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Theory and an example case in modelling driver distraction

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A generic multi-level framework for microscopic traffic simulation—Theory and an example case in modelling driver distraction

J.W.C. van Lint*, S.C. Calvert

Transport and Planning Department, Faculty of Civil Engineering and Geosciences, Delft University of Technology, Delft, The Netherlands

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A B S T R A C T

Incorporation of more sophisticated human factors (HF) in mathematical models for driving behavior has become an increasingly popular and important research direction in the last few years. Such models enable us to simulate under which conditions perception errors and risk-taking lead to interactions that result in unsafe traffic conditions and ultimately accidents. In this paper, we present a generic multi-level microscopic traffic modelling and simulation framework that supports this important line of research. In this framework, the driving task is modeled in a multi-layered fashion. At the highest level, we have idealized (collision-free) models for car following and other driving tasks. These models typically contain HF parameters that exogenously “govern the human factor”, such as reaction time, sensitivities to stimuli, desired speed, etc. At the lowest level, we define HF variables (task demand and capacity, awareness) with which we maintain what the information processing costs are of performing driving tasks as well as non-driving related tasks such as distractions. We model these costs using so-called fundamental diagrams of task demand. In between, we define functions that govern the dynamics of the high-level HF parameters with these HF variables as inputs. When total task demand increases beyond task capacity, first awareness may deteriorate, where we use Endsley’s three-level awareness construct to differentiate between effects on perception, comprehension, anticipation and reaction time. Secondly, drivers may adapt their response in line with Fullers risk allostasis theory to reduce risk to acceptable levels. This framework can be viewed as a meta model, that provides the analyst possibilities to combine and mix a wide variety of microscopic models for driving behavior at different levels of sophistication, depending on which HF are studied, and which phenomena need to be reproduced. We illustrate the framework with a distraction (rubbernecking) case. Our results show that the framework results in endogenous mechanisms for inter- and intra-driver differences in driving behavior and can generate multiple plausible HF mechanisms to explain the same observable traffic phenomena and congestion patterns that arise due to the distraction. We believe our framework can serve as a valuable tool in testing hypotheses related to the effects of HF on traffic efficiency and traffic safety in a systematic way for both the traffic flow and HF community.

* Corresponding author.
E-mail addresses: j.w.c.vanlint@tudelft.nl (J.W.C. van Lint), s.c.calvert@tudelft.nl (S.C. Calvert).

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1. Introduction

Incorporation of human factors (HF) in mathematical models for driving behavior has become an increasingly popular research direction in the traffic flow theory community the last decade. One may argue, however, that HF have always been at the core of traffic flow modelling. Since the pioneering work of (Greenshields, 1934,Lighthill and Whitham, 1955; Richards, 1956 and many others) on the fundamental relation and the fluid dynamical description of traffic, many schools of thought have emerged, each characterized by different behavioral assumptions on how drivers respond to stimuli—and which stimuli they respond to; and by different ranges of descriptive and (partial) explanatory power for the resulting phenomena. For example, safe-distance car following (CF) models (Laval and Leclercq, 2010a; Newell, 2002; Pipes, 1953) assume that drivers maintain a large enough distance headway in case the leader brakes at maximum deceleration; optimal velocity models (Bando et al., 1998; Davis, 2003) assume that drivers accelerate to their optimal velocity as a function of the distance headway; whereas approaches in the more general group of stimulus-response models (Gazis et al., 1961; Kerner and Klenov, 2006; Treiber et al., 2000) make assumptions on how drivers adapt their response (acceleration) to a range of different stimuli (distance headway, speed differences). Over the years, many approaches to incorporate more (HF) sophistication have been proposed. So-called psycho-spacing (or action point) models (Fritzsche, 1994; Wiedemann, 1974) incorporate drivers' inertia to observe and respond to small changes in stimuli; whereas for example multi-anticipatory models (Hoogendoorn et al., 2006,2007; Treiber et al., 2006) include terms for anticipation of drivers to traffic conditions further downstream. What "classic" (or as Saifuzzaman and Zheng, 2014) put it: "engineering" models) for car following (CF) have in common is that they are—by design—collision-free. This is no longer guaranteed, however, if we incorporate reaction times, i.e. delayed stimuli, and/or perception errors in these stimuli (headways, relative speeds) or both (Hamdar and Mahmassani, 2008; Treiber et al., 2006). An even wider diversity of behavioral assumptions and modelling approaches can be found for lateral driving behavior that governs when drivers change lanes, diverge, and merge (Choudhury, 2008; Cohen, 2004; Kesting et al., 2007; Laval and Daganzo, 2006; Schakel et al., 2012; Wei et al., 2000; Zheng, 2014). In most cases here, the underlying theory is based on conditional decision-making. The corresponding models usually incorporate decision trees, and models assessing the conditions (availability of gaps) and the appropriate response (intention and execution of crossings or lane changes). Also models for lateral driving are—in principle—collision free. Like CF models, the inclusion of reaction times and/or perception errors in lane changing (LC) models relaxes that assumption.

There are several good reasons why research has accelerated into more sophisticated and systematic approaches to incorporate HF in microscopic traffic flow models. First, there still are many phenomena in current traffic that we do not fully understand, such as the capacity drop, traffic hysteresis, and many phenomena related to lateral movement (Saifuzzaman and Zheng, 2014; Zheng, 2014). Second, we are at the start of a major transition towards higher levels of vehicle automation (VA). Paradoxically, traffic simulation models have always been capable of simulating automated vehicles; now that VA becomes a reality, we need to increase the HF sophistication in our human driver models. Since traffic flow operations are governed by interaction processes, we cannot predict the changes in those interactions and their consequences based on knowledge of the behavior of just one of the 'players' (the automated vehicle)—the human player may also fundamentally change in ways not catered for (sufficiently) by existing models. Third, whereas most emphasis of microscopic traffic modelling has been on reproducing safe traffic operations and the corresponding emerging phenomena (e.g. capacities, wave patterns), an increased need emerges to use these models to realistically predict also potentially unsafe traffic operations, and the corresponding indicators (statistics of accidents and surrogate safety measures) (Hamdar and Mahmassani, 2009; Hamdar et al., 2015b). These conditions are relevant not just in studying vehicle automation, but also in the here and now. To assess whether safety is at risk, explanatory psychological constructs are needed that can endogenously predict under which circumstances drivers take risks and/or make perception and judgement errors that may lead to unsafe situations and ultimately accidents. Several approaches have already been proposed in this direction, e.g. using prospect theory (in which drivers way faster travel time against the risk of rear-end crashes (Hamdar et al., 2015a, 2008); and using Fullers' Risk Allostasis Theory (Fuller, 2011) (in which risk taking and driver response is considered a result of comparing subjective task demand and task capacity using the so-called Task-Capacity-Interface model (e.g. Hoogendoorn et al., 2013; Saifuzzaman et al., 2015, 2017). However, more behavioral sophistication comes at a methodological and computational price, in terms of model identification, calibration and validation efforts; and computational efficiency. Therefore, the challenge for our community in the coming years, is to augment existing CF and LC models with a range of explanatory (HF) mechanisms that (a) endogenously predict where and under which circumstances drivers e.g. make errors, take more (or less) risks, suffer from longer reaction times; using (b) mathematics and simulation logic that is tractable and simple enough so that large-scale simulation is (still) possible; while (c) still reproducing plausible vehicle trajectories and (by implication) plausible macroscopic traffic patterns. There is an additional practical, but nonetheless important design criterion that relates to the (software) development of traffic simulation models. Such new additions to the already broad family of micro-simulation models need to find their way into both commercial (closed-source) (e.g. Casas et al., 2010; Fellendorf and Vortisch, 2009; Mahut and Florian, 2010; Sykes, 2010) and open-source (Krajzewicz et al., 2012; Treiber and Kesting, 2010; van Lint et al., 2016) traffic microsimulation packages. This requires a generic modelling framework that allows combination of different modelling approaches and implementations that are modular and maintainable.

The central contribution of this paper is such a generic multi-level modelling and simulation framework that supports this research challenge and that generalizes existing approaches to incorporate human factors in models for driving behavior. In this paper we focus on car following (CF) only, however, the framework can be naturally extended to support lane

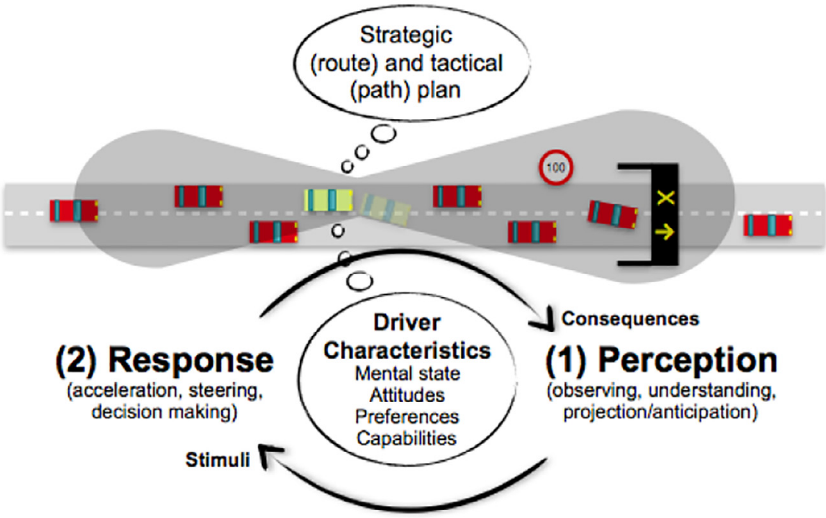

Fig. 1. Driving as a control task. For clarity, the many external factors affecting perception, response and driver characteristics (e.g. traffic conditions, environment, control, etc.) are not drawn.

changing (LC) or other driving behaviors (crossing, merging, etc). The paper is outlined as follows. In Section 2 we discuss human factors in CF models along two dimensions: the *what* (HF process is modelled) and the *how* (this is done). On the basis thereof we then present our conceptual framework and the theory behind it In Section 3. In Section 4 we operationalize this framework in a simulation case, and in section 5 we present the results. In Sections 4 and 7, we respectively synthesize and critically discuss these results and close with conclusions and an outlook for further research.

2. Human factors in car following models

There are many excellent reviews and taxonomies of longitudinal driving available in the literature, e.g. (Brackstone and McDonald, 1999; Saifuzzaman and Zheng, 2014; van Wageningen-Kessels et al., 2014), of which Saifuzzaman and Zheng (2014) specifically discuss HF in car following models. This section is not intended as an additional review, but as a motivation and underpinning for the framework we present in the next section. To this end, we review the literature along two dimensions that we informally depict as the *what* (process is modeled) and the *how* (this is done).

2.1. What (HF) processes are modeled

To explain the "what" dimension of human factors modeling in traffic, consider Fig. 1, in which the driving task is stylized as a control task. The figure highlights the two main processes to perform this control task, and HF plays a fundamental role in both. First, there is a *perception* process, in which the (observed) environment is recognized, understood and translated into (possibly predicted) stimuli, such as distance gaps and speed differences. This process is subject to driver traits, which encompass all relevant mental states, attitudes, preferences, skills, etc., and to the mechanical characteristics (inertia) of the vehicle. Second, there is a *response* process, in which drivers act based on the perceived and possibly predicted stimuli. Clearly, also the response process is subject to driver traits. In this paper, we consider the perception and response processes at the tactical (maneuver) and operational (control) level only, as described by Michon (1985) as illustrated in Fig. 2.

We prefer to use the terms tactical and operational for these levels, since also maneuvers and strategic behaviors are control processes that involve perception and response as well—albeit with longer control time-steps and -spans. Perception and response on the tactical and operational levels are both influenced by strategical (route- and path-planning) behaviors—these relationships are beyond the scope of this paper. Fig. 2 further highlights that tactical and operational driving are affected by the driving environment. These include traffic conditions, road lay-out, traffic rules and control, weather, and also distractions and technology (Farah et al., 2018). Finally, drivers also perform other tasks than driving (distractions), which may affect their perceptions, responses and ultimately driving performance. Note that some behaviors may be categorized at more than one level, e.g. path choice may emerge from maneuvering (rather than from active decision making) and speed choice may similarly emerge from control actions.

In Table 1, we have adapted the list of HF used in the review by Saifuzzaman and Zheng (2014) by structuring it along the "what" (perception and response) dimension. Note that contrary to other more detailed paths of thought in cognitive science, this classification simplifies the general flow of information processing to these two central aspects, which can be associated with input and output. The authors are well aware of the existence of intermediate constructs; however, these are not sufficiently understood to allow detailed application in the traffic modelling at this time and are therefore omitted.

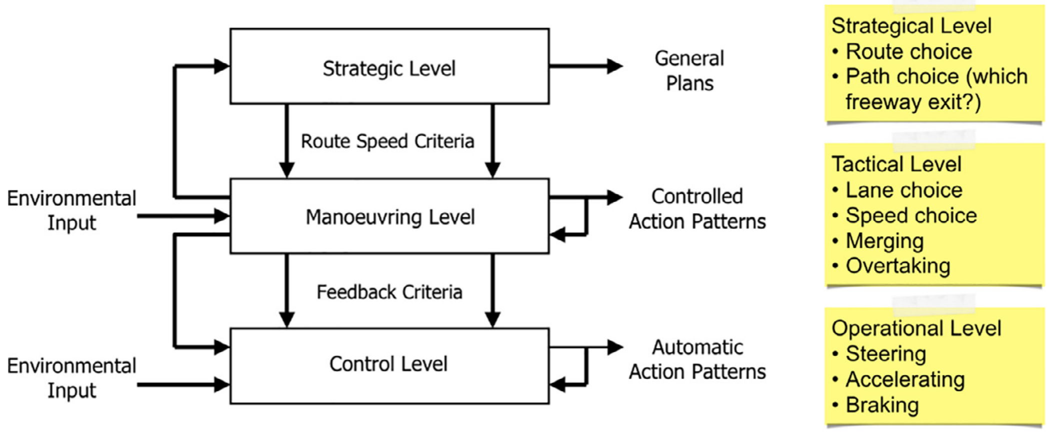

Fig. 2. The hierarchical structure of the road user task. Performance is structured at three intertwined levels. (Source: Michon, 1985, yellow "post-its" are added).

