# Getting the Human Factor into Traffic Flow Models

## New Open-Source Design to Simulate Next Generation of Traffic Operations

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**Automated driving may lead to much higher road capacities, combined with increased road safety, increased driver comfort, and lower costs. Although this vision may hold ground in the long run, first a transitional period will take place in which increasing percentages of vehicles with many levels of automation will drive on the world's road networks. This transition poses a fundamental scientific challenge. The models used today to simulate and predict vehicular traffic are not valid to predict emergent properties of traffic flows under increasing amounts of vehicle automation. For example, there is no idea of how drivers of nonautomated vehicles will respond to other drivers reading their morning papers behind the steering wheel or the consequences of such interactions on traffic safety and capacity. In this paper, the authors do not propose a new behavioral theory with which the effects of increasing vehicle automation can be predicted. What the authors propose is an advanced open-source simulation framework, OpenTrafficSim, which makes it possible to extend microscopic models incrementally with explanatory mental models, such that new behavioral theories can be tested and shared within the community. Given the societal importance of predicting the effects on safety and efficiency of vehicle automation, the authors sincerely hope this paper will fuel the discussion on how both open-source and closed-source simulation software can be adapted and made ready for the next generation of traffic simulation models that are needed in the coming decades.**

The appeal of automated driving for many politicians, leaders of industry, and scientists is the potential of much higher road capacities, combined with increased road safety and decreased vehicle emissions.

Indeed, higher capacities are possible by taking human drivers out of the loop. In countries with well-trained drivers, high-quality cars, and high-quality road facilities, the average minimum time headway is slightly above 1.5 s (which implies maximum flows of 2,400 vehicles per hour). This headway is close to average human reaction time.

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Clearly, technology can do the job at a fraction of the time and much safer, as demonstrated in many field trials over the past 3 decades (*1, 2*). There are also additional behavioral inefficiencies that can be resolved with technology, for example, more effective anticipation of downstream conditions and more efficient use of traffic lanes.

However, vehicle automation will not take place overnight. A transitional period of at least 15 to 20 years will take place, during which vehicle automation will gradually become commonplace in new vehicles. Many scientists and practitioners foresee a transition through five (or six) levels of automation—from none—via partial automation (with the driver as a permanent supervisor) to full automation (SAE J3016). During this transition, (*a*) increasing percentages of drivers with (*b*) cars equipped with different levels of automation will drive alongside drivers with nonequipped cars on road networks that (*c*) are potentially not designed optimally to facilitate safe and efficient traffic operations for these mixed traffic flows.

The central challenge for the traffic flow theory and simulation community is that there is no unified theory of driving (or even a set of candidate theories) yet that enables researchers to quantitatively predict the effects of increasing percentages of heterogeneous vehicle automation capabilities on capacity or safety during this transitional period. How will, for example, drivers of nonequipped vehicles respond to other drivers passing at high speeds in tight platoons while reading their morning papers behind the steering wheel? It is unclear whether the effective minimum time headway would actually decrease under those circumstances. Research shows, for example, how reaction time may double in case an accident causes a queue to build up (*3, 4*); perhaps the unfamiliar experience of being overtaken by such a platoon may have the same effect.

The obvious reason that existing mathematical models cannot be used for car following (*5–11*) and lane changing (*12–16*) to predict the consequences of vehicle automation is that existing models are mostly descriptive of driving behavior. That is, they do not endogenously compute behavioral responses of drivers to different traffic conditions or road layouts, for example. Instead, these models contain parameters (e.g., reaction time, degree of politeness, risk averseness) that are set exogenously and that are calibrated with data collected under current traffic conditions. Clearly, researchers do not have evidence yet for how nonequipped drivers respond to traffic conditions with, for example, 40% Level 5 automated vehicles or for the resulting dynamics. In fact, every change in the driving environment (in-vehicle assistance, road layout, traffic regulations, environmental conditions, etc.) that may cause structural changes in driving behavior (vehicle automation is an extreme example) requires, in the best case, circumstance-specific parameter calibration and validation of existing microscopic models and in the worst case, the identification and estimation of completely new models.

For predicting safety consequences, the situation is even more problematic. Most car-following and lane-changing models used today are by design collision-free, which means that deriving surrogate safety measures [e.g., time to collision (TTC)] as a proxy for safety from simulations is fundamentally flawed. To assess whether safety is at risk, explanatory psychological constructs are needed that can endogenously predict under which circumstances drivers will take risks or make mistakes that may lead to unsafe situations and ultimately accidents. However, a small but increasing number of papers incorporate behavioral theories into traffic flow models. For example, Hamdar et al. proposed a car-following model based on prospect theory, in which drivers weigh faster travel time against the risk of rear-end crashes (*17*), and Hoogendoorn et al. combined a task–capability interface model with the intelligent driver model to predict reaction time dynamics (*18*).

