assessment, since Underload (extremely low workload) is also considered undesirable ("Malleable Attentional Resources Theory," Young & Stanton, 2002), so there is instead an "optimal" low-but-not-too-low workload. The (fuzzy) boundaries between the different driver states are obtained from the thresholds where changes in driver behavior and adaptation effects are observed. In this cognitive framework, Driver State represents both the Dynamic Driver Characteristics as well as the Driver Capability, as defined by Fuller (2000): a reduction of driver competence due to human factors. However, this study focuses only on a limited subset of human factors: the stress related to increased cognitive workload, and the malleable attentional resources that are related to task complexity, especially in the context of automated driving (Young & Stanton, 2012). Because of these factors, Driver State (or Capability) is a dynamic subjective cognitive construct.

- **Perceived Driving Task Difficulty (TD_p)** is a construct based on Saifuzzaman's Task Difficulty formulation (2015a), simplified by removing the risk-taking parameter and the desired time headway factor, which are included in the car-following model, but retaining the objective factors of vehicle speed and space headway, as well as the human factors of driver sensitivity to the task difficulty and the reaction time. Therefore, TD_p is also a dynamic subjective cognitive construct.
- **Adaptation Effects (E_A)** are changes to longitudinal driving behavior imposed (in this model) by changes in Driver State. In Hoogendoorn's (2013) theoretical framework, adaptation effects result from changes in the relationship between task demand and driver capability following Fuller's (2000) Task-Capability Interface model. In this model, adaptation effects are based on the interaction of Driver State and Perceived Driving Task Difficulty. Hoogendoorn (2013) also assumed the existence of two types of adaptation effects: compensation and performance effects, which is a distinction adopted by this model as well.
    - **Compensation Effects (E_C)** according to Hoogendoorn (2013) are "conscious adaptations in longitudinal driving behavior in order to reduce or increase the difficulty of the driving task (task demand), such as changes in speed and spacing."
    - **Performance Effects (E_P)**, on the other hand, are "subconscious effects in longitudinal driving behavior following an imbalance between task demands and

driver capabilities" and can involve changes in driver reaction times, decision times, perception thresholds or even the sensitivity and accuracy of their acceleration towards their desired speed and spacing. Assumed by the definition of the two effects is that compensation effects usually occur first - when the imbalance between demand and driver capability is relatively low and attempt to mitigate it -, but if compensation effects are not sufficient then performance effects are also observed. In rare, special cases, such as when situational awareness is so low that drivers do not comprehend the need to apply compensation effects (Vidulich & Tsang, 2012), performance effects could possibly occur without compensation effects. However, this study always assumes that the presence of performance effects also includes the presence of compensation effects.

- **Automation Trust (AT_s)** is defined in the framework as an objective and static cognitive concept related to the static driver characteristics (age, experience, etc.). It is quantified on a scale of 0 (no trust) to 1 (complete trust) by observing and analyzing the circumstances under which the drivers engage or disengage the automated systems.

As shown in Figure 3-1, all of the above constructs (except performance effects and automation trust) appear in two versions, one for manual and one for automated driving. This is due to the assumption that automated driving, and especially when the driver's role change to a passive monitor of the automated system from an active participant (Merat et al., 2012), results in these concepts being defined in slightly different ways if automation is in effect. As for the exceptions: performance effects are obviously excluded because they cannot occur during automation, and automation trust relates to the threshold between the two states.

3.2.3. Relationships and Assumptions

To fully determine the behavioral framework and explain the diagram of Figure 3-1, it is necessary not only to establish the concept and structures that serve as its components, but also to describe the relationships between said components and the rules and assumptions that govern said relationships. The relationships that govern manual driving are addressed first, as they best reflect the model's most general case, followed by the changes and modifications in the model that are the results of incorporating automated driving.

3.2.3.1. Manual Driving

Competence-Complexity Interface (CCI). According to Fuller (2005), the task-capability interface (TCI) model "describes the dynamic interaction between the determinants of task demand and driver capability. It is this interaction which produces different levels of task difficulty." This study uses the CCI model instead of the TCI, by replacing driver capability and task demand with the following factors:

- Driver Competence (DC), either for manual or automated driving, as a direct result of the Static Driver Characteristics.
- Task Complexity (TC), is also determined solely from external factors, including the road design characteristics (alignment, surface condition, and other factors, the environment (including traffic conditions or weather), and the characteristics of the vehicle (steering, braking and acceleration capabilities, in vehicle-systems, including assistance and automation system) (Hoogendoorn, 2013). Included in the above, though, are the interaction with other drivers and the vehicle's longitudinal factors (speed, headway, acceleration) that are the results of the car-following models of this framework.

In the same manner that Hoogedoorn (2013) derives a causal relationship between the output of the TCI model and workload, this model asserts that the output of the CCI model affects both workload and situational awareness, and eventually the adaptation effects, but describes their relationships the following manner:

- First, it is considered that the CCI output affects Situational Awareness directly, not only through its complicated relationship with Workload. Also, due to the assumption that the driver is not inherently conscious of their level of situational awareness, the driver is not also not directly aware of that relationship and there are no perception thresholds involved. Finally, because the CCI model inputs are not measured, this relationship is not quantified in this model, but its effect is captured by directly measuring Situational Awareness.
- Second, a Perception Threshold (PT_{WL}) is introduced between the CCI output and changes in Workload. This emerges from the definition of Workload as the conscious effort of the driver towards fulfilling the driving task, therefore minor changes in task difficulty (below that perception threshold) would not result in any observable changes in workload, but instead lead to the "no change in behavior" node (NC), so that the driver would not alter their car-following parameters. PT_{WL} is not directly quantified either in this study but

inferred through the measurement of the subjective Workload of the drivers: if the latter changes, then the Workload Perception Threshold (PT_{WL}), is exceeded, otherwise it is not.