2.2. How (HF) processes are modelled

The second dimension relates to "how" HF are incorporated in CF models mathematically. To streamline the discussion, we frame CF models using the following general functional:

$$a_i(t + \tau_i(t)) = f(S_i(t), \theta_i(t), \omega_i(t)) \tag{1}$$

in which $a_i(t)$ denotes acceleration; $\tau_i(t)$ reaction time; $S_i(t)$ a set of available stimuli e.g. speeds, speed differences, distance gaps with respect to the ego-vehicle i and its leader(s); θ_i a set of driver preferences (e.g. car following parameters), amongst which his/her sensitivity to these stimuli; $\omega_i(t)$ a set of characteristics of the (perceivable) world $PW_i(t)$ for driver i that may affect the response (e.g. control, visibility, etc). In these variables, the subscript i denotes driver (i) specifity, and t denotes (continuous) time.

We can distinguish between two main approaches of how HF processes are modelled. The first, and most common, is that HF processes are incorporated *exogenously* by means of fixed parameters in the (core) stimulus-response car following logic, which in the simplest case are deterministic (i.e. mean values), or drawn from some (known) distribution, that is

$$\theta_i \sim g_\theta(\mu_\theta, \sigma_\theta) \tag{2}$$

The same holds for reaction time, e.g., $\tau_i \sim g_\tau(\mu_\tau, \sigma_\tau)$. This approach allows one to vary both response (behavior) and reaction time over drivers, but this approach cannot explain the dynamics of that behavior over time for the same driver. Ossen and Hoogendoorn (2011) show that both distributions (inter-driver and intra-driver, i.e. dynamics over time) are wide. The differences between drivers pertain not just to parameter distributions (i.e. trajectories of different drivers are best described with different sets of parameters fitted for the same car following models); but also to (car following) model distributions (i.e. trajectories of different drivers are best described with different car following logic; Ossen and Hoogendoorn, 2011). Perception errors, i.e. errors in stimuli input to car following models, can also be modelled exogenously. The challenge here is that such errors are typically auto-correlated. Treiber et al. (2006) suggest a Wiener process (with known parameters) to simulate consecutive perception errors. The same technique for exogenous modeling of perception errors is used in Van Lint et al. (2018). Exogenous modelling of perception errors allows one to study the robustness to erroneous inputs of the assumed control laws with which drivers follow leading vehicles, but do not reveal the mechanisms that may cause these errors. In sum, exogenous modelling of HF factors can be used to cater for inter-driver differences; and allow for "what-if" type analysis, but they do not provide insight in what causes intra-driver differences (dynamics over time) in the HF mechanisms governing perception, anticipation or response.

The second "how" approach overcomes this limitation and incorporates HF endogenously, by means of (dynamic) functions or algorithms that explain both dynamics in reaction time and response parameters, as well as inter-driver differences. These dynamics can be formulated in general as

$$\frac{d}{dt}\gamma_i(t) = h(\gamma_i(t), S_i(t), \omega_i(t)), \;\; with \;\; \gamma_i = [\tau_i, \theta_i] \tag{3}$$

in which the change in driver state (i.e. his/her reaction time and response parameters) is a function of their current state, the stimuli at hand and the environment. The perception threshold mechanism in the Wiedemann model (Wiedemann, 1974), the prospect theory based risk-taking mechanism in Hamdar and Mahmassani (2008), Hamdar et al. (2015a) and the task capability interface model implementations in Hoogendoorn et al. (2013), Saifuzzaman et al. (2017, 2015) are examples of such an approach (we discuss the TCI model of Fuller (2011) in more detail in Section 3.3.2). In

Table 1
HF modelling in car following along the “what” (process is modelled) dimension, adapted from (Saifuzzaman and Zheng, 2014).

What (process)	*Aspects and driver traits**	*Examples*
Perception How drivers translate signals from the environment to (anticipated) stimuli.	Reaction time. This involves the physical delay between observing (a braking light) and responding (braking), and the delay caused by diverted attention.	Most CF models have been extended with reaction time, e.g. (Davis, 2003; Gazis et al., 1961; Treiber et al., 2006). By and large, only for small reaction times do car following laws result in stable dynamics.
	Estimation errors. Humans observe stimuli with a limited accuracy as a function of distance and visibility conditions.	There is abundant evidence that drivers have systematic biases in judging both distances and speeds (Castro et al., 2005; Nilsson, 2000; Thiffault and Bergeron, 2003), and several CF models have been extensively tested under such errors, which are generally modelled as (auto-correlated) noise processes (Hamdar and Mahmassani, 2008; Treiber et al., 2006; Van Lint et al., 2018). No attempts have been made to our knowledge in modelling these errors endogenously (i.e. as the result of a HF process).
	Perception thresholds. Humans cannot perceive small changes in stimuli.	Wiedemann was among the first to formalize driver inertia to small stimuli in CF models (Wiedemann, 1974), after which various adaptations followed (Fritzsche, 1994). See also driver inertia
	Spatial anticipation. Drivers look ahead (downstream).	Spatial adaptation is usually modelled by incorporating gaps between leader-follower pairs further downstream (i.e. downstream density), e.g. (Hoogendoorn et al., 2006; Ossen and Hoogendoorn, 2011; Treiber et al., 2006, 2007; Van Lint et al., 2018). In general, spatial anticipation counter-effects the destabilizing effects of reaction times.
	Temporal anticipation. Drivers extrapolate conditions (over space and time).	Typically, some form of dead-reckoning (using constant speed or acceleration) is adopted (Treiber et al., 2006; Van Lint et al., 2018). Temporal anticipation also counter-effects reaction times.
	Distractions. Competing information processing activities affect perception	Distractions, and particularly visual distractions are detrimental for the driving task (Precht et al., 2017a, b; Rebecca et al., 2008). Various researchers have experimented with distractions in terms of consequences for the car following task (Chan and Singhal, 2015; Hansen et al., 2017; Hoogendoorn et al., 2010; Hoogendoorn et al., 2011; Kaber et al., 2012b; Saifuzzaman et al., 2015; Schömig and Metz, 2013) and the modelling thereof.
Response How drivers dynamically and context-specifically respond to these stimuli.	Sensitivity to stimuli (relative speed, position, etc)	Every CF model contains parameters that govern the degree in which drivers respond to stimuli. These may dynamically change due to circumstances (see context sensitivity)
	Preferences. Drivers' desired speed, spacing, headway, etc.	Similarly, most CF models contain one or more parameters describing driver preferences. In exploring inter-driver heterogeneity, these are typically modelled as distributions over drivers (Montanino and Punzo, 2015; Ossen and Hoogendoorn, 2011).
	Context sensitivity. Different contexts may (dynamically) affect driving response.	It is widely recognized that parameters in CF models are both driver and context dependent, e.g. (Laval and Leclercq, 2010a; Ossen and Hoogendoorn, 2011; Zheng et al., 2013). Clearly, as contexts dynamically change, so should the parameters.
	Inertia. Even if drivers perceive (small) stimuli, they may not respond to these.	Wiedemann-type models (Fritzsche, 1994; Wiedemann, 1974) are also termed action point models, since drivers are assumed to change their responses at discrete time instants (and continue according to the last response in between) rather than continuously.
	Aggressiveness or risk-taking propensity	Laval and Leclercq (2010b) show how even in very simple CF models differentiating between timid and aggressive drivers complex but realistic stop-and-go patterns can be reproduced. More generally, there is rich literature on the driver- and context specific role of risk taking in various driving tasks (Farah et al., 2008; Jamson et al., 2012; Michaels et al., 2017; Precht et al., 2017b), and a few attempts to explicitly model this endogenously in CF models (Hamdar et al., 2015a, 2008).

Saifuzzaman et al. (2015), for example, the Gibbs and IDM CF models are augmented with a dynamic term for task difficulty to adapt the acceleration response. The idea is that drivers increase their desired headway under conditions where the driving task becomes too difficult, which they assume is the case when their actual headway becomes too small. Task difficulty TD_i is considered proportional to the ratio of a driver's desired time headway T_i and the actual headway $\Delta v_i(t)/s_i(t)$, i.e.

$$TD_i(t+\tau_i) = \left(\frac{\Delta v_i(t) T_i}{(1-\delta_i)s_i(t)}\right)^{\gamma} \tag{4}$$

In which δ_i is a driver specific risk factor (the larger it is, the higher task difficulty) and γ a scaling factor (again, the larger it is, the higher task difficulty under similar circumstances). Saifuzzaman et al. (2015) estimate the scaling factor δ_i along with other model parameters using driving simulator data and show how incorporation of this dynamic term gives a (potential) explanatory mechanism for trajectories of aggressive (small or negative δ_i) and timid (large δ_i) drivers. In Saifuzzaman et al. (2017) the same idea is used as an explanatory mechanism for traffic hysteresis and traffic oscillations. As we will show further below, there are many other possible HF mechanisms that could explain such dynamics.

2.3. Synthesis

As argued in the introduction, there is already a huge diversity in models for driving behavior characterized by different assumptions on how drivers respond to stimuli—and which stimuli they respond to. Table 1 illustrates that the amount of assumptions and modelling approaches will most likely steeply increase once we start to incorporate more realistic HF processes into these different models. We propose a framework, with which it becomes possible to do this in a highly systematic way. This requires us to go one step further than the endogenous modelling examples above, in which a selection of HF parameters (e.g. task difficulty or risk propensity) are first endogenously computed and then embedded in the core car following logic. We generalize these approaches, by decoupling idealized and HF driving completely. We propose a multi-level representation of the driving task, with a “coarser level” in which idealized (collision-free) behavior is modeled; and an explanatory (HF) layer underneath that governs the dynamics of the inputs and parameters of this “idealized” level, and hence relaxes the collision-free assumption. By separating these layers completely, we allow analysts to mix a wide range models for driving behavior with a wide range of models for the underlying HF processes. In the remainder of this paper, we further detail this framework and explore its properties in a case where drivers are distracted.

3. Multi-level modelling and simulation framework

3.1. Scope and overall idea

We propose a modeling and simulation framework for operational driving (contingent to tactical and strategical driving as depicted in Fig. 1) in which we maintain the tasks a driver executes and the effects these tasks have on the two main HF processes considered while driving: perception and response. Most importantly, there is the driving task itself, which for now we restrict to just car following and free driving. We discuss possible generalization to other driving tasks such as lateral movement and conflict negotiation in the discussion section. Secondly, there are secondary tasks, that do not (directly) contribute to driving, but that may affect perception and response, for example in-vehicle or outside distractions. This effect is due to the fact that all tasks consume information processing capacity through the perception and interpretation of the driving environment as well as responding to these (car following, lane changing, etc.). To allow their effects on driving to be quantified, we propose to maintain a (minimal) set of key mental state variables, which are based on psychological constructs that are found in HF literature (e.g. (Endsley, 2000; Fuller, 2005, 2011; Kaber et al., 2012a; Teh et al., 2014)) and are used to describe operational perception and response processes in the context of driving behavior. These are situational awareness $SA(t)$, which encapsulates multiple dimensions of perception (including focus / distraction) (Endsley, 1995; Wickens, 2008); and driver task demand $TD(t)$, which is used in many studies as (one of the) explanatory concepts when it comes to explaining driving performance (Precht et al., 2017b; Teh et al., 2014) under a broad range of conditions. In simple terms, $TD(t)$ describes the cumulative workload of each cognitive task that a driver is subjected to, whereas $SA(t)$ describes how well a driver is aware of their environment, particularly of those stimuli in the environment that a driver needs to safely and efficiently perform the driving task. The manner in which information is processed from perception through to the cognitive decision process is caught within the SA construct and depends on a drivers' traits and current state but goes beyond the scope of this contribution. In our framework, both $TD(t)$ and $SA(t)$ are dynamic (i.e. they change over time and space); and they affect driving parameters (reaction time, frequency and magnitude of perception errors) and the response of drivers (sensitivities to e.g. distance gaps). We describe this in more detail below. Clearly, many more social/psychological/physiological factors (e.g. interaction with passengers, emotional state, fatigue, etc) are relevant in describing (and simulating) perception and response processes. However, it is important to stress that we need to strike balance between a *description* that is

- sufficiently accurate, so that valid inference is possible of both the efficiency and safety effects of the traffic operations resulting from interactions between drivers;
- sufficiently generic, so that many different approaches to modelling HF processes in models for driving behavior can be cast in the framework (directly or via natural extensions);
- sufficiently simple (mathematically / computationally), so that simulation in large congested networks is still possible. Simplicity also relates to the level of detail with which non-driving tasks are modelled. For our purposes, we do not care about the details of the HF processes involved in non-driving tasks (in this paper we consider e.g. distractions); we care only for the net result in terms of how much information processing these tasks consume and how that affects driving behavior.