Treiber et al. concluded that the most probable reason why the traffic flow community has stuck to simple descriptive models for so long is "the destabilizing effects of reaction times and estimation errors can be compensated for by spatial and temporal anticipations: one obtains essentially the same longitudinal dynamics, which explains the good performance of the underlying simple models" (*19,* p. 71). In hindsight, explanatory psychological constructs were not needed to describe and predict most phenomena observed. With the transition to partial or full vehicle automation at hand, this is a luxury that can no longer be afforded.

There are many phenomena in current traffic that researchers do not fully understand, such as the capacity drop and most phenomena related to lateral movement. Incorporation of psychological concepts in simulation can help in explaining such variations in driver behavior.

The authors of this paper do not propose a new behavioral theory with which the effects of increasing vehicle automation can be predicted. What the authors propose is an open-source simulation framework, OpenTrafficSim (OTS), that makes it possible to extend microscopic models incrementally with explanatory mental models, so that new behavioral theories can be tested and shared. This framework builds on the design of microsimulation model MOTUS (*20*) with which a number of ex ante evaluations of advanced driver assistance systems have been performed (*21, 22*). The OTS Framework is also designed to facilitate macroscopic and even reservoir simulation (*23*); this paper discusses microsimulation only.

The paper is organized as follows. The next section briefly discusses some of the research challenges relevant to the transition toward vehicle automation. Basic requirements for the design of a generic simulation framework that can support this research are then derived. The section thereafter discusses the resulting agent-based design of OTS, in particular the generic traffic unit (GTU) concept. Next, a small experiment with a first prototype is presented. The paper finishes with a discussion of results and outlook toward the further implementation of the presented framework.

## GETTING HUMAN FACTORS IN SIMULATION MODELS

### Challenges for Driving Behavioral Research

In the past decade, many research groups have worked on the behavioral response to in-vehicle information (*21, 24*) and automation systems (*25–28*), and there are many open research challenges.

Simulating drivers with Level 1 or Level 2 automation systems requires an understanding of how and under which conditions these systems are used. For example, it is largely unknown whether drivers are prepared to give up the steering wheel under conditions in which improved efficiency really matters (*18*). These conditions include dense high-speed traffic, under which the task load of drivers is already high, but during which the potential gain in capacity from vehicle automation is highest. Field trials of connected adaptive cruise control systems show that the opposite is true: drivers are more likely to turn off such systems under those conditions (*29*). Moreover, many such advanced cruise control systems allow drivers to configure the system to their own preferences, including the minimal time headway. There is evidence that under high percentages of vehicles equipped with cooperative cruise control, drivers are willing to reduce their headway well below 1 s (*30*), but the distribution of those settings is wide.

When drivers do give up the steering wheel (either voluntarily or automatically as in Level 3 automation systems) and substitute their role as driver for one as supervisor, additional problems occur. In recent studies, researchers concluded that drivers of automated vehicles may be vulnerable to fatigue when normal vehicle control is restored (*25–27*). It takes time for a driver to reengage with the driving task (especially in the lateral control of the vehicle) after a longer period of automatic driving (*25*). The editors of a special issue of *Human Factors* on automation in vehicles tentatively concluded that one "should not assume that automation can substitute seamlessly for a human driver" or "assume that the driver can safely accommodate the limitations of automation" (*31*).

A related challenge is that whereas some in-car innovations will make the driving task simpler (lane keeping and adaptive cruise control), other systems (advisory and information systems) may well do the opposite. The reason is that these innovations may provide many opportunities for distraction that would likely increase the complexity of the driving task (*27*).