- Third, the Driver State construct is incorporated in order to encompass the multifaceted relationship and effects of the Workload and Situation Awareness constructs, as described above in the definition of Driver State.
- Fourth, it is considered that Adaptation Effects are derived from the Driver State and the Perceived Driving Task Difficulty according to a series of thresholds:
  i. An indifference threshold (IT_{DS}) is introduced between the Driver State and the (conscious) Compensation Effects to capture the cases of drivers that acknowledge an increase in their Workload, but that increase is not sufficiently high to take any compensatory action. That threshold compares the difference between the Driver Capability (as expressed by the Driver State) and the Perceived Driving Task Difficulty via the ratio of the "Dynamic Observed Driver Capability" $\bar{C}_n(t)$ and the "Relative Driving Task Difficulty" $\overline{D}_n(t)$ variables, which are described in Chapter 3.3 and defined in Equations 3.3 and 3.4, respectively. If the indifference threshold is not exceeded, the process leads again to the "no change in behavior" node (NC).
  ii. An unconscious threshold (which is also not measured directly, as Task Difficulty is not quantified, but identified through its effects) is introduced, after (and only if) the IT_{DS} is exceeded. This threshold governs whether the task difficulty is so high and/or the compensation efforts prove insufficient to reduce it that Performance Effects also appear, in conjunction with Compensation Effects.

Adaptation Effects (Compensation and Performance effects). They appear only if the aforementioned thresholds are exceeded, and in turn affect the parameters and the outputs of the car-following models (Hoogendoorn, 2013). The intensity of the effects is captured by their respective parameters (E_c for compensation and E_p for performance effects) and is assumed to be a function of the driver state. Specifically:

- **Compensation Effects (E_c)** affect the conscious driver preferences as they attempt to reduce task difficulty. These include the desired speed, desired time gap and the decision to start or stop using vehicle automation. Compensation effects are identified by observed changes in these parameters, while their magnitude is related to the difference between Driver Capability (Driver State) and Perceived Driving Task Difficulty.

- **Performance Effects (E_P)** affect parameters that the driver has no control over (such as increasing their reaction speed) and also result in suboptimal decisions. For example, the driver choosing an acceleration level that is different from what would be required in order to approach their desired speed or time gap. Performance effects are identified by secondary characteristics (not necessarily longitudinal) that indicate lack of control, such as increased lateral oscillation.

Car-following model. Any car-following following model that inherently takes into account dynamic human factors (Driver State and Adaptation Effects), or is modified accordingly to incorporate them, can be applied to translate the model's inputs and field-measured variables into longitudinal vehicle factors. For manual driving cases, this study uses a modified version of Treiber's "Intelligent Driver Model" (IDM), named the "Naturalistic Human Driving Model" (NHDM), the equations of which are described in the next subsection. If the input to the car-following model is the "no change in behavior" node (NC), then the dynamic human factors and the model variables related to them, such as driver preferences, are not altered.

Longitudinal Vehicle Factors. They are the direct output of the selected car-following model's equations, but also serve as input into the external factors, affecting interaction with other vehicles, and thus completing the feedback loop that forms the hypothesized behavioral framework's structure.

3.2.3.2. Automated Driving

Adding the automated driving layer, results in the following changes and modifications in the model's relationships:

- Driver competence is assumed to be different depending on the level of automation in effect, as the very nature of the task differs accordingly, from active decision-making to passive monitoring (Merat et al., 2012). Therefore, an Automated Driver Competence (DC_A) is added alongside the Manual Driver Competence (DC_M)
- Task Complexity is affected in the same manner (since the task itself changes) and Automated Task Complexity (TC_A) is separate from Manual Task Complexity (TC_M).

- The Competence - Complexity Interface functions similarly in the case of automation, using the difference between DC_A and TC_A instead of the difference between DC_M and TCD_M used in the manual driving case. Therefore, the Workload Perception Threshold is also different for automated ($PT_{WL/A}$) and manual ($PT_{WL/M}$) driving conditions, as are Situational Awareness (SA_A versus SA_M), Workload (WL_A versus WL_M) and the Driver State itself.
- The Adaptation Effects are affected significantly in the automated driving layer:
  - Performance Effects – and their related unconscious threshold – are not applicable, since the driver is not in direct control of the longitudinal trajectory of their vehicle.
  - Compensation Effects though still apply, but since they are derived from the automated driver state they – and their related indifference threshold – are also defined differently for automated ($E_{c/A}$ and $IT_{DS/A}$) than for manual driving ($E_{c/M}$ and $IT_{DS/M}$). More specifically, Perceived Task Difficulty is not a factor considered for $IT_{DS/A}$ or $E_{c/A}$, with the latter taking the form of a step function derived from measurement. These compensation effects still affect the conscious driver preferences, which in this case are the user-selected parameters (desired speed, gap) they choose for their automated system.
- Car-following model. A different car-following model is applied when automation is activated, such as the NADS Adaptive Cruise Control algorithm (Moeckli et al., 2015) described in section 2.4.4, which uses the selected user preferences to derive the longitudinal vehicle factors.
- Automation Trust (AT_s) is derived from the static driver characteristics and contributes along with the car-following outputs (which include adaptation effects) into the decision of the drivers to engage or disengage their automated systems (control transitions), when automation is available.

3.3 Naturalistic Human Driving Model (NHDM)

This car-following model was developed by enhancing the original Intelligent Driver Model (Treiber et al., 2000) so that it takes into account a subset of human factors (which define the Driver State and the Adaptation Effects), and also acknowledges the "naturalistic" nature of driving as a series of abrupt and discrete choices ("action points") as opposed to a continuous process. Task difficulty is considered via a modified version of Saifuzzaman's Task-Difficulty framework (2015a), while adaptation effects are based on Hoogendoorn's framework (2013). The addition of action points, based on perception threshold and indifference regions, are used in the car-following models of Wiedemann (1974) and Fritzsche (1994), acknowledged and even advocated by Treiber himself in his 2013 book ("Traffic Flow Dynamics") and a 2017 study ("The Intelligent Drive Model with Stochasticity") respectively. Though the latter study also makes a compelling case for the stochasticity of the model parameters and thresholds, while Hoogendoorn (2013) correctly identifies that fuzziness plays an important role when human decision-making is involved, this study assumes that the car-following parameters are deterministic and non-fuzzy as a necessary compromise for calibrating them. The NHDM model is thus presented in equations 3.1 to 3.13:

$$\tilde{a}_n(t) = a_{max}^{(n)}\left[1 - \left(\frac{V_n(t)}{\tilde{V}_n * \left[1 - E_c^{(n)}(t)\right]^{\beta_n}}\right)^4 - \left(\frac{\tilde{S}_n\,(t)}{S_n(t)}\right)^2\right] \qquad (3.1)$$

where $\tilde{a}_n(t)$ is the ideal acceleration that the driver of vehicle (n) would like to enact at time (t) in order to achieve their desired speed and time headway if they were able and willing to change their acceleration in a continuous manner and with zero reaction time;