We make two more overall points. Firstly, the word *description* here above is in italics because the models cast in this framework may not provide causal explanations as to WHY (or how) driving performance deteriorates. What we want is a descriptive model that—using variables available in the simulation *only*—is able to predict THAT this happens under certain conditions, analogously to how in a macroscopic traffic flow model the fundamental diagram is not a causal model relating

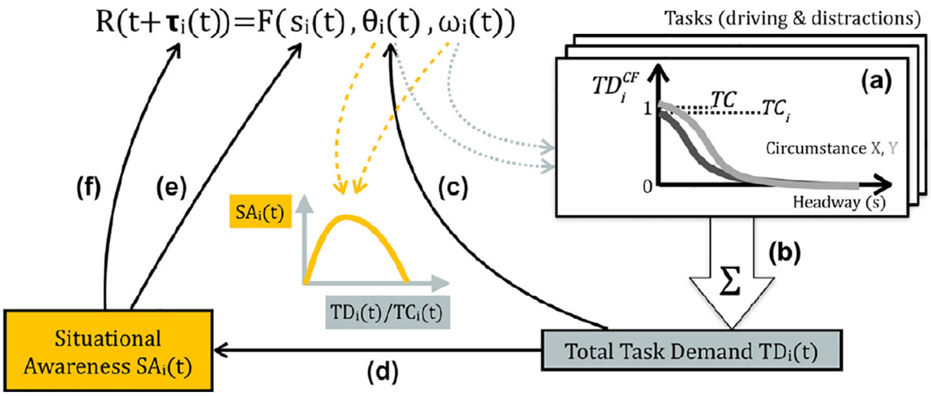

Fig. 3. Conceptual modelling & simulation framework.

speed to density, but a descriptive (statistical) model that describes that speed drops with increasing density.[1] Secondly, the framework outlined in this paper is a theoretical framework. We provide some face-validation in this (and a follow-up) paper, but virtually every component and relationship in it (Fig. 3) constitutes of many hypotheses that require testing with elaborate experimental methods (driving simulator or field research, mathematical analysis, simulation, etc.) to result in valid mathematical and simulation models. However, due to the multi-level structure, the framework allows researchers to do this in a systematic way.

Fig. 3 outlines the main mechanisms in our framework, using the functional in Eq. (1). First total task demands are computed using (a) so-called fundamental diagrams of task demand and (b) task demand aggregation. Then the effect of those accumulated task demands is computed on (c) personal traits (desired speed, headway, etc.); on (d) situational awareness and as a consequence on (e) perception errors and (f) reaction time dynamics. Below we elaborate on each of these components.

3.2. State variables & basic relationships

3.2.1. Task demand and task capacity

In our simulation framework we define task demand as *the amount of information processing effort (per unit time) needed to fulfill a task* (i.e. to reach an objective such as not colliding into the leading vehicle)[2] We define the following variables:

TC	Nominal Task Capacity	Information processing capacity a nominal (standard) driver has available to execute tasks safely and efficiently. $TC = 1$ (*or* 100%).
$TC_i(t)$	Driver Task Capacity	Information processing capacity for driver *i* in units of *TC*
$TD_i^a(t)$	Driver Task Demand	Variable that describes how much information processing effort driver *i* requires performing a particular task *a* (safely and/or satisfactorily) in units of *TC*
$TD_i(t)$	Total Driver Task demand	Sum of all task demands for driver *i*, that is,

$$TD_i(t) = \sum_a TD_i^a(t). \tag{5}$$

$TS_i(t)$	Driver Task Saturation	Variable that expresses total driver task demand $TD_i(t)$ relative to $TC_i(t)$, that is,

$$TS_i(t) = \frac{TD_i(t)}{TC_i(t)}. \tag{6}$$

Clearly, in cases when driver task saturation $TS_i(t)$ is close to (or larger than) 1 the performance of a driver deteriorates. This performance deterioration may take the form of changes in awareness (larger perception errors, longer reaction times);

[1] In free flow drivers may reduce their speed based on decreasing distance gaps, whereas in congestion, drivers may adjust their distance gaps based on decreasing speeds. The direction of causality does not matter for the validity of the predicted traffic conditions with macroscopic traffic flow theory. A descriptive (statistical) model suffices.

[2] We realize this definition differs from what is commonly used in the HF field; e.g. De Waard (2002) defines task demand in terms of goals that have to be reached and (mental) workload as the proportion of a drivers mental processing capacity that is allocated for task performance (such that those task demands are met). However, for simplicity reasons, and because of the intuitive analogy with traffic flow modelling, we prefer to define driver task demand as a variable that expresses how much mental processing is *demanded* by a task versus driver task capacity that expresses how much processing "power" a driver has available for it.

changes in responses (smaller or larger sensitivities) and driver state (changes in other driver traits). These effects and how to model them are discussed in the following sub-sections. We first focus on how to maintain total driver task demand as a state variable, which requires that it can be endogenously computed within the simulation, using whatever information is available in the simulation

3.2.2. Fundamental diagrams of task demand

Consider a car following task as in Fig. 3(a). In the limit, with very short time headways under dense near capacity conditions, this task will require virtually all (driver specific) information processing capacity, i.e. $TD_i^{CF}(t) \approx TC_i(t)$, whereas with longer headways under light(er) conditions, this task may consume not only a fraction of a drivers' information processing capacity, with some steep transition beyond a critical time headway value. This idea, a so-called "fundamental diagram of task demand" (FDTD) for car following, is illustrated in the example in Fig. 3(a), in which the relationship between task demand and time headway of a driver is depicted under two different circumstances—say rainy and dry weather. Note that in the figure, driver task capacity $TC_i(t)$ is slightly below nominal task capacity $TC(t)$, implying this driver has car following skills slightly below average. We propose the following requirements for FDTD's:

Req. 1. Task demand is expressed in units of "nominal" task capacity—this is an arbitrary "red line of workload" (Rebecca et al., 2008) beyond which additional task demand results in performance degradation (we return to this further below)

Req. 2. Task demand *must* be expressed as a function of variables (made) available in the simulation.

For car following time headway seems a logical choice, for lane change maneuvers a combination of headway, density, and available gaps may work whereas for merging additionally distance / time to diverge point may provide a good basis. Possibly, variables (constructs) derived from these primary variables may be used such as measures for complexity of the driving task (e.g. Hoogendoorn et al., 2013; Teh et al., 2014). See also Req. 4.

For non-driving tasks, FDTD's could be expressed as function of the location, time duration or severity of the distraction (see the example below). It is important to note that we exclusively consider secondary tasks that affect information processing capacity required for safe and efficient driving. Precht et al. (2017a) for example conclude that particularly high-risk visually/visual-manually distracting secondary tasks (looking away because of distractions outside or inside the vehicle) result in aberrant driving behavior. They also point out that some distractions (e.g. conversations) may distract the driver under some conditions (e.g. at decision points); but may actually support safe(r) driving under other conditions (in case of fatigue). Both such tasks could fit in the framework, however, the direction in which a secondary task interferes with the driving task (positive or negative) is considered *input* to our framework.

Although we restrict the discussion in this paper to the car following task only, we believe that in principle, driver trait and circumstance-specific FDTD's *can* be formulated for a wider selection of relevant operational and tactical driving tasks (e.g. overtaking, weaving, responding to signaling, etc.), in which task demand and task saturation play a role in the performance of executing such tasks. We return to this claim in the discussion and synthesis section. To cater for that discussion, we do propose a third requirement:

Req. 3. FDTD's that express task demand at the tactical (maneuver) level prevail over (are considered to subsume) task demands at the operational (control) level. For example, a FDTD for executing a lane change maneuver should incorporate task demand for the inherent car following subtasks within that maneuver.

Req. 3 is important for two reasons. First, the amount of information processing for a task is context sensitive. Very short headways may be comfortable during a lane change maneuver, but highly uncomfortable when following a truck on a narrow freeway lane. Second, it seems a priori very difficult (if not impossible) to empirically validate a model that disentangles a lane change move into all its constituent subtasks and to quantify separate task demands for each along the maneuver. It makes more sense to keep it simple and formulate a FDTD for different maneuvers (free driving, car following, lane changing, merging, etc) in terms of their total driver task demand.

There is good reason, however, to consider separation between secondary tasks such as distractions, particularly those that require visual perception (Precht et al., 2017a, b; Rebecca et al., 2008), since these all utilize the same information processing channel (vision). Whether or not multiple distractions have an additive effect (as in Eq. (5)) is a hypothesis that requires testing. For lack of evidence otherwise, in this paper we assume an additive effect, so that given a stack of tasks one can—as often as deemed necessary (in the limit at every simulation time step)—compute a drivers' total task demand and task saturation (Fig. 3(b)) and consequently, the resulting performance deterioration (if any). This deterioration may involve two things:

- Deterioration in awareness in terms of increased reaction time and increased perception errors (Fig. 3(d)–(f))
- Response adaptation in terms of changes in preferences (desired speed, headway, etc) and other personal traits (Fig. 3(c))

Before discussing both with an illustrative example, we first further detail a conceptual model for awareness.

3.2.3. Conceptual model for situational awareness

Following Endsleys' dynamic situational awareness model (Endsley, 1995; Wickens, 2008), we consider three levels of SA. These are (1) sensing the relevant objects and information; (2) comprehension (i.e. correctly interpreting this information);

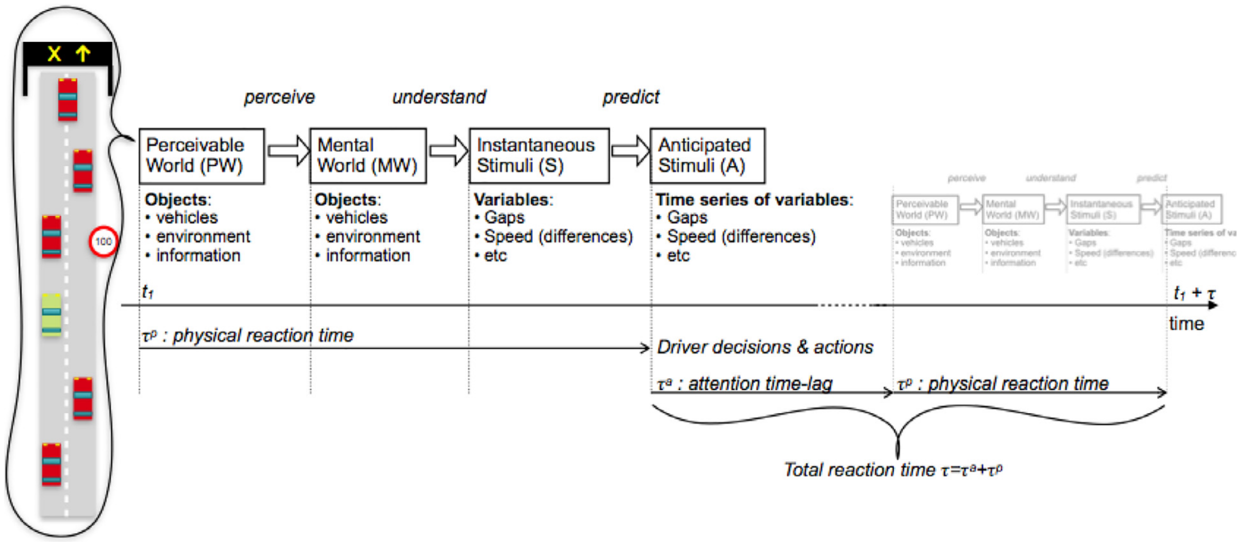

Fig. 4. Conceptual model for awareness based on Endsley (Endsley, 1995; Wickens, 2008).

and (3) anticipation (making short term predictions for decision making). These three levels of awareness constitute three stages in the perception process, as schematically outlined in Fig. 4. In SA step 1 (sensing), a driver perceives a selection of the available pieces of information from the total *perceivable world* (PW_i, i.e. everything a driver could physically observe) needed to perform the driving task (other vehicles, traffic signs, control signals, geometry, etc) and stores these in its *mental world* (MW_i). In SA, step 2 (comprehension), the driver derives from these objects the set of stimuli $s_i(t)$ with which it can make decisions (overtake, brake, etc). Depending on the (CF, LC and other) models used, $s_i(t)$ may include (relative differences in) gap, and speed; traffic signals, etc. In SA step 3 (anticipation), finally, a (time series) prediction $S_i(t) = \{s_i(t),\ldots, s_i(t+T)\}$ of these stimuli is made. We thus define three levels:

$SA_i^n(t)$	Situational Awareness Level 1 (sensing)	Variable that describes how aware a driver *i* is of all the objects (other traffic participants and information sources) required for performing the driving task.
$SA_i^c(t)$	Situational Awareness Level 2 (comprehension)	Variable that describes how well (in terms of accuracy and efficiency) a driver is able to translate this information into stimuli.
$SA_i^a(t)$	Situational Awareness Level 3 (anticipation, prediction)	Variable that describes how well (in terms of accuracy and efficiency) a driver is able to anticipate (predict) the future evolution of these stimuli.