There are also research challenges that to the authors' knowledge have received little or no attention at all but that are fundamental in making predictions (through simulation) of partially automated traffic flows. In the view of the authors, the most important one concerns the response and driving behavior of unequipped (or Level 1 or 2) drivers under increasingly heterogeneous traffic conditions with a mix of Level 3 to 5 automation. The complexity of this challenge was pointed out by Zheng in his recent review of lane-changing models: in heavy traffic, "a typical lane changing decision-making process closely involves at least two players—the lane changer and the follower in the target lane. This is because the follower is often also required to make decisions as a result of someone else's lane-changing decision. Thus, at least two decision-making players and processes are involved in the lane-changing process in heavy traffic" (*32,* p. 28). In other words, lane changing, much more than car following, is an interactive process rather than an individual decision-making process, and a similar argument goes for gap acceptance, crossing intersections, and so forth. These interactions that are already poorly understood may fundamentally change if one of the players is an automated or partially automated vehicle. To unravel this interaction, experimental methodologies other than single driver simulator (or instrumented vehicle) methods are needed. Moreover, new mathematical formalisms (e.g., game theory) need to be used to quantify these interactions in simulation. Much can be learned from pedestrian research [see, for example, work by Duives et al. (*33*)].

Clearly, these challenges require a huge amount of research in the coming years. The paper now focuses on what these challenges imply for next generation simulation models.

### Requirements for OTS

From the human factors literature, the relevant (or at least most popular) mental constructs and capacities used to explain the driving process can be listed:

- Workload is a construct that expresses the total amount of mental effort [i.e., the amount of information-processing resources used per time unit to meet the level of performance required (*34*)]. Workload can be considered a driver state variable [WL($t$)] that dynamically evolves.
- Task capability is a construct that describes the driver's capabilities to perform driving tasks. TC($t$) can be considered a driver state variable that is determined by his or her baseline driving skills, experience, and so forth, and that may evolve as a result of circumstances. The relationship between task demands and capacities has been modeled by Fuller (*35*) and used by Hoogendoorn (*18*) as the task–capability interface model of the driving process.
- Situational awareness is a construct that was operationalized for air traffic simulation and control by Endsley and defines the degree to which a driver is aware of the environment, specifically elements that are relevant to the driving task (*36*). Situational awareness can also be considered a state variable [SA($t$)] that may dynamically evolve as a function of workload, task capability, and other factors. Different SA($t$) variables could exist for different stimuli or threats. Awareness closely relates to the next construct.
- Subjective perception translates the physical driving environment into what the driver subjectively makes of it.
- Subjective task complexity is a construct that is often used but is not clearly defined. Teh et al. interpreted complexity as a measure for traffic conditions (denser traffic is more complex) (*34*), whereas Edquist et al. considered it a measure that rates the clarity of visual information (*37*). Subjective task complexity or simply complexity can be understood as a state variable [STC($t$)] that rates the difficulty of the driving environment.

In the view of the authors, the key to incorporating these constructs in a modular and generic way is by formulating them as dynamic (explanatory) models for the parameters common to most microscopic traffic simulation models, such as reaction time and sensitivity to stimuli (e.g., distance gaps, speed differences). For example, in their literature review, Hoogendoorn et al. concluded that the changed role of the driver from automation Level 1 upward may have a substantial influence on driver workload and situational awareness and result in an increase in reaction time (*38*). The delineation in work by Treiber et al. was used to identify a potential list of key parameters and their possible explanatory constructs (*19*):

- Reaction time can probably be expressed as a function of most constructs (workload, task capability, and situational awareness) and a range of driver and vehicular characteristics.
- Estimation capabilities of stimuli such as speed differences, headways, and so forth (inputs to car following and lane changing) are typically subject to subjective perception and situational awareness.
- Both temporal and spatial anticipation are manifestations of the predictive capabilities (with different degrees of accuracy) of humans. These capabilities may be modeled via subjective perception or through a dedicated predictive mental component.

There are, of course, many additional variables relevant for car following and lane changing, such as those that govern decision making (affected by all constructs), inertia (related to situational awareness and subjective perception), and aggressiveness (related to personal characteristics and probably also workload).

## MODULAR AGENT-BASED DESIGN FOR MICROSCOPIC TRAFFIC SIMULATION

### Overall Structure of the OTS Simulation Process

To facilitate simulation of these mental processes (with implementations of the appropriate psychological models), the authors propose the simulation process schematically outlined in Figure 1. In this scheme, GTU is a person or vehicle. On-GTU units (OGUs) represent technologies that either enhance the vehicle (e.g., vehicle automation) or assist the driver (e.g., route navigation and information systems).

Following is a simplified algorithm for a single simulation step:

Step 1. The simulation environment provides each driver with the prevailing system state (infrastructure, controllers, positions, speeds of drivers in the vicinity, etc.).

Step 2. If perception is activated, the state may be altered as a result of limited visual capacities, for example. However, a driver assistance system (OGU) may enhance perception.

Step 3. Mental constructs, if instantiated, are updated. This step may further degrade or enhance subjective perception and likewise affect some or all driving parameters (reaction time, sensitivity, etc.).