$a_{max}^{(n)}$ is the maximum acceleration/deceleration of subject vehicle (n), based only on its technical characteristics;

$V_n(t)$ is the actual speed of vehicle (n) at time (t);

$\tilde{V}_n$ is the desired speed of the driver of vehicle (n);

β_n is a sensitivity parameter that indicates how sensitive the desired speed of the driver of vehicle (n) is to compensation effects. It cannot take negative values: $(\beta_n \geq 0)$;

$S_n(t)$ is the actual spacing between vehicle (n) and its lead vehicle (n-1) at time (t); and

$\tilde{S}_n(t)$ is the desired spacing between vehicle (n) and its lead vehicle (n-1) at time (t). It is calculated in equation (3.2):

$$\tilde{S}_n(t) = S_{jam}^{(n)} + V_n(t) * \tilde{T}_n * \left[1 + E_c^{(n)}(t)\right]^{\gamma_n} + \frac{V_n(t) * \Delta V_n(t)}{2\sqrt{a_{max}^{(n)} * b_{comf}^{(n)}}} \quad (3.2)$$

where $S_{jam}^{(n)}$ is the minimum stopping distance at standstill;

$\tilde{T}_n$ is the desired time headway of the driver of vehicle (n);

γ_n is a sensitivity parameter that indicates how sensitive the desired time headway of the driver of vehicle (n) is to compensation effects. It cannot take negative values: $(\gamma_n \geq 0)$;

$\Delta V_n(t)$ is the speed difference between vehicle (n) and its lead vehicle (n-1) at time (t);

$b_{comf}^{(n)}$ is the comfortable deceleration of the driver of vehicle (n); and

$E_c^{(n)}(t)$ is the compensation effect parameter for vehicle (n) at time (t). It takes values between -1 and 1 and is calculated in equation (3.3):

$$E_c^{(n)}(t) = \overline{D}_n(t) - \bar{C}_n(t) \quad (3.3)$$

where $\bar{C}_n(t)$ is the driver's "Dynamic Observed Driver Capability" (in contrast to the Static Driver Capability – or Competence, which is derived only from the Static Driver Characteristics).

$\bar{C}_n(t)$ is derived from the two-dimensional Driver State (DS) as follows: both Workload (WL) and Situational Awareness (SA) *objective* measurements are converted to a scale from 0 to 0.5, where 0 represents the minimum and 0.5 the maximum score obtained by the driver of vehicle (n). Then, they are combined, as shown in equation (3.4) to produce $\bar{C}_n(t)$, which thus takes values from 0 to 1:

$$\bar{C}_n(t) = SA_n(t) - WL_n(t) \quad (3.4)$$

$\overline{D}_n(t)$ is also a dynamic variable that considers the Relative Driving Task Difficulty for the driver of vehicle (n). It also takes values from 0 to 1 and it is given in equation (3.5):

$$\overline{D}_n(t) = \left(\frac{D_n(t - \dot{\tau}_n)}{D_{max}^{(n)}\left(t - \dot{\tau}_{max}^{(n)}\right)}\right)^{\delta_n} \quad (3.5)$$

where δ_n is a sensitivity parameter which reflects how sensitive the driver of vehicle (n) is to the driving task difficulty. It cannot take negative values: ($\delta_n \geq 0$).

$D_n(t - \dot{\tau}_n)$ is a formulation that represents the difficulty of the driving task for the driver of vehicle (n), based on Saifuzzaman's Task difficulty car-following (TDCF) framework (2015a), but simplified for this application. It is calculated in equation (3.6):

$$D_n(t - \dot{\tau}_n) = \left(\frac{V_n(t) * \dot{\tau}_n}{S_n(t)}\right) \quad (3.6)$$

where $\dot{\tau}_n$ is the modified reaction time of the driver of vehicle (n), given in equation (3.7):

$$\dot{\tau}_n = \tau_n + \varphi_n \quad (3.7)$$

where τ_n is the standard (or ideal) reaction time of the driver of vehicle (n), in seconds; and

φ_n is the additional reaction time of the driver of vehicle (n) due to human factors. In this model, φ_n is a direct result of performance effects, and thus it is considered 0 of there are none of the latter. The value of φ_n is considered to be a function of the Driver State (DS) and it is measured during the experiment, where the form of the $f[DS]$ function is also determined:

$$\varphi_n = \begin{cases} 0\,, if\ E_P^{(n)}(t) = 1 \\ f[DS(t)], if\ E_P^{(n)}(t) \neq 1 \end{cases} \quad (3.8)$$

$D_{max}^{(n)}\left(t - \dot{\tau}_{max}^{(n)}\right)$ is the maximum observed difficulty for the driver of vehicle (n) and given by equations 3.9 and 3.10:

$$D_{max}^{(n)}\left(t - \dot{\tau}_{max}^{(n)}\right) = \left(\frac{V_{max}^{(n)}(t) * \dot{\tau}_{max}^{(n)}}{S_{min}^{(n)}(t)}\right) \quad (3.9)$$

$$\dot{\tau}_{max}^{(n)} = \tau_n + \varphi_{max}^{(n)} \qquad (3.10)$$

$E_P^{(n)}(t)$ is the performance effect parameter for vehicle (n) at time (t). If no performance effects are present (no indications of performance effects are detected, thus the unconscious performance effect threshold is not exceeded), $E_P^{(n)}(t) = 1$. Otherwise, it is calculated as shown in equation (3.11). The form of the $f\left[E_c^{(n)}(t)\right]$ function is determined by the experiment.

$$E_P^{(n)}(t) = \begin{cases} 1 \quad , & if\ E_c^{(n)}(t) \le 0 \\ \max\left\{1, f\left[E_c^{(n)}(t)\right]\right\}, & if\ E_c^{(n)}(t) > 0 \end{cases} \quad (3.11)$$

Finally, the actual acceleration of vehicle (n) at time (t) is given by equation (3.12):

$$a_n(t) = \begin{cases} a_n(t - \tau_n), if\ IT_{AP} = 0 \\ \tilde{a}_n(t - \tau_n), if\ IT_{AP} = 1 \\ a_n(t - \tau_n) * E_P^{(n)}(t), if\ IT_{AP} = 0\ and\ E_p^{(n)}(t) \neq 1 \\ \tilde{a}_n(t - \dot{\tau}_n) * E_P^{(n)}(t), if\ IT_{AP} = 1\ and\ E_p^{(n)}(t) \neq 1 \end{cases} \quad (3.12)$$

where $a_n(t - \tau_n)$ is the actual current acceleration of vehicle (n), used in the previous time step, so it means that the driver chooses to not change his acceleration during this time step even if it differs from the ideal acceleration $\tilde{a}_n(t)$.