Fig. 4 also illustrates that in our framework we distinguish between a *physical reaction time* τ_i^p, which is the result of the three-stage perception process; and an *attention time lag* τ_i^a, which is the result of competing (secondary) information processing activities while driving. The total reaction time that is ultimately used in the upper-level models for CF (LC, GA, etc), equals the sum of both components, i.e.

$$\tau_i = \tau_i^a + \tau_i^p \tag{7}$$

Like task demand, the SA variables may be chosen as continuous values (e.g. between 0 and 1), but one may equally argue for categorical, ordinal or fuzzy values (e.g. “bad”, “moderate”, “good”), or whatever parameterization works in a particular case. These three aspects affect driving performance in different ways and may also be (positively or negatively) influenced in different ways. For example, drivers behind a large truck have limited sensory awareness: they will miss relevant downstream information but may still have an excellent comprehension and prediction on the basis of what they *can* notice (and perhaps have noticed in the past). Under adverse weather conditions drivers may still notice all relevant aspects of the environment, but the conditions may affect comprehension (level 2 awareness), because it’s more difficult to judge distances in heavy rain. Their anticipation/prediction skills may not suffer directly, although indirect predictions based on erroneous inputs may be less reliable. Adverse weather may also increase physical reaction time (the duration of the perception process) because it takes more “processing time” under limited visibility to judge distances and relative speeds.

3.3. Conceptual framework using an example

We now discuss the conceptual framework of Fig. 3 on the basis of the illustrative example in Fig. 5, in which we follow (through a sequence of events) a particular nominal driver *i* ($TC_i(t) = TC$) who is car following. At time t_1, a vehicle merges in front of vehicle *i*, significantly decreasing the headway. A little later at t_2, driver *i* receives a telephone call, which (s)he finishes at time t_6. First note that we propose two FDTD’s, one for the car following task (Fig. 5(a)-left) and one for a distraction: making a telephone call (Fig. 5(a)-right). For the former, we consider a simple linear function in which

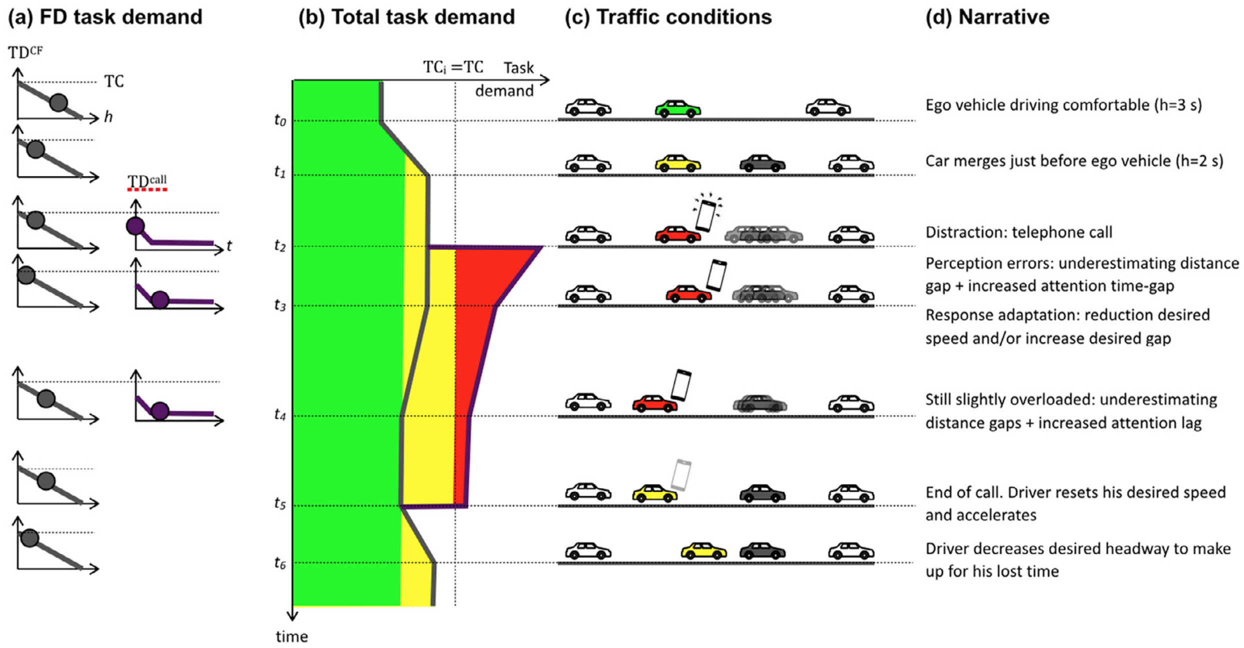

Fig. 5. Illustrative example dynamics task demand and the use of fundamental diagrams of task demand.

$TD_i^{CF}(t) = TC_i(t)$ for headways near zero seconds ($h\downarrow 0$) and $TD_i^{CF}(t) = 0$ for say $h > 4$ seconds. For the latter, we consider a function with a short peak at the start (hearing and accepting the call) and a constant task demand during the rest of the conversation. At every stage in the sequence of events, the task demand level for both activities are indicated with a thick circle in each FDTD graph. Under Fig. 5(b), total task demand is drawn at each time instant, computed according to Eq. (5); under Fig. 5(c), the vehicle positions are schematically drawn and under Fig. 5(d) a narrative to the example is provided.

3.3.1. Initial state(s) of the driver

At t_0, the driver follows the leader at a comfortable time headway (e.g. $h = 3$ s). This consumes some cognitive information processing capacity but has no detrimental effect on either perception or response—the driver operates according to his base level parameters (reaction time, sensitivities, SA levels, etc). In the period $[t_0, t_1]$, a vehicle merges onto the roadway and becomes the new leader. Time headway now decreases ($h = 2$ s) and the car following task demand increases accordingly. Possibly, we see a small effect (increased perception errors), although these may be counter effected by appropriate anticipation strategies (Treiber et al., 2006; Van Lint et al., 2018).

3.3.2. Effects of a distraction

At t_2, the driver receives a telephone call. This results in a steep increase in total task demand due to an additional task TD_i^{call}, such that $TD_i(t) > TC_i(t)$ (i.e. $TS_i(t) > 1$). The driver is now oversaturated, which will (immediately) result in a deterioration of perception / awareness levels on an operational level:

- Deterioration in sensing: the driver may miss relevant information (e.g. a vehicle on an adjacent lane). This in a sense is the worst possible effect (overlooking vehicles or other safety critical information), which in this simple car following case will not occur.
- Deterioration in comprehension: the driver will increasingly misjudge relative distances and speeds. There is much evidence in terms of *which* factors cause drivers to make errors, and visual distractions form an important category (Precht et al., 2017a, b; Wickens et al., 2008). There is also evidence in terms of the direction of specific perception biases that affect driving. For example, the findings in Nilsson (2000) suggest that gaps (perceived while driving at 80 km/h) are generally underestimated, and that the front gap is more underestimated than the rear gap. Additionally, humans typically find it even more difficult to judge speed differences than distance gaps (Hunt et al., 2011), and also here, the bias is towards underestimation. There is also some evidence for distance *overestimation* under specific circumstances and conditions (e.g. gap assessment, night time driving (Castro et al., 2005; Lee and Sheppard, 2017)). We will vary with both biases in the simulations.
- Deterioration in anticipation, either directly (the driver resorts to simpler more erroneous anticipation strategies) or indirectly (since the input to a drivers' "anticipation algorithm" is now more unreliable)
- A possible increase in overall reaction time. One may argue this increase relates to attention time-lag (the driver looks at the phone regularly) or to physical reaction time (the conversation eats up cognitive processing, so particularly comprehension and anticipation take more time), or to a combination of the two. The net result is the same.

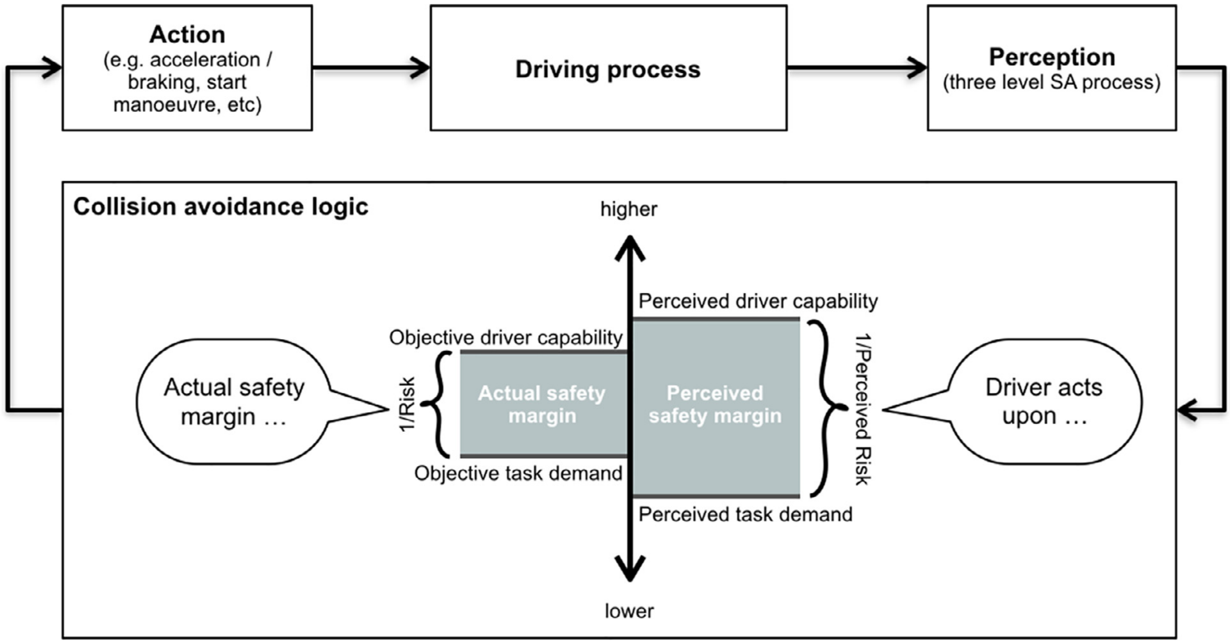

Fig. 6. Central ideas of Fullers' task capability interface model (based on Fuller, 2011) for operational driving. Note that in this paper we use the term driver task *capacity* (instead of capability)—the reader may interpret these as synonyms (see running text).

A second effect takes place on a tactical level: the driver will adapt his/her driving behavior to accommodate for the increase in task demand. This behavioral adaptation is the key principle in Fuller's task capability interface (TCI) model (Fuller, 2005, 2011) and is illustrated in Fig. 6. Note that in this paper we use the term driver task *capacity* instead of *capability*, the reader may interpret these as synonyms (the Cambridge dictionary defines capability as "the ability to do something", and capacity as "the ability to do a particular thing"). We prefer the term capacity for its second connotation as a quantitative measure (for *how much* ability someone has "to do a particular thing"). When discussing Fuller, we use his term (capability), but in the ensuing we will stick to our term (capacity). Fuller conceptualizes driving as a control task, in which drivers at the operational level at the very least avoid collisions. According to his theory drivers monitor the difference between (perceived) task demand and task capability. This results in a perceived safety margin: the difference between what a driver believes (s)he is capable of handling and the perceived demands of a particular task (Fig. 6 right). The smaller this safety margin, the higher the risk and level of arousal drivers experience. In the original paper (Fuller, 2005), the theoretical background is that of task difficulty homeostasis, i.e. drivers seek for and return to a constant level of risk (arousal). Later (Fuller, 2011) Fuller relaxes the theory with a *risk allostasis* principle, in which drivers dynamically adapt their "risk set-point". Either way, whereas a driver reacts on a *perceived* risk, the actual consequences follow from the *objective* safety margin, which is typically smaller, since drivers typically overestimate their capabilities and underestimate the actual task demand. In our framework, the difference between perceived and objective task demand and capacity can be easily catered for, but even if we grant drivers an objective judgement about both, their decisions will be based on perceived stimuli (L2 awareness) and derived anticipation thereof (L3 awareness), which can be wrong as outlined above.

Returning to the example of Fig. 5, the driver in this simple car following case has one choice to return to an acceptable risk level (safety margin), and that is (between t_3 and t_4) to decrease speed and (as a result) to increase time headway. Both can be achieved in various ways in different car following models (e.g. by reducing desired speed, increasing desired headway, etc.). Despite this adaptation, the driver in this example still operates in an oversaturated state, which implies considerable perception errors and—depending on the characteristics of the distraction—increased reaction time. When the call finishes at t_5 we assume the driver responds again by returning to (e.g.) a desired speed preference slightly above his base level resulting in a level of risk slightly higher than just before the call.

3.4. Summary

The proposed conceptual framework models the driving task in a multi-layered fashion. At the highest level, we have ideal (in principle collision-free) models for car following and other driving tasks. These models typically have reaction times and a set of other high-level HF parameters that exogenously "govern the human factor" (typically sensitivities to stimuli, desired speed, etc). At the lowest level, we define state variables that maintain how many tasks drivers execute and what the information processing costs are of performing these tasks—this we model using so-called fundamental diagrams of task demand (Fig. 3(a)). In between these two, we define functions that govern the dynamics of high-level HF parameters with these state variables as inputs. When total task demand (Fig. 3(b)) increases beyond task capacity two processes take place:

- Firstly, different levels of awareness (based on Endsley) may deteriorate (Fig. 3(d)): reaction time may increase (Fig. 3(e)) and perception errors may become more severe (Fig. 3(f))
- Secondly, drivers adapt their response in line with Fullers risk allostasis theory to reduce risk to acceptable levels (Fig. 3(c)), where "acceptable" may be driver, circumstance and maneuver specific. During a lane change manoeuver temporarily very short headways will not result in such high task saturations (recall Req 4 in Section 3.2.2)
- Thirdly, over time other driver specific traits may experience a (temporary) temporal adjustment. In the example, the driver increased desired speed after finishing a phone call to make up for lost time. Any hypothesis on longer term feedback between increased levels of task demand and behavioral response could be incorporated.