Step 4. The fundamental difference of OTS with other simulation environments is in the update (reevaluation) scheduling of driving behaviors (car following, lane changing, gap acceptance, etc.). This scheduling is not the product of the (arbitrary) choice for a numerical time step, but a process that is explicitly modeled. For example, Hoogendoorn et al. showed that action points have a wide distribution and are themselves a function of the traffic circumstances and possibly many other factors (*39*). On the basis of a plan (route and destination) and the driver's experience (if instantiated), the driver computes a continuous (possibly two-dimensional or three-dimensional) path over the infrastructure for the next $n$ time units by using the models that are implemented for car following, lane changing, and gap acceptance. The schedule interval $n$ can be as short (e.g., one time step) or as long (20 s) as needed and can be modeled as a function of circumstances. To compute such a path, the driver needs to make assumptions (predictions) about nearby drivers. In the example in the second part of the paper, this point is further explained. With computing this path come intentions (flashing lights, next time instant the driver wants to reevaluate, etc.). A driver assistance system (OGU) may change or override this path. Reevaluation of this path will occur either at the intended reevaluation interval or as soon as circumstances dictate.

Step 5. If physical models for the driving task have been instantiated, the models execute the driving intentions, resulting in activities of the driver's body and the vehicle's clutch, pedals, transmission, and engine that result in actual physical movement.

Step 6. During the interval $n$, the Distributed Simulation Object Library (DSOL) simulation environment executes the movement

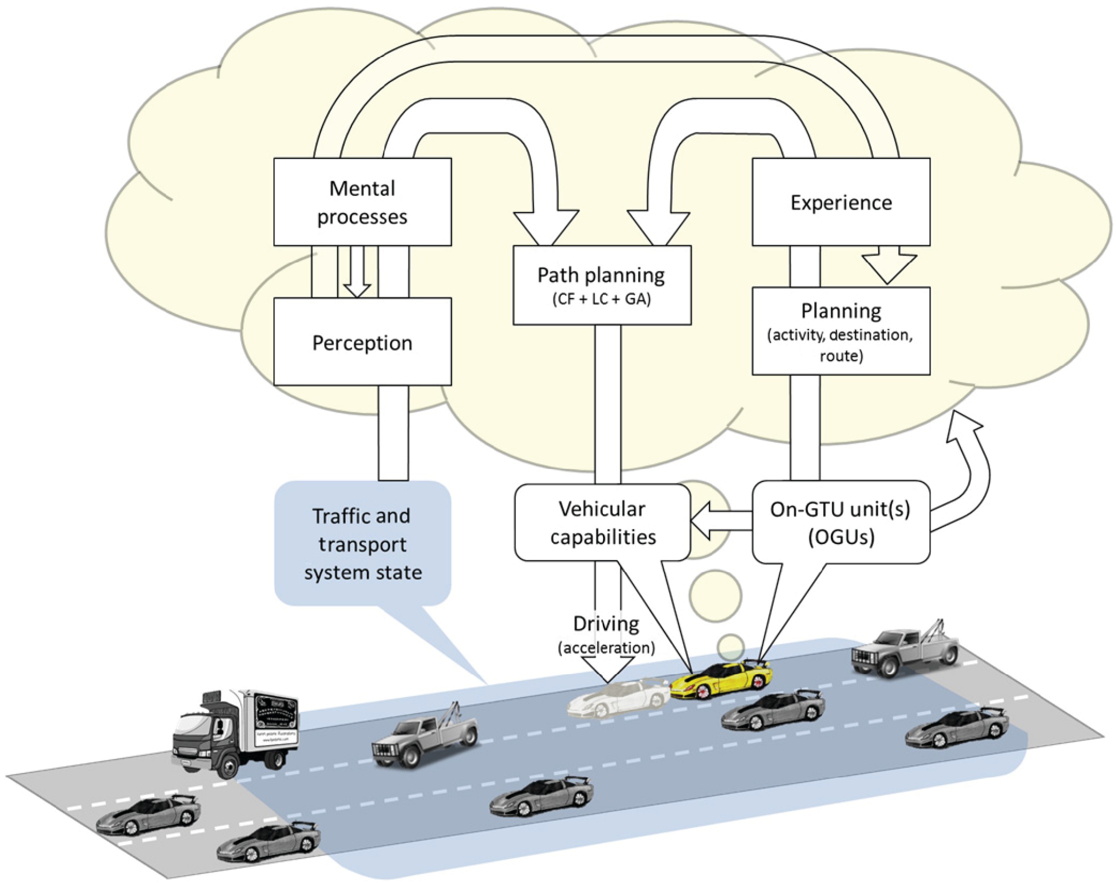


**FIGURE 1 Schematic representation of the microscopic driving process in OTS (CF = car following; LC = lane changing; GA = gap acceptance).**

resulting from the computed path, unless circumstances require reevaluation before the simulation of the path is finished.