IT_{AP} is the indifference threshold of the driver that determines when an Action Point is reached. Upon reaching an Action Point, the driver chooses to act and update his acceleration according to the ideal acceleration of the NHDM. IT_{AP} is a binary variable, as shown in equation (3.13):

$$IT_{AP} = \begin{cases} 1, if\ \left|V_n(t) - \tilde{V}_n\right| > \Delta V_n \\ 1, if\ \left|S_n(t) - \tilde{S}_n\right| > \Delta S_n \\ 0, otherwise \end{cases} \quad (3.13)$$

where ΔV_n and $\Delta S_n$are parameters that determine the acceptable deviation of the current speed and space gap from the desired speed and space gap of the driver of vehicle (n) and their values are the target of the model calibration.

CHAPTER 4 – DATA COLLECTION AND ANALYSIS PLAN

4.1 Introduction

The theoretical behavioral framework described in Chapter 3 needs to be validated via experimental data before it can be considered for future applications. In addition, a number of model parameters of the both the general framework and of the NHDM car-following model require calibration in order to reflect the actual observed behavior of human drivers. Therefore, an experiment must be designed in order to collect such behavioral driving data from heterogeneous human participants performing under several diverse driving task scenarios. These scenarios need to be purposefully tailored around the assumptions inherent in the model, so that the collected data can statistically prove or disprove the hypotheses that define the structure of the behavioral framework. In addition, the conditions of these scenarios need to be designed with the goal of relatively isolating each variable that needs to be calibrated, by controlling all other factors and extraneous sources of variation that may affect the outcome of the measurement. Finally, using sufficient amount of data it should be possible to ascertain the most likely form of functions that represent the relationship between parameters, such as the $\varphi_n = f[DS]$ function that relates additional reaction time with the Driving State, and the $E_P^{(n)}(t) = f\left[E_c^{(n)}(t)\right]$ function that connects performance and compensation effects.

The level of detail and control of scenario conditions necessary to achieve the above goals, as well as safety concerns and the ability to study high-risk events, necessitate the use of a driving simulator for the experiment instead of obtaining field data from instrumented vehicles. The latter though, can be potentially used as supplementary evaluation regarding the applicability and statistical generalization of the behavioral framework and the car-following model under field conditions, after the simulation studies have first sufficiently demonstrated their validity and calibrated their parameters.

4.2 Driving Simulator Characteristics

A driving simulator involves a sensory (primarily visual, but also potentially auditory and motion-based) representation of a vehicle, its functions (e.g. moving along a certain trajectory within a timeframe), its surrounding environment (e.g. roadway geometry), and interactions with elements of that environment (e.g. other vehicles). Driver simulators accept user input (steering, accelerating, breaking) and provide appropriate feedback with varying degrees of realism, but they are also recording both the input and its outcome (e.g. vehicle trajectory, headway with preceding vehicles or relative speed) for use in data analysis. Additional recording equipment (e.g. video cameras, eye-tracking devices, heart-rate monitors, EEC electrodes) can also be applied as needed, though usually not natively integrated with the simulator itself.

The characteristics and capabilities of a driver simulator depend on its respective hardware and software configurations. The former refers to the physical equipment used. It can vary from a simple chair-and-monitors desktop setup, a partial or full – but static – actual vehicle cabinet with projected images across a wide – but not comprehensive – field of view, and up to an immersive enclosed (full spherical field of view) cabinet with movement capabilities (degrees of freedom) across several axes. The latter involves the computer programs responsible for designing and implementing the driving scenarios, interpreting driver inputs and generating the virtual environments and the interactions therein. Simulator hardware and software may also define the type of measurement techniques available to the researchers. For example, freeze-probe situational awareness measurement techniques, such as SAGAT, have as prerequisite the capability to pause (and then resume) the simulation at any given moment.

This study is designed so that the suggested experimental procedure can be performed with the use of the University of Kansas Transportation Center driving simulator setup, the exact specifications of which as of August 2019 are described in Figure 4-1, plus some easy-to-obtain additional equipment. This is a static (zero degrees of freedom) simulator which consists of a fixed-base half cab Acura MDX vehicle chassis, three front projector screens which combined provide a 120^{o} horizontal field of view, and a fourth rear screen that is used by the mirror displays. A digital instrument panel is also included, as well as a surround sound and vibration system. The described configuration is seen in Figure 4-2, and depictions of the simulation setup are shown in Figure 4-3. The simulation software running the scenarios is miniSim 2.2.2, provided by the National Advanced Driving Simulator (NADS). It provides SAE level 0, 1, or 2 capabilities, but does not have the capability to pause the simulation for application of freeze-probe techniques. Equipment available but not directly integrated with the simulation software includes (i) four high-definition digital cameras recording facial cues, the pedals, the dashboard, and the front view, (ii) eye-tracking equipment capable of eyelid tracking, gaze tracking (60Hz), head tracking with six degrees of freedom and automatic task-evoked pupillary response (TERP) analysis (1Hz) using the Index of Cognitive Activity Protocol (ICA), (iii) a 3D (depth-capturing) video rendering Kinect 2.0 Sensor, and (iv) a heart rate (1Hz) chest strap monitor. DRT, EEG, and ECG devices can become provisionally available as well.