Finally note that whereas very high task saturation may reduce awareness, the same may be true for very low task saturation (e.g. Thiffault and Bergeron, 2003), which is why relationship (d) in Fig. 3 has the characteristic "reverse U" shape. In this case, we would most likely observe sensing (SA level 1) errors and long(er) attention time-lags. We will not further elaborate on this issue, other than that it is possible to incorporate this behavior in the framework.

4. Case: simulating driver distraction

The conceptual framework that we presented in the previous sections is demonstrated in a simulation case in which we apply different task demand components and sensitivities to these components. Our aim is twofold. First we want to verify that implementation of the mechanisms in Fig. 3 indeed result in plausible changes (deterioration) of performance in driving ability, which aligns to that found in literature (e.g. Hoogendoorn et al., 2010; Saifuzzaman et al., 2017). Second, and related, we want to explore the sensitivity of those results with respect to our (many) assumptions.

4.1. Case description and applied traffic model

We consider car-following only and use the IDM + Schakel et al., 2012) for this purpose, which is an adaptation of the Intelligent Driver Model (IDM) (Treiber et al., 2000). The IDM + separates the free and car-following terms and takes the minimum, rather than superimposing the terms. This allows more realistic capacity values under reasonable parameter values. The car-following acceleration is determined using Eqs. (8) and ((9), where τ_i denotes the reaction time; parameter a^i_{max} is the maximum acceleration; b^i_{comf} the maximum comfortable deceleration (expressed as a positive number); v^i_0 the desired speed; T_i the desired headway, and s^i_0 is the stopping distance. Furthermore, we have three stimuli, these are the prevailing speed $v_i(t)$ of driver i; speed difference with the leader $\Delta v_i(t) = v_{i-1}(t) - v_i(t)$ and (net distance) gap with the leader $s_i(t) = x_{i-1}(t) + s_0^{i-1} - x_i(t)$. For the base case we choose the following values: $\tau_i = 0$; $a^i_{max} = 3\,\mathrm{m/s^2}$; $b^i_{comf} = 3\,\mathrm{m/s^2}$; $v^i_0 = 35\,\mathrm{m/s}$; $s^i_0 = 8\,\mathrm{m}$ and $T_i = 1.2\,\mathrm{s}$. Finally, for parameter δ we use a standard value of 4, which reduces the maximum acceleration as speed increases.

$$a_i(t+\tau_i) = a^i_{max}\ min\left(1 - \left(\frac{v_i(t)}{v^i_0}\right)^{\delta}, 1 - \left(\frac{s_i(t)}{s^*_i(t)}\right)^2\right) \tag{8}$$

$$s^*_i(t) = s^i_0 + v_i(t)\cdot T_i + \frac{v_i(t)\cdot\Delta v_i(t)}{2\sqrt{a^i_{max}\ b^i_{comf}}} \tag{9}$$

We consider an arbitrary homogeneous single lane road corridor of $L = 3\,\mathrm{km}$, without ramps or any other infrastructural disturbances. At a certain location x_{acc} an incident is presumed on the opposite carriageway that causes a distraction (rubbernecking) as schematically sketched in Fig. 7(a). Traffic is generated during 15 minutes (900 seconds) upstream according to a demand profile with a pulse of high (near capacity) demand after 100 seconds (Fig. 7(c)), which leads to the supply pattern as in Fig. 7(b) (dashed line indicates incident location). The total time spent (TTS) in this case equals 451 minutes (see further below).

4.2. Specification relationships for task demand and awareness

Fig. 7(d) and (e) depict the fundamental diagrams of task demand for the car following and distraction tasks, respectively. Our (arbitrary) assumption is that a driver who is car following with headways smaller than h^i_{min} requires some maximum level of information processing capacity ($TD^{CF}_i = TD^i_{max,CF}$) to drive as an "ideal driver" Eqs. (8) and ((9)); whereas from headways larger than h^i_0 seconds, (s)he requires a much lower level ($TD^{CF}_i = TD^i_{0,CF}$). In between, we assume a linear decrease in task demand. Specifically, we specify the FDTD for car following as a function of time headway $h = v_i(t)\Delta s_i(t)$ as

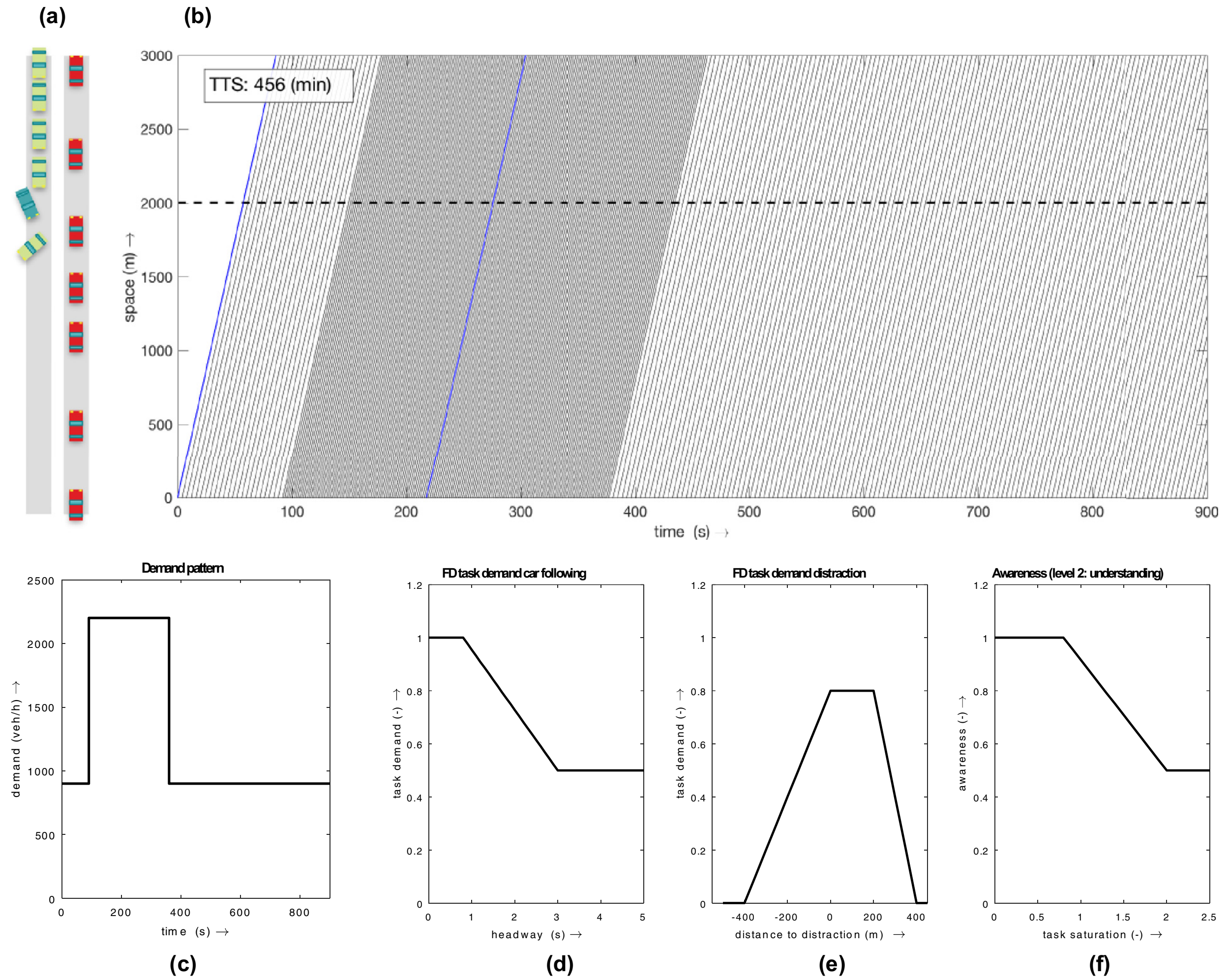

Fig. 7. Base case lay-out, base demand and supply pattern and HF functions for drivers with nominal task capacity. In this case the total time spent (TTS) by all vehicles in the simulation is 456 min.

follows (see Fig. 7(c))

$$TD_i^{CF}(h) = \begin{cases} TD^i_{max,CF} & h \le h^i_{min}(a) \\ TD^i_{max,CF} - \dfrac{h - h^i_0}{h^i_{min}(a) - h^i_0}\left(TD^i_{max,CF} - TD^i_{0,CF}\right) & h^i_{min}(a) < h \le h^i_0, \\ TD^i_{0,CF} & h > h^i_0 \end{cases} \tag{10}$$

In which $TD^i_{0,CF} = 0.5$; $TD^i_{max,CF} = 1$ (100%) are the minimum and maximum task demand level while car following and $h^i_0 = 3$ (in seconds) and $h^i_{min}(a)$ the associated maximum and minimum threshold headway values respectively. We express the minimum headway as a function of deceleration $a = a_i(t)$, to account for the effect that task demand specifically increases in case of strong decelerations (emergency braking). We propose

$$h^i_{min}(a) = \begin{cases} \left(1 + \dfrac{a + b^i_{comf}}{b^i_{max} - b^i_{comf}}\right) h^i_{min} & a < -b^i_{comf}, \\ h^i_{min} & otherwise \end{cases} \tag{11}$$

In which $b^i_{max} = 8\ m/s^2$ represents the maximum braking acceleration we assume in this paper. Recall that b^i_{comf} is a deceleration expressed as a positive value (in our case 3 m/s^2)

For the distraction task (Fig. 7(e)), the assumption is that this distraction “eats up” task capacity along the same lines as in the example in the previous paragraph. We (again arbitrarily) assume a linear increase in task demand from 400 m towards the distraction until some maximum level ($TD_i^{ACC} = TD^i_{max,ACC}$), after which a driver maintains this level for 200 m and then recuperates again. We specify the FDTD for the distraction task thus as a function of distance to the distraction $d = x_i(t) - x_{acc}$ as follows (see Fig. 7(e))

$$TD_i^{acc}(d) = \begin{cases} TD^i_{max,ACC}\left(\max\left(0,\ 1 - \dfrac{d}{d^i_{min}}\right)\right) & d < 0 \\ TD^i_{max,ACC} & 0 \le d < d^i_{med} \\ TD^i_{max,ACC}\left(1 - \min\left(1,\ \dfrac{d - d^i_{med}}{d^i_{max} - d^i_{med}}\right)\right) & d^i_{med} \le d < d^i_{max} \end{cases}, \tag{12}$$

In which $TD^i_{max} = 0.8$ (80%) is the maximum task demand level; and $d^i_{min} = -400$; $d^i_{med} = 200$; and $d^i_{max} = 400$ (all in meters) are the three distance parameters in the FDTD function respectively. A possible way to interpret this maximum task demand of 80% while passing the distraction is that the driver takes prolonged glances at the accident with brief looks straight-ahead with a ratio of about 4:1 (80/20). Since both visual tasks use the same information channel (vision) they are mutually exclusive. The distance values are a reasonable estimate of where (at high speed) a driver may feel compelled to look at the accident.

Filling in Eqs. (10) and (12) in (5) and (6) gives us total task demand $TD_i(t)$ and task saturation $TS_i(t)$ (which as long as task capacity $TC_i(t) = 1$ are equal). A third relation between awareness $SA_i(t)$ and task saturation $ts = TS_i(t)$ (Fig. 7(f)) now governs the effect on awareness. We specify this relation as follows

$$SA(ts) = \begin{cases} SA^i_{max} & ts < TS^i_{crit} \\ SA^i_{max} - \dfrac{ts - TS^i_{crit}}{TS^i_{max} - TS^i_{crit}}\left(SA^i_{max} - SA^i_{min}\right) & TS^i_{crit} \le ts < TS^i_{max}, \\ SA^i_{min} & ts \ge TS^i_{max} \end{cases} \tag{13}$$

In which $SA^i_{max} = 1;\ SA^i_{min} = 0.5$ are the maximum and minimum SA levels; $TS^i_{crit} = 0.8$ the critical task saturation above which awareness decreases; and $TS^i_{max} = 2.0$ the maximum task saturation level beyond which awareness no further deteriorates. Clearly, both the shape and the parameters values in Eqs. (10), (12), and (13) are arbitrary; we choose them to accommodate the main assumed tendencies.

4.3. Scenarios, hypotheses and specification of effects on perception & response

We consider four behavioral scenarios, in which we explore increasingly complex combinations of HF effects as a result of the distraction:

I. Distraction with effects on perception errors, i.e. errors in distance gaps, speed differences and both
II. Distraction with effects on perception errors and reaction time
III. Distraction with effects on perception errors, reaction time and response adaptation in desired speed, desired headway and both
IV. Same as 3, now with driver heterogeneity (varying task capacities)

We describe them in the subsections further below. In each of these four scenarios, we consider four physical reaction times: $\tau_i^p = \{0,\ 0.2,\ 0.5,\ 1\}$ seconds. Clearly, setting physical reaction time to zero is an idealisation; however, one could interpret this idealisation as follows. In the case $\tau_i = 0$, we implicitly assume that drivers are able to fully compensate their physical reaction time due to the information processing for sensing, comprehension and anticipation, with the result of that very same perception process: an adequate anticipation strategy. Put differently, $\tau_i = 0$ reflects a *net* result of the perception process. Even under dense traffic conditions, this is a reasonable assumption to make, in line with e.g. (Treiber et al., 2006; Van Lint et al., 2018). Similarly, $\tau_i^p = 0.2,\ 0.5,\ 1$ represent cases in which drivers are not able to fully compensate physical reaction time with an adequate anticipation strategy.