## GTU and Other OTS Classes

The core objects in OTS simulations are GTUs. The GTU class hierarchy has two major branches: person and vehicle. In many aspects, these classes are mirrors of one another. A person has perceptive capabilities, and so does a vehicle (with sensors). A person has mental capabilities, and a vehicle has computing capabilities. Figure 2 schematizes the GTU in relation to some of the other main classes.

The key message is that with this GTU design (Figure 2) and the simulation process organized as in Figure 1, OTS offers maximum flexibility for microsimulation:

- In the simplest scenario, perception simply copies the system state (list of vehicles, network, etc.); both mental and experience are dummy objects; and vehicle contains only parameters (length, maximum acceleration, etc.). The result is a normal microsimulation.
- Every person can drive any type of vehicle according to any combination of models for both planning and driving, either very simple or highly complex.
- All vehicle automation or person information systems are modeled through OGUs that may affect all person or vehicle objects, parameters, and methods.

Finally, this design and the underlying DSOL simulation engine also allow for true multimodal simulation, that is, a simulation in which multiple modes plan and move in the same (virtual) environment.

- The mover class of a person can also be used to model pedestrians, cyclists, motor drivers, barge or plane pilots, and, conversely, the vehicle class can represent any type of car, tram, train, vessel, and so forth.
- The DSOL engine, briefly introduced below, makes it possible for objects to run on different clocks (i.e., it can be updated with their own time steps).

## OTS Software Design

The OTS framework has been built on top of the open-source simulation package DSOL (*40, 41*). The DSOL package is a Java-based, object-oriented, multiparadigm simulation environment that prepares for distributed and parallel execution of the simulation model. The DSOL package adheres to the best practices in the simulation field, such as strict separation between simulator and model (*42*), strict notions of time and state (*43*), state-of-the-art random number generators (*44, 45*), probability distribution functions (*46*), and a clear structure for experiments and run control conditions (*47*). That DSOL is object oriented makes it easy to extend the available simulation objects in the library such as simulators, experiments, and statistics,