Body:	
Acura MDX chassis	Fixed-base half cab with an automatic gear selector, steering wheel, pedals, and powered seats, windows, and side-view mirrors.
Digital Instrument Panel	1280 X 1024 screen to display the gauge cluster.
Visualization:	
4X Flat Projection Screens	Three front and one rear (both screens and projectors) providing a 170-degree horizontal field of view. 1920 X 1080 resolution HD projectors.
4X BenQ 1085ST Projectors	
3X HD Monitors	Three HD monitors at 1920 X 1080 resolution for the three available PCs.
Simulation Platform:	
miniSim 2.2.2	SAE level 0, SAE level 1, and SAE level 2 capabilities (future software updates to include higher levels of automation in development). Software outputs data at 60Hz.
Computation and Audio:	
miniSim PC	Custom build: Intel core i7-5930K 3.50 GHz (12 CPUs) with 32 GB memory and three dedicated graphics cards (1X NVIDIA Quadro M6000-4GB, 2X NVIDIA Quadro M4000-8GB).
Video Capture PC	Custom build: Intel core i5-6600K 3.50 GHz (4 CPUs) with 16 GB memory.
Eye Tracking PC	Alienware Area 51R5: Intel core i7-7800X 3.50 GHz (12 CPUs) with 16 GB memory and a dedicated graphics card (NVIDIA GeForce GTX 1070-16GB).
2X ART SLA-1 Amplifier	Surround sound with subwoofer for vibrations and shaker effect.
EuroPower EPQ304	300-Watt Four-speaker system within the cab for driving/scenario audio.
Equipment On-board:	
AccuForce Steering Wheel	Capabilities include the following: horn, turn signals, headlights, cruise control, setting gap for adaptive cruise control, engaging lane keep assist.
4X HD Cameras	HD video output showing facial cues, pedals, dash and media center, and scenario overview.
FOVIO FX3 Eye Tracker	Capable of gaze tracking (60Hz), 6 DoF head tracking, Task evoked pupillary response (TERP) (1Hz), and eyelid tracking.
Kinect Sensor	Capable of 3D video rendering and visualization.
Polar H10 Sensor	Heart rate chest strap monitor capable of data output at 1Hz

Figure 4-1: KU driving simulator specifications.

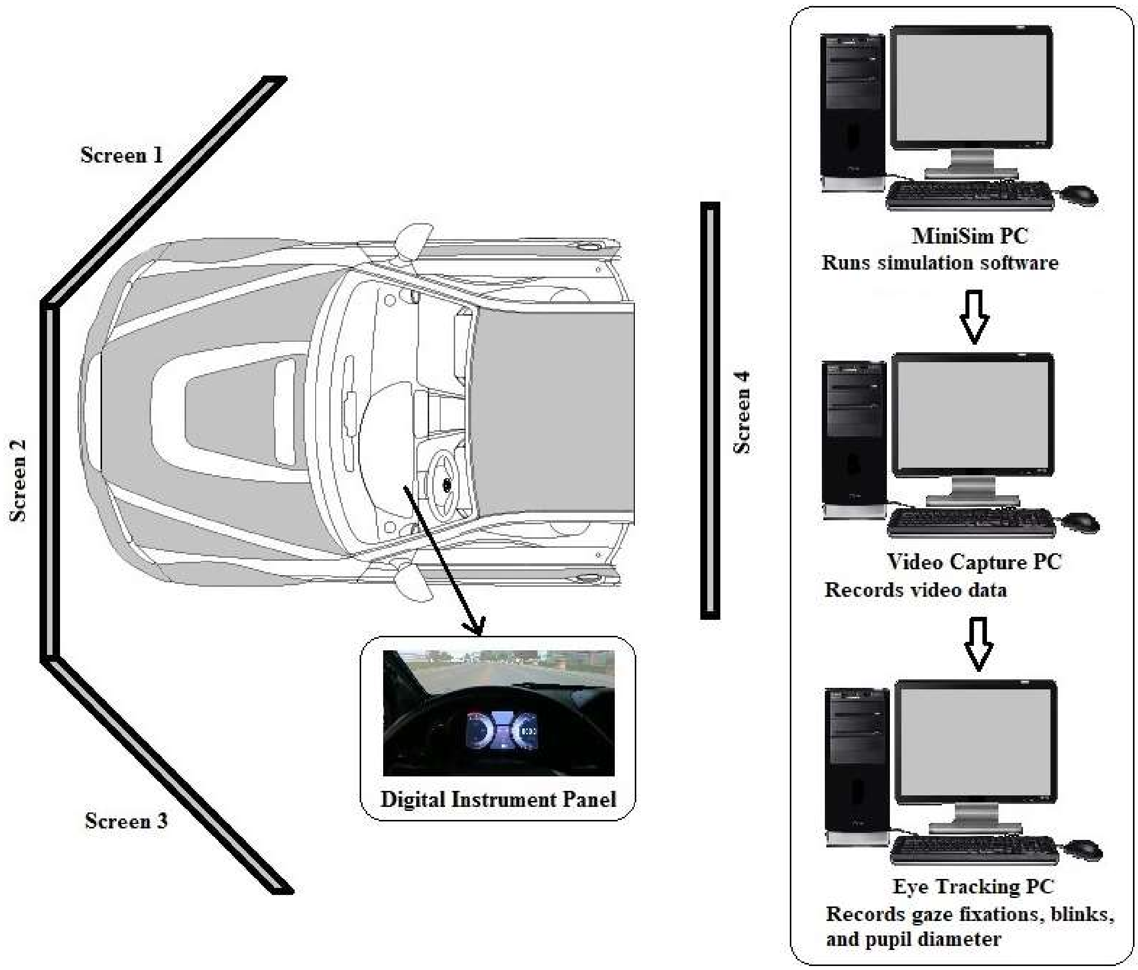


Figure 4-2: Configuration and layout of the KU driving simulator.

Top View

Side and Rear View

Driver View

Inside-Cab View

Operator View

Figure 4-3: KU driving simulator equipment and setup depictions.

4.3 Population Sample Selection

Population sample selection is a crucial first step of the experimental process in order to avoid biased results or conclusions that cannot be reasonably generalized for a broader population. The subjects must exhibit diversity in their static driver characteristics and be adequately representative of the overall driver population. The sample needs to include enough participants to allow for statistically confident research results, while also being manageable in terms of cost, convenience, and time.

For this reason, the use of a pre-screening questionnaire is suggested. The questionnaire is used to determine personal, demographic, and driving information such as age, gender, possession of a valid U.S. driver's license, model/year of current vehicle, experience with ACC systems, estimate of what constitutes a safe car following distance, existing medical conditions (including history of motion sickness), willingness to use automation systems (ACC, lane-keeping assistance), and willingness to participate in a simulator-based study. Some of that information serves to exclude participants not suitable for the experiment (e.g. people without an active driving license, with less than a minimum one year of driving experience, with medical conditions, motion sickness, or not comfortable with using a simulator), but the rest of the data can be used to ensure the presence of varied static driver characteristics among the study population.