4.3.1. Scenario I: effects on perception errors

In this scenario, we consider effects on level 2 awareness (comprehension) errors, which result in incorrect stimuli. The assumption is that reduced awareness exacerbates known perception biases, that is, either an *under-* or *overestimation* of both distance gaps and (relative) speeds (see Section 3.3.2). We propose

$$s_i^{perceived}(t) = \left(1 + \delta_i \epsilon_i^{SA}(t)\right) s_i(t) \tag{14}$$

$$\Delta v_i^{perceived}(t) = \left(1 + \delta_i \epsilon_i^{SA}(t)\right) \Delta v_i(t) \tag{15}$$

in which

$$\epsilon_i^{SA}(t) = SA^i_{max} - SA_i(t)$$

is a factor between 0 and $(SA^i_{max} - SA^i_{min})$ that determines the magnitude of the perception error, and

$$\text{T} \quad \delta_i = \begin{cases} -1 & \text{Driver } i \text{ systematically underestimates gaps and speeds} \\ 1 & \text{Driver } i \text{ systematically overestimates gaps and speeds} \end{cases}$$

represents a factor that governs the direction of the perception bias. Note that we assume that a single driver has a fixed direction toward either under- or overestimating both distance and speed differences. We consider three driver populations such that

$$\delta_i = sign(\mathcal{D} - \nu)$$

with ν a random variable drawn from a uniform distribution over [0, 1], and

$$\mathcal{D} = \begin{cases} 0 & \delta_i = -1,\ \forall i.\ \text{(all drivers underestimate)} \\ 0.5 & 50-50\,\text{mix} \\ 1 & \delta_i = 1,\ \forall i.\ \text{(all drivers overrestimate)} \end{cases}$$

4.3.2. Scenario II: effects on perception and reaction time

In this scenario, we do consider an increase in (net) reaction time with an attention time-lag, again proportional to the decrease in awareness, that is,

$$\tau^a_i(t) = \epsilon^{SA}_i(t)\tau^{a,max}_i$$

in which $\tau^{a,max}_i = 2\,\text{s}$ depicts the maximum attention time lag we consider for this case. Clearly the (arbitrary) setting of $\tau^{a,max}_i$ determines the magnitude of the effect. For the total reaction time (Eq. (7)) we then have

$$\tau_i(t) = \epsilon^{SA}_i(t)\tau^{a,max}_i + \tau^p_i \tag{16}$$

With $\tau^p_i = \{0,\ 0.2,\ 0.5,\ 1\}$ as discussed above. Note that since we do not implement spatial or temporal anticipation, drivers thus simply base their responses on stimuli of $\tau_i(t)$ seconds ago, and they do this every simulation time step.

4.3.3. Scenario III: effects on perception, reaction time & response

In this scenario, we additionally consider two kinds of response adaptations that both result in larger gaps; but which may have different consequences for the resulting traffic operations. First, we assume drivers increase their desired speed, and second, we assume an increase in desired time headway, which in the IDM+case boils down to an increase in desired distance gap (Eq. (9)). To this end, we propose a reduction factor similar to the one in Eq. (16):

$$v^0_i(t) = \left(1 - \beta^{v_0}_i \epsilon^{TS}_i(t)\right)v^0_i \tag{17}$$

in which $\beta^{v_0}_i$ is a scaling parameter that governs the maximum reduction effect (e.g. $\beta^{v_0}_i = 0.9$ implies a maximum reduction of 90% in desired speed), and

$$\epsilon^{TS}_i(t) = \min\left(1, \max\left(0,\ TS_i(t) - TS^i_{crit}\right)\right)$$

is a factor between 0 and 1 that in this case depends on the prevailing driver task saturation. The higher task saturation, the larger the response adaptation. This rationale is in line with Fullers TCI model (Fuller, 2011); we essentially use $\epsilon^{TS}_i(t)$ as a proxy for perceived risk. The higher it is, the stronger the behavioural adaptation in the direction of a safer gap and speed difference. Analogously to Eq. (17) we have for desired time headway

$$T_i(t) = \left(1 - \beta^T_i \epsilon^{TS}_i(t)\right)T^0_i \tag{18}$$

4.3.4. Scenario IV: driver heterogeneity (varying task capacities)

In the final scenario, we look at the effects of driver heterogeneity. By varying driver task capacities $TC_i(t)$ (and thereby task saturation) in units of nominal task capacity (Section 3.2.1), we effectively vary driver skill level with just a single parameter. This parameter affects the fundamental diagrams of task demands, leading to lower (higher) task saturations for more (less) skilled drivers (for whatever reasons) under similar conditions. Task saturation, in turn, serves as input for the awareness relation (Eq. (13)), implying also awareness deteriorates with lower driver task capacity. At the start of the simulation we generate task capacity values as follows

$$TC_i(t) = \min\left(TC_{max},\ \max\left(TC_{min},\ TC + \psi_i\right)\right),\ \psi_i \sim \mathcal{N}(0, 0.1) \tag{19}$$

In which TC_{min} and TC_{max} are set to 0.8 and 1.2 respectively. Clearly, one could vary with many more parameters and driver characteristics, and we return to this in the discussion section.

Table 2
Overview of simulation scenarios. For each scenario we vary over 4 physical reaction times. "AND/OR" means that within a scenario we consider varying with and without the particular effect.

	Perception errors			Response adaptation		Heterogeneity
	s (14)	Δv (15)	τ (16)	v_0 (17)	T (18)	TC (19)
Scenario I	AND/OR$\mathcal{D}=0.5$, 0, 1	AND/OR $\mathcal{D}=0.5$, 0, 1				
Scenario II	AND/OR $\mathcal{D}=0.5$, 0, 1	AND/OR $\mathcal{D}=0.5$, 0, 1	AND			
Scenario III	AND/OR $\mathcal{D}=0.5$		AND	AND/OR	AND/OR	
Scenario IV	AND $\mathcal{D}=0.5$		AND	AND	AND	AND

Table 3
Quantitative results over all simulations in terms of total time spent (TTS) and number of accidents. The shaded cells depict scenarios in which disturbances caused (light or severe) congestion; the numbers in red indicate scenarios in which rear-end collisions took place.

		Base	Scenario I									Scenario II			Scenario III				Scenario IV
			s			Δv			s+Δv			τ						s+Δv	s+Δv
			D=0.5	D=0	D=1	D=0.5	D=0	D=1	D=0.5	D=0	D=1	ds	dv	ds+dv	v0	T	v0+T	v0+T	v0+T
TTS (min)	τ= 0	456	492	603	455	456	456	456	497	651	455	491	456	488	890	729	1018	1079	1136
	τ= 0.2	456	488	605	455	456	456	456	491	657	455	921	456	506	891	737	1019	1078	1123
	τ= 0.5	456	486	604	455	456	456	456	510	660	455	922	456	1517	837	733	955	955	991
	τ= 1.0	457	2109	2027	456	457	457	457	2017	2027	1195	2260	457	2123	2097	2136	2135	2120	2130
# Incidents	τ= 0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	τ= 0.2	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0
	τ= 0.5	0	0	0	0	0	0	0	0	0	0	42	0	45	0	0	0	0	0
	τ= 1.0	0	146	161	0	0	0	0	147	162	89	165	0	155	157	166	166	166	172

4.4. Summary and assessment criteria

Table 2 summarizes the scenarios we consider. The header row depicts for each scenario witch variables are affected by HF (with reference to the governing equations). The words "AND/OR" mean that within a scenario we consider varying with and without the particular HF effect on either perception or response. For example, in Scenario III, we consider response adaptation in v_0 and T separately as well as combined (denoted with AND/OR), in scenario IV only the combined case (denoted with AND). Additionally, in scenario I we consider under- and overestimation biases in s and Δv separately as well as combined (50–50 mix); in all other scenarios we consider a 50–50 mix (of "over- and underestimators") only. In total we consider 72 scenarios, see Table 3

As overall indicators per scenario, we consider total time spent (TTS), which is defined as the total amount of time spent by all vehicles on the road stretch during the simulation run, i.e. $TTS = \sum_i TS_i$; with TS_i the time spent by driver i on the road stretch during the simulation. We also keep track whether and how much rear-end collisions take place in each simulation. If a collision takes place the followers' speed remains zero for the remainder of the simulation. For a selection of scenarios, we then qualitatively discuss the resulting traffic dynamics in terms of trajectory patterns and resulting fundamental diagrams; the driver dynamics in terms of individual speed, acceleration and time-to-collision (TTC) profiles, and the HF dynamics in terms of total task demand, SA level and reaction time dynamics. TTC is defined as the time instant at which a follower would collide onto his leader given the speeds of both vehicles stay constant, i.e.

$$TTC_i(t) = \frac{s_i(t)}{\Delta v_i(t)}, \quad \Delta v_i(t) > 0$$

5. Results

We first make some overall observations on the basis of the quantitative results listed in Table 3, in which the grey cells depict scenarios with disturbances that lead to (mild to severe) congestion, with TTS values > 456 minutes (see the base case in Fig. 7), and the red text indicates those scenarios in which rear-end collisions took place. The first overall remark is that there is a large variation in TTS results. Clearly, it is possible to generate a wide variety of congested patterns by varying with the proposed HF mechanisms—we will analyze these in more detail below. Secondly, and expectedly, we are able to generate rear-end collisions in scenarios with disturbances and reaction times $\tau_i > 0$. A large enough fixed reaction time and the additional HF dynamics can easily push the model out of the controllable input/parameter region. In our simulations, collisions occur in all cases with a base reaction times of 1 s, and in some cases—with large enough perturbations and a dynamic reaction time component—also with base reaction times of 0.2 and 0.5 s. We return to this point in the discussion section. We first present the results in more detail per scenario.

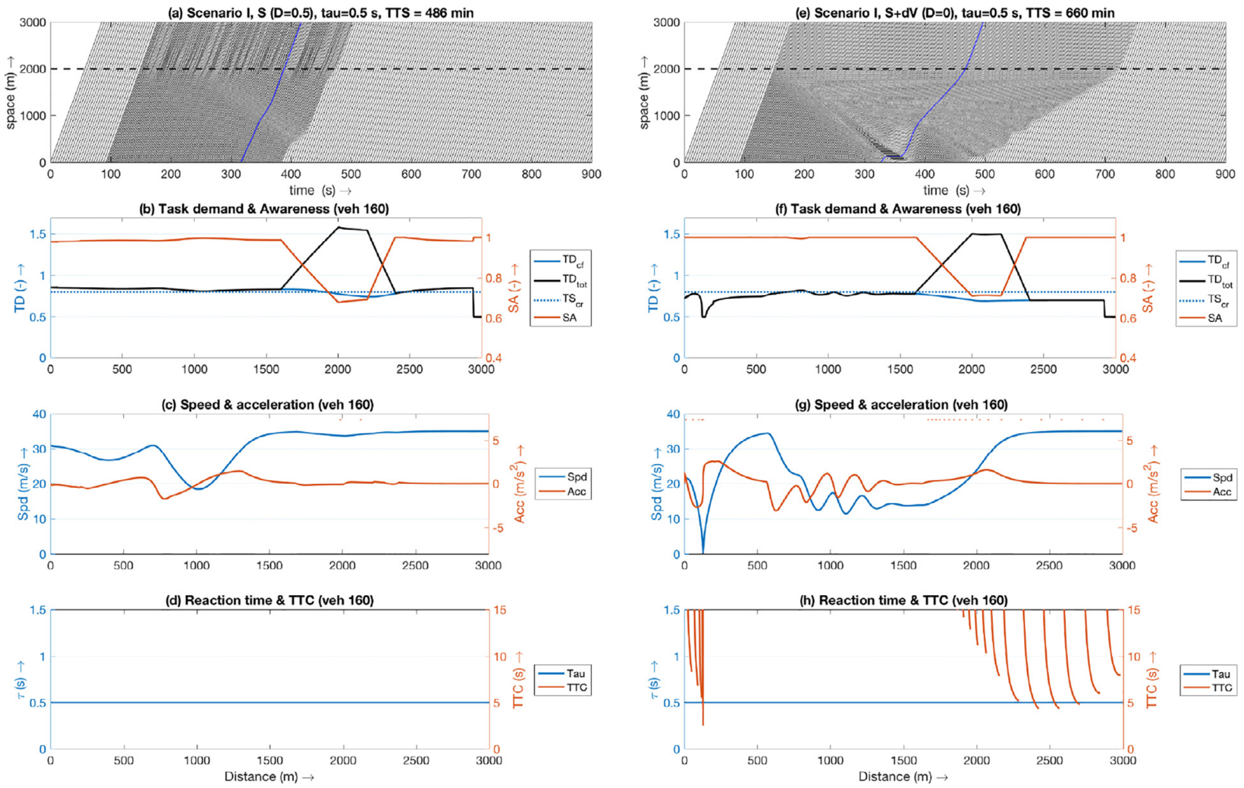

Fig. 8. Effects of HF dynamics on perception (Scenario I): (a)–(d) show results of a case with 50–50% mix of over- and under-estimators (of gaps and speed differences); (e)–(h) shows the results of 100% under-estimators. From top to bottom rows we see the resulting traffic conditions (a), (e); and the dynamics of total driver task demand and awareness (b), (f); the speed and acceleration (c), (g); and the reaction time and TTC profile (d), (h) of driver 160 (colored blue in (a) and (e)). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