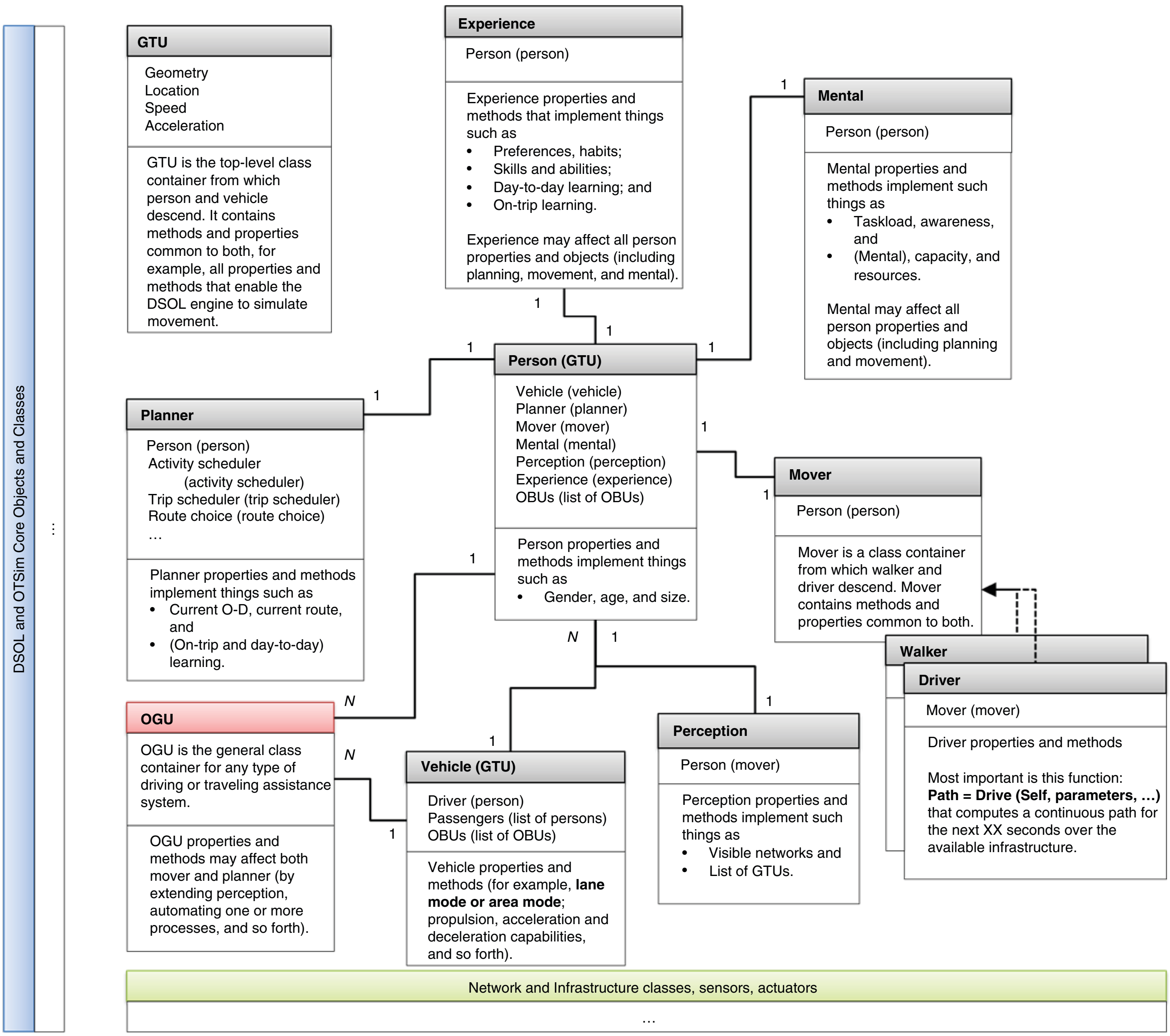


**FIGURE 2 Pseudo-unified modeling language schema for the generic travel unit, the core simulation object in OTS (O-D = origin–destination; OBU = onboard unit, a technological device such as adaptive cruise controller on board a vehicle).**

into traffic-specific building blocks for OTS, while still being able to use all other simulation objects that have not been specialized for use in a traffic environment (*48*). The use of Java has several key advantages over other programming languages: the availability of a very large ecosystem of open-source libraries, the ability to compile into stand-alone programs that can run on any computer with a Java Runtime Environment installed, and platform independence (e.g., Windows, Mac, and Linux).

The DSOL package is a multiparadigm simulation platform that runs event scheduling simulations [DEVS (Discrete Event Systems Specification)], time stepped models [DTSS (Discrete Time Systems Specification)], or differential equations [DESS (Differential Equation Systems Specification)]; for more information, see work by Zeigler et al. (*42*) and Wainer (*49*). Combinations are also possible, and extensions such as cell-based models and agents have been built as well (*50*).

## ILLUSTRATIVE EXPERIMENT

In this section, a small experiment is presented. The authors do not propose or implement a new mental model; they adjust parameters of driving behavior (reaction time and desired speed) to demonstrate why integration of human factors into simulation is crucially important for predicting emerging effects on both traffic efficiency and safety caused by changes in the driving environment.

### Test Case Description

The authors investigate the phenomenon of viewers jam. Such traffic jams arise at the location of an incident on the other direction of the freeway. While drivers pay attention to the incident, their driver behavior deteriorates as speeds drop and reaction times increase (*51*).

The authors simulate this finding on a 5-km single-lane road stretch with an incident at 3 km. The authors assume that driver distraction grows linearly from zero to a maximum value over 600 m up to 300 m upstream of the incident and stays at its maximum over 300 m upstream of the incident (see Figure 3*a*). In the initial state are 300 vehicles at their desired speeds and desired headways, with the first vehicle at $x = 0$. Simulations are of 1,000 s with a numerical time step $\Delta t = 0.25$ s.

Car-following behavior is simulated with the intelligent driver model+ (*52*); the discrete equation for acceleration of a single vehicle is given in Equation 1. The following parameters are used: $b_0 = 0.75$ m/s$^2$, and the default desired speed $v_0$ is set at 120 km/h. Other values are taken from work by Schakel et al. (*53*): maximum acceleration $a_{\max} = 1.25$ m/s$^2$, maximum comfortable deceleration $b = 2.09$ m/s$^2$, stopping distance $s_0 = 3$ m, and desired headway $T = 1.2$ s. Vehicle length $l = 4$ m is used. Finally, $s$ is the net headway, and $\Delta v$ is the approaching rate to the leading vehicle.