Specifically, it is desirable that the sample includes a balanced (ideally equal) gender split, participants that represent each of the following four age cohorts: (i) less than twenty-five years old, (ii), twenty-five to forty years old, (iii) forty to sixty years old, and (iv) over sixty years old, and both drivers with experience and willingness to use automation systems as well as those without.

The required sample size depends on various factors, such as inter-driver heterogeneity, which will affect the standard deviation and thus the estimation confidence of the measured variables. The quality of the design of the experimental scenarios also matters. Most of the parameters, such as vehicle trajectory, driver workload, and situational awareness can be measured for all participants. However, it is possible due to different driver characteristics (e.g. greater than average driving capability) or the design of the driving scenarios (e.g. lack of high enough task complexity), that some of the variables, such as the compensation effects, manifest for only some of the participants. Such an occurrence necessitates the use of a greater sample size in order to ensure that a sufficient number of performance effects are captured. As there is no available data in the literature for either the expected driver variance nor the expected percentage of high-performance subjects that can avoid experiencing performance effects, the most economical way to determine the required sample size is through estimates obtained from conducting a smaller pilot study (chapter 4.5). Since the subjects are not tested simultaneously, it is also possible to expand the scope of the study and subsequently the sample size after analyzing the first results. Considering realistic budgetary and time constrains of an average study of that type, it is suggested that the performance effects of at least thirty participants need to be measured. Then, if a conservative assumption is made that high-performance drivers are at most 25% of the sample, it can be concluded that a minimum sample of forty participants is necessary in order to collect enough data on performance effects to use in the statistical analysis.

4.4 Measured Variables and Data Collection Techniques

The following static and dynamic (functions of time *t*) variables need to be measured in the experiment for the purpose of calibrating the target variables of the model:

- Static Driver Characteristics (age, gender, years of driver experience, experience with automated driving systems);
- Longitudinal Vehicle Factors: Speed $V_n(t)$ and Spacing $S_n(t)$;
- Baseline (static) Desired Speed $\tilde{V}_n$ and Desired Time Gap $\tilde{T}_n$;
- Cognitive Workload (objective): WL_{ob} (t);
- Cognitive Workload (subjective): WL_{sub} (t);
- Situational Awareness: SA (t);
- Presence of Compensation (adaptation) Effects: $E_c(t) \neq 0$;
- Presence of Performance (adaptation) Effects: $E_p(t) \neq 1$;
- Standard (or ideal) reaction time τ_n of the driver of vehicle (n); and
- Additional reaction time $\varphi_n(t)$of the driver of vehicle (n) at time *t* due to human factors.

Appropriate techniques must be utilized in order to obtain the above measurements. Following are candidate measurement methods for each variable, and a discussion of why these methods are deemed the most suitable for the purposes of this study:

- The Static Driver Characteristics are captured through the use of the pre-screening questionnaire applied during the population sample selection.
- Speed $V_n(t)$ and Spacing $S_n(t)$ are automatically recorded by the simulation software.
- The Baseline Desired Speed $\tilde{V}_n$ and Desired Time Gap $\tilde{T}_n$ need to be measured in control scenarios with average task complexity and difficulty, where no adaptation effects are present.
- Objective Cognitive Workload WL_{ob} (t) can be measured dynamically through an objective psychophysiological measurement. Eye-tracking (task-invoked pupillary response) using the Index of Cognitive Activity Protocol is an automated and non-intrusive process that can provide dynamic workload measurements. An alternative or additional method is the use of Secondary-task performance objective measurement. This is a more intrusive measurement technique, but serves a dual purpose (measuring another variable – reaction time – as discussed below), so using it as a second way to measure objective workload only increases the robustness of the collected data. For the purposes of this study a Tactile (vibrating) Detection-Response Task (TDRT) technique is suggested, because the tactile input is less intrusive to the visual demands of the primary driving task and to situational awareness than visual stimuli. The TDRT uses an electrical vibrator taped on the subject's shoulder to deliver the stimulus, and the driver needs to respond to it by pressing a button on the steering wheel. And additional advantage of using the TDRT in addition to the eye-tracking ICA is that the results of this technique interpret workload directly on a scale of 0 to 1, according to the method developed by Manjunatha and Elefteriadou (2018), as discussed in Chapter 2.3.1.3.2. On the other hand, the eye-tracking ICA provides a continuous assessment of workload which is necessary for the equations of the NHDM car-following model. Thus, it is suggested that both methods are employed, with the less frequent TDRT results used as a guide to rescale the eye-tracking ICA results between the values of 0 and 1.
- Subjective Cognitive Workload WL_{sub} (t) can be measured through on-line self-report, such as the Instantaneous self-assessment (ISA) and the Continuous Subjective Ratings (CSR) techniques. The main difference between the two is that ISA involves drivers self-rating their workload during a task on a scale of 1 (low) to 5 (high) on standard intervals (normally every two minutes), while with CSR drivers give a new rating whenever they

perceived a change of their subjective workload, instead of at specific trigger points. Adaptations of these techniques aim to reduce their high intrusiveness: ISA can use auditory instead of visual triggers and vocal numeric responses instead of pressing buttons on a keyboard, while CSR can also be administered offline: post-hoc, using video recordings of the drive instead, with the obvious disadvantage of introducing memory issues. A pilot study is required to determine the most suitable of these two techniques (and the most appropriate of their variations), taking into account potential conflicts with the intrusive workload measurement techniques (TDRT) and the situational awareness measurement techniques, to ensure that the drivers are not overwhelmed with secondary tasks. A post-study multidimensional self-report workload technique such as the NASA Task Load Index (NASA-TLX), the Driver Activity Load Index (DALI) or the Subjective Workload Assessment Technique (SWAT) can also be considered, in order to increase the diagnosticity of the unidimensional on-line techniques, by contextualizing the causes of workload.

- Situational Awareness SA(t) can be measured through a non-intrusive real-time objective process index technique such as eye-tracking (measuring gaze overlay and eye fixation), or a real-time probe technique that delivers questions about the driver's environment during the driving task. Due to the limitations of the driving simulator, the Situational Awareness Global Assessment Technique (SAGAT) cannot be applied, but the Situation Present Assessment Method (SPAM) is a possibility. The latter, however is an intrusive method, especially in conjunction with the various workload measurement techniques discussed above, especially since measuring changes in workload is more important for the purposes of the study than changes in situational awareness. On the other hand, the non-intrusive eye-tracking techniques are generally considered insufficient in effectively measuring situational awareness due to their indirect nature (cannot verify whether drivers perceived what they looked at) and because they do not capture all three levels of Situational Awareness. Thus, a concurrent verbal protocol analysis (VPA) is usually required for interpretation of these results, and SPAM can assume that role (examples of questions that address all three levels of SA are shown in Table 4-1). Finally, a third option that can be considered is to perform a smaller-scale preliminary study focusing on eye-tracking and SPAM measurements of situational awareness in order to derive sufficient correlation between their results that would allow for the use of only the non-intrusive process index technique for SA measurement in the full study.