5.1. Scenario I: perception errors

From Table 3 we immediately see that disturbances occur only (a) in scenarios with perception errors in distance gaps; and (b) given (at least some) drivers have a bias towards *underestimation*, that is $\delta_i = -1$ in Eqs. (14) (systematic error in gaps). Both perception errors in $s_i(t)$ and $\Delta v_i(t)$ affect the term $1 - (s_i(t)/s_i^*(t))^2$ in IDM Eq. (8), but in different directions and with different magnitudes. In case of an underestimation bias we find that smaller $s_i(t)$ values affect the numerator, implying smaller accelerations (more conservative driving); whereas smaller $\Delta v_i(t)$ values affect the denominator implying larger resulting accelerations (more aggressive driving). Vice versa, an overestimation bias in $s_i(t)$ will yield larger accelerations, whereas overestimating $\Delta v_i(t)$ leads to more conservative acceleration. Put simply, only underestimating gaps or overestimating speed differences lead to more conservative driving, larger headways and thus disturbances that propagate upstream. However, in our simulations only gap underestimation leads to disturbances; overestimation of speed differences does not. This also can be explained by looking at the IDM + equations. Since $\epsilon_i^{SA}(t) \in [0, SA_{max}^i - SA_{min}^i]$ and $SA_{max}^i - SA_{min}^i = 0.5$ (see Fig. 7(f)), the maximum perception error in $s_i(t)$ equals 50% due to (14). This effect does not depend on prevailing speed or speed differences and will cause a driver to decelerate thus causing disturbances. The mechanism for errors in $\Delta v_i(t)$ *does* depend on the prevailing speed and speed difference. Substituting (15) with $\delta_i = 1$ (overestimation speed difference) and $\epsilon_i^{SA}(t)$=0.5 into IDM Eq. (9) (computing $s_i^*(t)$) gives

$$s_i^*(t) = s_0^i + v_i(t)\left(T_i + \left(\frac{1+\epsilon_i^{SA}(t)}{2\sqrt{a_{max}^i\, b_{comf}^i}}\right)\Delta v_i(t)\right) \tag{20}$$

As long as the actual speed difference $\Delta v_i(t)$ is small, even a large error factor (e.g. $\epsilon_i^{SA} = 0.5$) has very little or no effect. But even with larger speed differences (due to e.g. an external disturbance we did not consider in our simulations) of say 5 km/h, the effect of errors in gaps is larger than those in speed differences. Filling the IDM parameter values Section 4.1) into ((20) yields a maximum error in $s_i^*(t)$ of about 20%, which is much smaller than the maximum effect in $s_i(t)$ (which is 50%). Note however, that both direction and magnitude of these effects are model-specific.

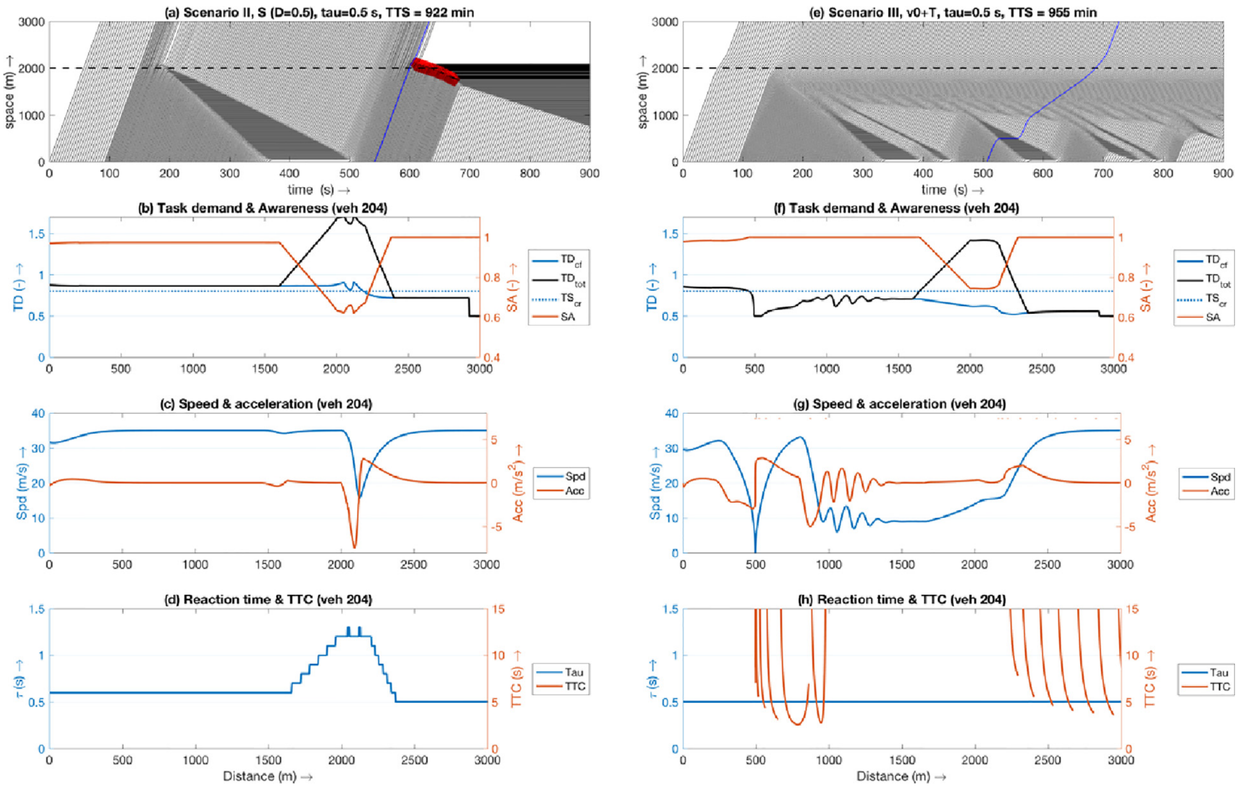

Fig. 9. Scenario II (a-d) reaction time dynamics with $\boldsymbol{\tau_i^p} = 0.5$, $\mathcal{D} = 0.5$ (mix of over- and under estimators of distance gaps)—note that collisions occur in this scenario; and scenario III (e)–(h) with adaptation of both $\boldsymbol{v_0^i}$ and $\boldsymbol{T_i}$ and no perception errors or reaction time dynamics.

Fig. 8 shows two examples of Scenario I simulations. Fig. 8(a)–(d) show the results of a sub-scenario with just errors in $s_i(t)$ ($\mathcal{D} = 0.5$: 50–50% mix of over- and under-estimators) and $\tau_i^p = 0.5$ s; whereas Fig. 8(e)–(f) show the results of a sub-scenario with underestimation errors only ($\mathcal{D} = 0$) in both $s_i(t)$ and $\Delta v_i(t)$, also with $\tau_i^p = 0.5$ s. Fig. 8(a) illustrates how with a mix of perception biases, small disturbances at the distraction site occur that only slightly increase delays (TTS = 486); whereas Fig. 8(e) shows that in case all drivers have a bias towards underestimation the distraction acts as a regular bottleneck. As explained above, underestimation of Δv potentially yields more aggressive accelerations in the presence of larger speed differences, and it turns out that this indeed results in more oscillatory dynamics than in case of just underestimation in $s_i(t)$ (TTS = 660 versus 604 minutes—see Table 3). As a result, Fig. 8(e) also shows the emergence of stop-and-go waves. In Fig. 8(a) and (e) one vehicle trajectory is highlighted (vehicle 160). For this vehicle, Fig. 8(b) and (f) show the corresponding dynamics in task demand $TD_{160}(t)$ and awareness $SA_{160}(t)$. Clearly, $TD_{160}(t)$ increases as the distraction task starts to consume workload around the distraction area, which simultaneously results in a decrease of awareness. In Fig. 8(f) at around $x = 200$, we see a small increase and then a sharp dip in $TD_{160}(t)$ as a consequence of the disturbance (a jam wave) driver 160 encounters—which is also clearly visible in the speed and acceleration dynamics Fig. 8(g) and in the occurrence of a few small TTC values in Fig. 8(h). The initial increase in $TD_{160}(t)$ is due to these short time headways Eqs. (10), ((11)), the decrease thereafter is due to the associated increase in time headway in the jam wave.

5.2. Scenario II: perception errors and reaction time dynamics

With HF effects on perception (and fixed reaction times) we thus obtain already rich and diverse traffic dynamics. We now add a dynamic component of reaction time (Eq. (16)) to the mix. Fig. 9(a)–(d) show the traffic conditions (a); HF dynamics (b); speed and acceleration profile (c); and reaction time and TTC profile of a scenario II case, with $\tau_i^p = 0.5$, $\mathcal{D} = 0.5$ (mix of over- and under estimators) and we consider errors in $s_i(t)$ (gaps) only this time. We follow driver 204, a systematic under-estimator of gaps, who passes the distraction area just before a collision takes place, and the driver (HF) dynamics explain why this happens. Due to Eq. (16) τ_{204} increases to well over 1 s around the distraction. Structural underestimation of leading gap $s_{204}(t)$ essentially countereffects the high reaction time. The rear-end collision that occurred between driver 206 and 205 is caused by overestimating $s_{206}(t)$ around the distraction. From a TTC perspective, the collision may come at a surprise—driver 206 in principle had enough time to respond. However, the combination of a long reaction time and an unfortunate perception bias results in—as it turns out—a chain of rear-end collisions. This is an interesting finding. TTC is an intuitive surrogate safety measure, but small TTC values are neither a necessary nor a sufficient condition

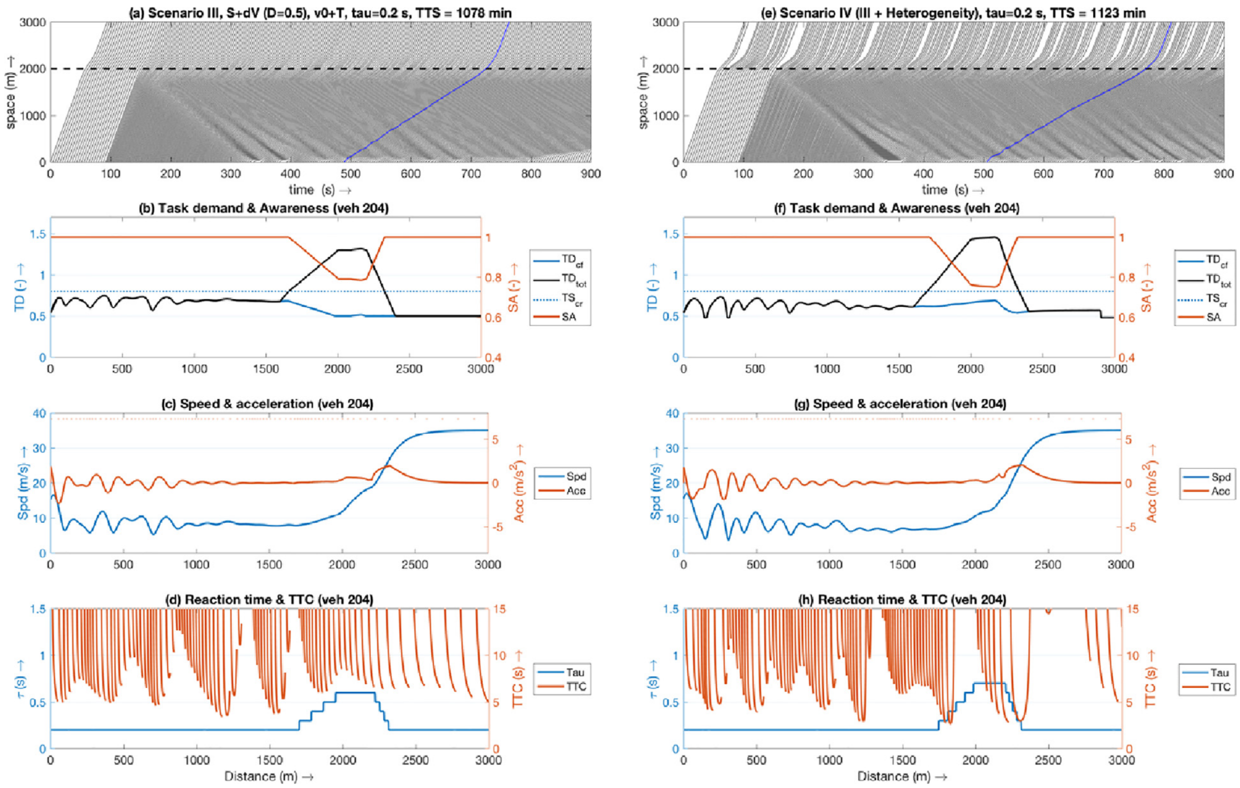

Fig. 10. Scenario III: combination of all HF effects (a)–(d); and scenario IV: same combination but with heterogeneity in terms of driver task capacity.

for the occurrence of rear-end collisions. This is nicely illustrated by Fig. 9 (e)–(h), that shows the results for one of the scenario III cases.