Reaction time $T_r$ is incorporated in a similar way as in the human driver model (*19*). The input to Equation 1 is delayed, but drivers do anticipate each time step $\Delta t$ in the period $[t - T_r, t)$ to compensate for $T_r$ by assuming constant acceleration of both the ego vehicle and the leader.

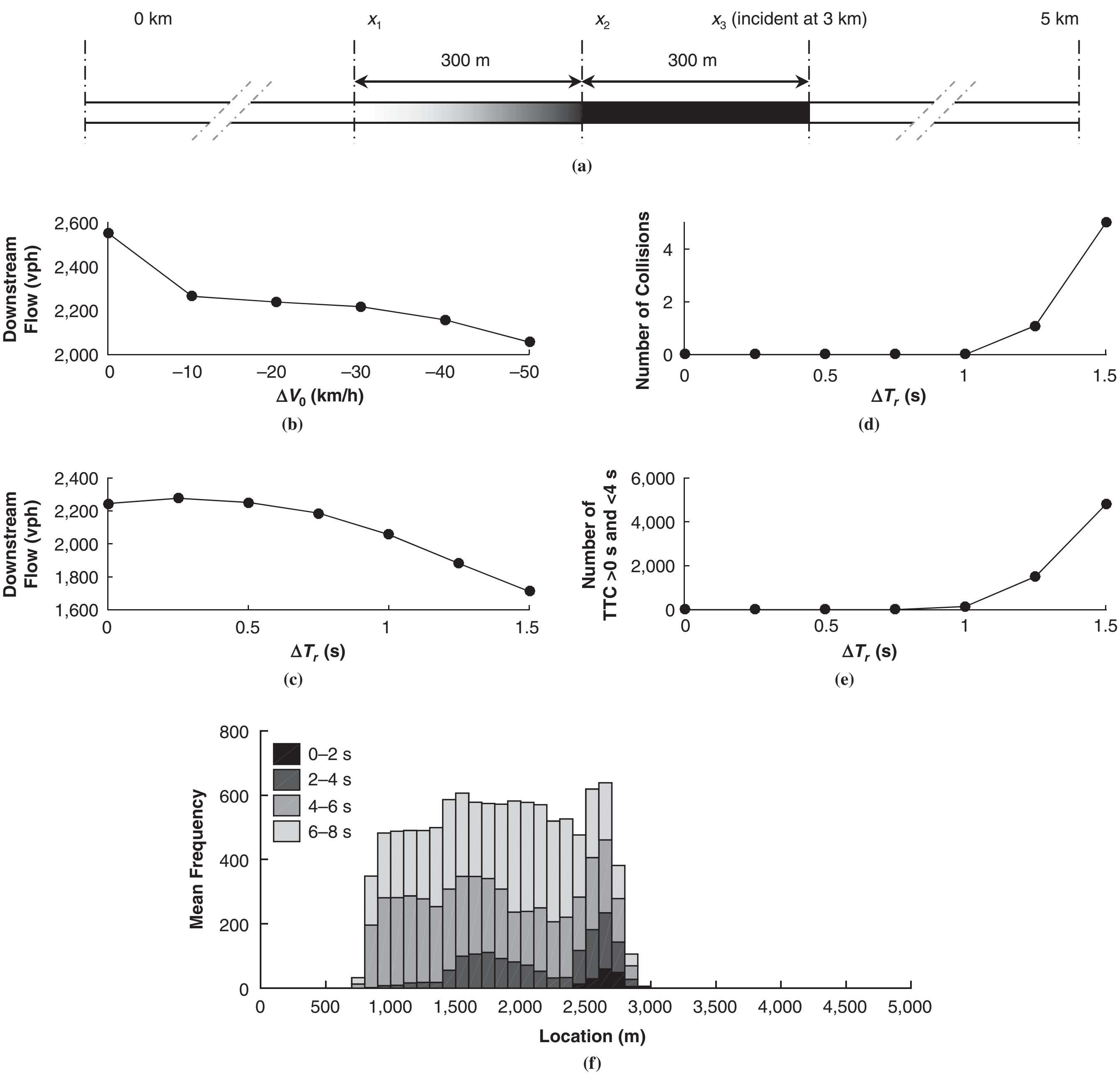


FIGURE 3 Illustrative experiment: (*a*) layout, (*b*) influence of $\Delta v_0$ on downstream flow, (*c*) influence of $\Delta T_r$ on number of collisions, (*d*) influence of $\Delta T_r$ on downstream flow, (*e*) influence of $\Delta T_r$ on TTC, and (*f*) TTC distribution (vph = vehicles per hour).