Table 4-1: SPAM example questions across the three levels of Situational Awareness

SA Level	Example Questions
Level 1 - Perception	• Did you notice passing a wild animal at the edge of the roadway? • Are you travelling above or below the speed limit?
Level 2 - Comprehension	• Is an off ramp approaching soon? (after an exit sign has passed by) • What is the relative speed of the traffic compared to your vehicle?
Level 3 - Projection	• Is the green car two vehicles ahead in the adjacent lane about to initiate a lane-changing maneuver into your lane? • Are you losing or gaining on the preceding vehicle?

- The presence of Compensation Effects can be inferred by changes in the longitudinal driving variables that are not consistent with the car-following model equations when $E_c(t) = 0$ (thus it is necessary to assume that $E_c(t) \neq 0$).
- The presence of Performance Effects can be inferred through primary task performance measurements. Longitudinal indexes such as speed or headway could be applied, but they may be the results of car-following factors other than performance degradation. Thus, lateral variation/instability measures, such as the standard deviation of the lateral position (SDLP) or the standard deviation of the steering wheel movements (SDSTW) are more suited for this occasion. In addition, significantly increased reaction times results from the TDRT technique can also indicate the presence of Performance Effects.
- The standard reaction time τ_n of the driver of vehicle (n) can be assumed based on the existing literature or measured through the TDRT process in control scenarios with average task complexity and difficulty, and no adaptation effects (the same as the desired speed and time gap measurements).
- Finally, the additional reaction time $\varphi_n(t)$of the driver of vehicle (n) at time *t* due to human factors is also measured through the TDRT process by subtracting the standard eaction time τ_n from total reaction time $\dot{\tau}_n$ measured. This measurement is only necessary to take place if performance effects are present.

Table 4-2 summarizes the variables that need to be measured and the candidate measurement methods by which that data can be collected.

Table 4-2: Measured Variables and Candidate Measurement Methods

Variable	Measurement Method	Description
Static Driver Characteristics	Pre-screening Questionnaire	Age, gender, years of driver experience, experience with automated driving systems
Speed and Spacing	Driving Simulation Equipment	Vehicle Trajectory under all scenarios
Desired Speed & Time Gap		Vehicle Trajectory under control scenarios
Standard reaction time		
Compensation Effects		Changes in the longitudinal variables (speed & spacing)
Performance Effects		Deviation of the lateral position (SDLP) or the standard deviation of the steering wheel movements (SDSTW)
Situational Awareness (SA)	Eye-tracking (gaze overlay and eye fixation)	Real-time objective technique. Concurrent verbal protocol analysis (VPA) required for interpretation of results
	Situational Awareness Assessment Method (SPAM)	Real-time probe technique (questions about the driver's environment). Objective technique
Workload (WL)	Eye-tracking (task-invoked pupillary response)	Physiological objective measurement. Using the Index of Cognitive Activity Protocol (ICA)
	Continuous Subjective Rating (CSR)	Subjective measurement, based on the unidimensional Self-Assessment (ISA) scale, using an auditory trigger to which the driver must elicit a numeric verbal response
	Tactile (vibrating) Detection-Response Task (DRT)	Secondary-task performance objective measurement. Both reaction time and misses taken into account
Additional reaction time φ	Tactile (vibrating) Detection-Response Task (DRT)	Only reaction time is considered

4.5 Pilot Study

The need to simultaneously measure situational awareness and cognitive workload (both objective and subjective) on a continuous basis creates a conflict between the more intrusive measurement methods (SPAM, CSR, and DRT) which compete for the same cognitive resources that the driver requires to perform the driving task. For this reason, a pilot study with a limited number of participants should be performed in order to evaluate whether the data collection process can be simplified by relying on more non-intrusive methods, such as eye-tracking. Specifically, the correlation between SPAM and eye-tracking should be assessed for the measurement of situational awareness, with the purpose of relying only on eye-tracking for measuring SA in the final study scenarios. Similarly, the participants of the pilot study should be asked to answer questions of comfort after the experiment with regards to using the two intrusive workload measurement techniques (CSR and DRT) at the same time. As mentioned in chapter 4.3, the pilot study also serves as a guide for determining the desired sample size for the study scenarios.

4.6 Practice and Control Scenarios

A five-minute long practice scenario should be designed for participants to get acclimated to the simulator environment, since participants generally take between four to six minutes for a satisfactory initial acclimation (Ariën et al, 2013). A Simulator Sickness Questionnaire (SSQ) (Kennedy et al, 1993) should then be administered to check for simulator sickness.

Then, participants should then be asked to drive in two control scenarios in order to infer their Desired Speed and Time Gap and measure their standard reaction time:

1. A five-minute scenario on a straight, two-lane highway, operating at HCM LOS A, with varying speed limits, while recording their speed limit compliance.
2. A five-minute scenario in which the participants are required to follow a vehicle which was scripted to travel straight at a constant speed under the speed limit, with no other traffic on the road in order to observe the car following patterns of the participants. Three different lead vehicle speeds should be employed.

4.7 Study Scenarios

The study scenarios should be designed in a way that allows for the drivers to experience significant variation in task complexity, with regards to their driver capabilities, in order to produce measurable compensation and performance effects. It is also essential to provide opportunities and reasons for the drivers to activate or deactivate the automation capabilities of their vehicles. Though not all drivers are required to inhabit the full range of the capability-difficulty spectrum (on account of the differences between drivers), nor it is necessary for all of them to exhibit performance effects, it is desirable that as many of them as possible do so. For this reason, a multi-dimensional matrix of scenarios of escalating complexity should be developed. The components of the scenario matrix include: three levels of traffic density (low, medium, and high) which correspond approximately to HCM LOS B/C, D and E respectively, with freeway merge segments included for every density level, two levels of visibility settings (daytime and nighttime), two levels of vehicle interaction difficulty (low lane-changing activity versus the presence of aggressive drivers who perform sudden dangerous lane-changing maneuvers with small gaps) and two levels of information density (typical, and workzone with an overload of signs and variable message billboards). This leads to a total of twenty-four short-length (two to three minute) scenarios. These are then split into two half-hour sessions, one during daytime (twelve scenarios) and one during nighttime (twelve scenarios).