5.3. Scenario III & IV: perception errors, reaction time, response adaptation and driver heterogeneity

We first look at the effects of response adaptation without perception errors or dynamic reaction time, illustrated using the familiar graphs in Fig. 9 (e)–(h). Here we consider a scenario in which drivers adapt both v_0^i and T_i. Again, by looking at the IDM + model Eqs. (8), (9), the results are predictable. A reduction in v_0^i decreases the term $1-(v_i(t)/v_0^i)^\delta$ in Eq. (8); whereas an increase in T_i reduces the second term $1-(s_i(t)/s_i^*(t))^2$. Both adaptations thus lead to smaller accelerations, and safer, but less efficient driving, and thus congestion. The effect on v_0^i in our case is larger than on T_i (compare the first and second columns of scenario III in Table 3). This finding is a product of the specific model used (the IDM +), as well as the parameters chosen in both model and task demand relations. The combined response adaptation leads to highly congested traffic conditions Fig. 9(e) and to oscillatory dynamics of HF variables Fig. 9(f); speed and acceleration Fig. 9(g) and reaction time and TTC Fig. 9(h).

In the final two scenarios in Fig. 10, we now combine *all* HF effects, with $\tau_i^p = 0.2$, and again $\mathcal{D} = 0.5$. Clearly, combining all effects has the most severe effect in terms of delays. Varying with driver task capacity (effectively: skill level) is most visible at the distraction site, where—as one of the anonymous reviewers put it—the distraction now effectively works as a “floodgate”, with small platoons separated by larger gaps driving by the distraction. The reason is that the variation in TC_i causes a variation in response adaptation. The differences in adaptation of v_0^i then result in this phenomenon, which in itself is plausible. A distraction likely does cause an uneven spread in accelerations away from the distraction simply because some drivers are more and/or longer distracted than others.

Fig. 11 finally shows the state trajectories of two vehicles, each from one of last two scenarios, expressed in flow $q(t) = 1/h_i(t)$, density $\rho(t) = 1/s_i(t)$, and speed $v(t) = v_i(t)$. The state trajectories are plotted in the equilibrium fundamental diagrams of the IDM + model (see Appendix A).

Fig. 11 clearly shows similar hysteretic patterns as in (Saifuzzaman et al., 2017), in which the recovery paths out of congestion waves lie under the paths with which drivers move into disturbances. This is particularly well visible for driver 204 in the $Q^e(\rho)$ plot (Fig. 11 left). Note also that due to the HF effects, both drivers perform way under the “ideal” driver.

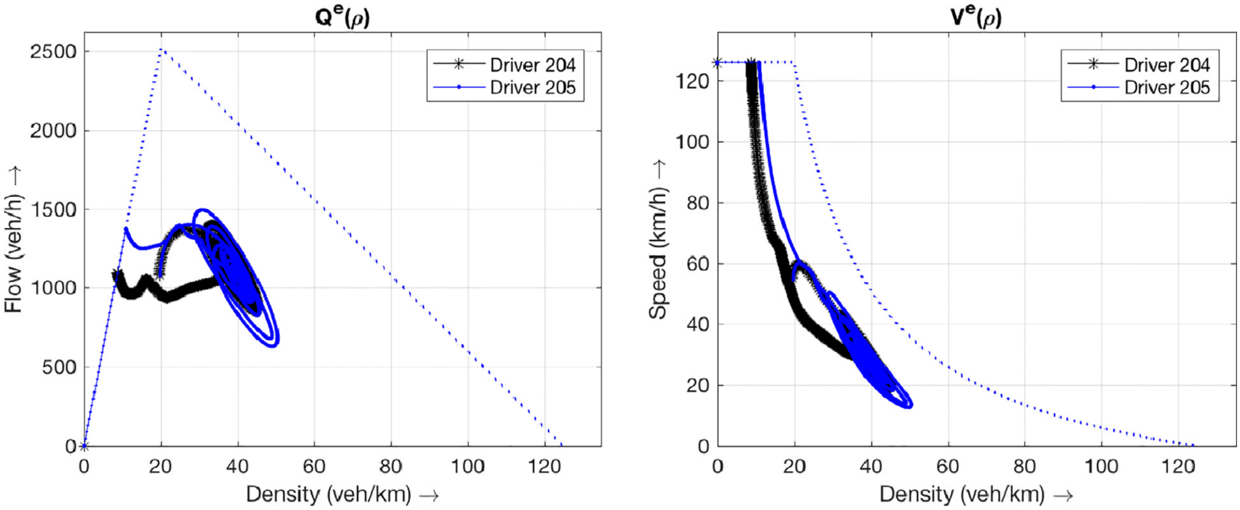

Fig. 11. Equilibrium flow-density and speed–density relations (dotted) and state trajectories of two drivers. Driver 204 comes from scenario IV, and driver 205 from scenario IV.

6. Discussion

First, a genuine disclaimer. In the previous section, we demonstrated the proposed framework by applying plausible behavioral mechanisms. Many such relationships are known to exist between different dimensions of driving behavior (perception, response, driver traits and attitudes) and a wide range of influencing factors, such as distractions, fatigue, environmental conditions, et cetera, but they are typically very case specific and rarely generic. This means that we have to make (many) assumptions on the generic influence of these factors. Errors can be made in defining the correct relationship mechanism and response (e.g. the FDTD and awareness functions in Fig. 7), while errors can also be made in the strength or direction of an effect. Below we synthesize our main findings and discuss the assumptions and limitations of our approach, and thus possible sources of errors.

6.1. Main findings and implications

The first main finding is that the idea of using fundamental diagrams of task demand, and functions that relate awareness and driver traits to the resulting total task demand, results in plausible and explainable traffic patterns. By varying a single parameter (task capacity) over the driver population, we effectively vary over car following skills, which results not just in inter-driver differences, but also in intra-driver differences (dynamics) in behavior. This makes our framework a powerful tool. To increase heterogeneity, we could vary over many more parameters, including the CF logic itself (i.e. vary with different CF models). To this end, we could even formulate endogenous HF models that govern under what circumstances a driver would switch from one CF logic to the next. The second main finding is that—given our assumptions—both perception errors and response adaptations may result in similar, and plausible mechanisms that both explain (a) how a distraction may cause a bottleneck under high demand; and (b) how an increase in reaction time around such a distraction does not necessarily lead to accidents. That perception errors may be a cause of congestion seems logical, and in our simulations (and in reality) they also cause rear-end collisions. Counter-intuitively, they may also be a blessing in disguise when it comes to safety. Gap underestimation results in more conservative driving, which counter-balances the increased risk due to larger reaction times. As noted in (Treiber et al., 2006), even small reaction times in ideal car following models like the IDM(+) may cause an unreasonable amount of accidents. However, in combination with “favorable” perception biases (underestimation of distance gaps) and/or response adaptations (e.g. larger desired headway), we were able to run several simulations in which serious disturbances occurred *without accidents occurring* even though reaction times went up to a second and more. The HF model essentially “forces” the driver to operate within larger safety margins. In other scenarios with less favorable settings (e.g. where we considered gap over-estimation), the HF model does the opposite with many rear-end collisions as a consequence, in line with (Treiber et al., 2006). This we believe is also a powerful aspect of our multi-level framework: the HF models essentially control the driver-specific safety (and stability) margins within which the (chosen) CF models operate, and this provides a mechanism to test the face validity of both the HF models (e.g. do they result in reasonable traffic conditions?); and of the CF models (e.g. do the parameters represent quantities that can be related to HF aspects of driving behavior in a meaningful way?)

6.2. Limitations

However, many implementation details of our framework in this paper are speculative. First, the assumption that drivers reduce their speed and/or increase their headway when task saturation is too high has a solid theoretical basis in Fullers TCI model (Fuller, 2011). In the distraction case there is also ample empirical underpinning that drivers do this; bottlenecks due to rubbernecking are a well-known phenomenon. However, there are multiple ways in which this relationship can be formalized. *Do drivers adapt their desired speed or do they adapt their desired headway (or both)?* Desired speed adaptation seems to be the most straightforward interpretation of Fullers theory. Reducing (increasing) desired speed then is a proxy (conceptualization) for dynamically reducing (or increasing) acceptable risk level. Note, however, that this interpretation of the desired speed parameter is very different than that of a maximum speed which drivers are inclined to maintain while driving freely. More generally, the desired speed and headway parameters are both abstractions and it is unclear whether drivers really work with these constructs as decision variables. Second, there is evidence in the literature for different perception biases under different circumstances (under- and over estimation, e.g. Nilsson, 2000; Thiffault and Bergeron, 2003, and Castro et al., 2005; Lee and Sheppard, 2017, respectively). However, the assumption that task oversaturation exacerbates these perception biases is tentative at best. We have no empirical evidence to support this. Quantitative empirical research into perception error dynamics is needed to shed light on this issue. Third, a clear limitation in our simulations is that we do not explicitly consider spatial and/or temporal anticipation, which would have provided yet an additional mechanism to counter-effect the destabilizing effects of reaction times (Treiber et al., 2006) at the distraction location. In fact, one could come up with many more behavioral hypotheses and mechanisms that lead to a (net) increase in time headway around the distraction and extend our framework with additional psychological/physiological constructs (e.g. risk attitude, emotional and physical state) which may be relevant in describing (and simulating) perception and response processes.

6.3. Synthesis

The strength of the proposed framework is that it provides a means to test the consequences of these many different possible hypotheses related to how HF affect perception and response, including those already reported in the literature. The multi-level conceptualization is generic in the sense that it makes it possible to mix a variety of CF models with different HF mechanisms, depending on which HF are studied, and which phenomena need to be reproduced and explained. Therefore, it is possible to compare the same HF models in terms of descriptive and explanatory power on the same cases, using different idealized CF logic, or vice versa, using different HF mechanisms with the same core CF logic. Moreover, decoupling idealized models from the underlying HF models, makes it possible to more systematically calibrate and validate HF models—one HF effect at a time.

These two arguments support our belief that this multi-level structure can also work for lane changing (or more generally movement in a 2D or even 3D space), in the sense that also these behaviors can be formalized as a system of idealized models on top, and HF mechanisms that govern the dynamics of the parameters underneath. We realize that idealized models for such tactical behaviors are much more complex than idealized CF models, and that many more sophisticated HF mechanisms and constructs need to be specified that describe aspects of tactical decision making that do not play a role in acceleration modeling. These include gap acceptance, cooperation between drivers, relationships with strategical (planned) behavior (this exit or the next?), and many more. One can argue that the distinction between idealized models and HF models in itself is much more diffuse in lateral behavior than in acceleration modelling. However, also in lateral behavior, perception and judgement errors can be separated from the actual decision logic, and, as with CF models, also lateral models contain parameters that may dynamically change due to HF. The point is that the multi-level framework offers a possibility to abstract driving behaviors along hierarchical levels, which allows the analyst to systematically disentangle the complexity, and to introduce HF sophistication step-by-step. This in turn leads to better structured and more easily maintainable simulation software.

7. Conclusions and outlook

The central contribution of this paper is a generic multi-level modelling and simulation framework that supports the inclusion of Human Factors (HF) in simulating driving behavior. The performed simulation cases demonstrate the frameworks' ability to allow specific aspects of driver psychology to be included in traffic simulation, resulting in feasible and face-valid results. Our results show how the framework results in endogenous mechanisms for inter- and intra-driver differences in driving behavior, and in multiple plausible HF mechanisms that may explain the same observable traffic phenomena. Full verification of the framework is virtually impossible at the moment, due to limitations in generic empirical evidence of behavioral mechanisms and parameter values. However, making use of reasonable assumptions based on the evidence and literature that is available makes the step-by-step development, and the rigorous analysis and comparison of new mathematical models for driving behavior possible. This process will only accelerate as more empirical evidence for calibration and validation becomes available in time.

This multi-level framework fits well within a more general agent-based framework in which an agent executes operational (driving), tactical (maneuvering) and strategical (decision-making) tasks. Unravelling these different modelling components makes it easier to collaborate interdisciplinary (traffic flow, choice modelling and HF scientists)—a key prerequisite to make progress in this area. Finally, from a simulation software design perspective, multi-scaling enables a rigorous modular design, in which it becomes much easier to define generic classes for response, perception, anticipation, and specific classes of CF and LC approaches, which leads to a natural hierarchy of classes and a disentanglement of driving and traveling processes. We argue this is beneficial for developing next-generation microscopic traffic simulation models and ultimately for how these tools are going to be used.

Acknowledgment

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Appendix A. Equilibrium solution IDM+

Filling in $a_i(t+\tau_i)=0$ and $\Delta v_i(t)=0$ in Eqs. (8) and (9) leads to a simple speed-spacing relation

$$V^e(s) = \begin{cases} \min\left(v_0, \dfrac{s-s_0}{T}\right) & s > s_0 \\ 0 & otherwise \end{cases}$$

With $\rho = 1/s$, $\rho_{max} = 1/s_0$, and $q_{max} = 1/T$ we have for the equilibrium speed-density relation

$$V^e(\rho) = \begin{cases} \min\left(v_0, q_{max}\left(\dfrac{1}{\rho} - \dfrac{1}{\rho_{max}}\right)\right) & \rho < \rho_{max} \\ 0 & otherwise \end{cases}$$

And for the equilibrium flow density relation

$$Q^e(\rho) = \rho V^e(\rho)$$

Appendix B. Additional material

As additional material we provide the Matlab scripts and functions with which all simulations and visualizations in this paper are conducted, so researchers can reproduce and extend our results. We are also implementing the framework in OpenTrafficSim (opentrafficsim.org: our open source micro simulation environment), so we can test more sophisticated scenarios including those involving lateral behavior. What we hope is that these tools are going to be used in interdisciplinary research that involves (a) the (step-by-step) development and validation of the lower level HF hypotheses and resulting models, and (b) a move towards convergence in terms of which of the higher level (idealized) models are more effective and realistic in simulating (car) traffic. Both are needed to bring our discipline forwards.

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