The order by which the participants will experience the short-length scenarios during their drive is a potential source of unwanted order and sequence effects, that can confound the results of the experiment. This problem can be solved through counterbalancing, a systematic variation of the order of conditions in the study. A counterbalanced design across subjects reduces the chances of the order of scenarios influencing the results. A complete counterbalancing method would require the use of each possible sequence, and thus one participant for each of them. Due to complexity of the experiment, and the multiple conditions, the great number of possible permutations make complete counterbalancing unpractical. However, if there are not enough participants, incomplete (or partial) counterbalancing is a possible compromise. Incomplete counterbalanced measures include the Latin Square, where each scenario only occurs once at each order position (1^{st}, 2^{nd}, 3^{rd}, etc.). Another possibility is to randomize the allocation of scenarios across the sample subgroups, a technique called randomized partial counterbalanced design.

4.8 Variable Calibration and Model Validation

The following target variables, coefficient, and thresholds for both manual and automated conditions need to be calibrated in order to be incorporated into the NHDM car-following model and the broader behavioral framework:

- Workload Perception Threshold (PT_{WL}): The threshold is calibrated based on the objective and subjective workload measurements. Since this study does not measure the components of the Competence-Complexity Interface (CCI), this threshold will reflect what is the minimum change in objective workload that causes a change in subjective workload.
- Indifference Adaptation Threshold (IT_{DS}): This threshold is calibrated in order to indicate what value of the Dynamic Observed Driver Capability to Relative Driving Task Difficulty $[\bar{C}_n(t)/\ \bar{D}_n(t)]$ ratio is sufficient to result in driver compensation effects.
- Unconscious Performance Threshold: This threshold is also calibrated via the $[\bar{C}_n(t)/\ \bar{D}_n(t)]$ ratio. However, this time the query is which value is sufficient to result in driver performance effects.
- Automation Transition: A discrete choice model can be used to describe automation transition choices, where the longitudinal vehicle factors and the automation trust derived from the static driver characteristics are used as inputs in the utility function, while the weights assigned to each of them are the parameters than require calibration.
- The sensitivity parameter (β_n) that indicates how sensitive the desired speed of the driver of vehicle (n) is to compensation effects can be calibrated through the observed change in desired speed, given the calculated magnitude of $E_c^{(n)}(t)$ from Equation 3.3.
- The sensitivity parameter (γ_n) that indicates how sensitive the desired time headway of the driver of vehicle (n) is to compensation effects can be calibrated through the observed change in desired time headway, given the calculated magnitude of $E_c^{(n)}(t)$ from Equation 3.3.
- The sensitivity parameter (δ_n) to the driving task difficulty can be calibrated through substituting the measured quantities $[SA_n(t), WL_n(t), \varphi_n(t)]$ in equations 3.3 to 3.7 and solving for (δ_n).
- The Action Point Threshold (IT_{AP}) has two components that both need to be individually calibrated: ΔV_n and ΔS_n. These values represent the acceptable deviation of the current speed and space gap from the desired speed and space gap of the driver of vehicle (n).

- Finally, the magnitude of the performance effect $E_P^{(n)}(t)$ can be calibrated via 3.12 by substituting all other known values.

Subject of the statistical analysis also need to be the functional forms of the following two equations: $E_P^{(n)}(t) = f\left[E_c^{(n)}(t)\right]$ and $\varphi_n(t) = f[DS(t)]$.

The behavioral framework, NHDM car-following model and the calibrated parameters can be validated by means of cross-validation. This includes partitioning the data sample into unequal in size but complementary subsets, using the largest partition for the analysis and model calibration, and then using the smallest partition as a validation data set that can provide an estimate of the model's predictive strength. Additionally, follow-up studies can be conducted in order to validate the results, either with the use of driving simulators or instrumented vehicles in field conditions.

CHAPTER 5 – SUMMARY AND FUTURE RESEARCH STEPS

5.1 Research Summary

This thesis aimed to develop a driver behavior framework that considers human factors and can be applied to describe both traditional manual driving, as well as driving of vehicles with varied automation capabilities, and driver-initiated transitions between the manual and the automated driving states.

For this purpose, a comprehensive literature review of driver car-following behavior research, human psychology and cognition during the driving task, as well as vehicle automation characteristics and effects was conducted. Advantages and limitations of the most prominent car-following models, with emphasis on those that consider human factors were analyzed. Psychological factors and cognitive concepts that have been developed in order to explain human driving behavior were defined in a manner that allows for their quantification and implementation in the driving behavior framework. Various measurement techniques of these cognitive concepts were evaluated, with regards to their advantages and disadvantages, as well as their applicability to this study. Finally, vehicle automation classification systems were presented, as well as a review of studies investigating how car-following behavior and driving-related cognitive concepts are impacted by the introduction vehicle automation features.

The proposed behavioral framework, car-following model and control transition system are described in detail in the methodology chapter. This includes the model's independent input variables, the dependent target variables and thresholds, which require calibration and validation, and the output variables that serve as the calibration performance measures. Finally, the equations of the proposed car-following model, the Naturalistic Human Driving Model (NHDM), including its calibration coefficients and sensitivity parameters, are listed.

A theoretical data collection experiment using a driving simulator that can be applied to calibrate and validate the proposed framework and car-following model is also detailed, including candidate strategies for measuring and analyzing the required parameters. The data collection plan proposes experimental processes that would capture the impact of varying levels of automation and traffic conditions on manual and automated driving preferences of demographically diverse test subjects (drivers with different individual static characteristics) via measurable changes in their workload and situational awareness under purposefully designed and implemented scenarios.

5.2 Future Research Steps

Following the proposed theoretical behavioral framework and car-following model, several future research steps can be pursued. The most obvious includes applying the data collection methodology and analysis plan with human subjects (drivers) with the goal of validating or rejecting the assumptions of the framework. Additional studies involving instrumented vehicles in the field instead of simulated scenarios can then further investigate the applicability of the model and framework in actual driving conditions.

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