$$a(t) = a_{\max} \cdot \min\left(\max\left(1 - \left(\frac{v(t)}{v_0}\right)^4, \frac{-b_0}{a_{\max}}\right), 1 - \left(\frac{s^*(t)}{s(t)}\right)^2\right)$$

$$s^*(t) = s_0 + v(t) \cdot T + \frac{v(t) \cdot \Delta v}{2\sqrt{a_{\max} \cdot b}} \tag{1}$$

Driver distraction is integrated in two ways. It is assumed that desired speed drops and that reaction time increases. The level of distraction $d$ for driver $i$ at time $t$ is given in Equation 2 in line with Figure 3*a*. There are differences between drivers for $d^0$, which is the level to which a driver's behavior is affected. For each driver it is a fixed random value taken from a uniform distribution between 0 and 1.

$$d_i(t) = d_i^0 \cdot \begin{cases} 0 & \text{if } x_i(t) < x_1 \text{ or } x_i(t) > x_3 \\ \dfrac{x_i(t) - x_1}{x_2 - x_1} & \text{if } x_i(t) \geq x_1 \text{ and } x_i(t) < x_2 \\ 1 & \text{if } x_i(t) \geq x_2 \text{ and } x_i(t) \leq x_3 \end{cases} \tag{2}$$

The change in desired speed is given in Equation 3 (driver and time step index omitted for clarity), where $v_0^{\text{def}}$ is the default desired speed of 120 km/h and $\Delta v_0$ is the maximum change for a fully distracted and most affected ($d^0 = 1$) driver. The change $\Delta v_0 \leq 0$ is changed between scenarios.

$$v_0 = v_0^{\text{def}} + d \cdot \Delta v_0 \tag{3}$$

The change in reaction time $T_r$ is done in a similar way, according to Equation 4. Here, $T_r^{\text{def}}$ is the default reaction time of 0.5 s, whereas $\Delta T_r$ is the maximum change for a fully distracted and most affected driver. The change $\Delta T_r \geq 0$ is changed between scenarios.

$$T_r = T_r^{\text{def}} + d \cdot \Delta T_r \tag{4}$$

## Test Scenarios and Performance Indicators

Twelve scenarios were defined to assess the effects of $\Delta v_0$ and $\Delta T_r$ on the resulting traffic operations. For six, $\Delta v_0 = \{0, -10, -20, -30, -40, -50\}$ km/h with $\Delta T_r = 1$ s, and for the remaining six, $\Delta v_0 = -50$ km/h with $\Delta T_r = \{0, 0.25, 0.5, 0.75, 1.25, 1.5\}$ s. The change $\Delta T_r = 1$ s is missing in this array because it is part of the first six scenarios. For each scenario, 30 runs were used as $d^0$ is a random value.

A number of indicators were derived to assess traffic efficiency and safety. The overall efficiency was measured by the average outflow (the production) expressed in Equation 5, where $t_1$ is the time when the first vehicle crosses the downstream end and $t_{300}$ is the time when the last vehicle crosses the downstream end.

$$q = \frac{299}{t_{300} - t_1} \tag{5}$$

For large values of $T_r$, collisions may occur. A collision occurs in case a specific vehicle has a negative net headway for a consecutive number of time steps (headways < 0 are truncated to 0 in Equation 1 to prevent simulation artifacts). Because collisions were allowed, the TTC value was computed:

$$\text{TTC} = \begin{cases} 0 & \text{if } s < 0 \\ \dfrac{s}{\Delta v} & \text{if } s \geq 0 \end{cases} \tag{6}$$

## Results

The influence of $\Delta v_0$ and $\Delta T_r$ on downstream flow is shown in Figure 3, *b* and *c*. For $\Delta v_0 = 0$ km/h, there were no disturbances at all and temporal anticipation was completely able to compensate for reaction times as high as 1.5 s. For $\Delta v_0 = 10$ km/h, there was a strong drop because disturbances occurred. Together with $T_r^{\text{def}} = 0.5$ s and $\Delta T_r = 1$ s, mild disturbances produced a strongly deteriorated traffic efficiency. For larger values of $\Delta v_0$, efficiency dropped slowly as disturbances are slightly larger. Even for $\Delta v_0 = -50$ km/h, values of $\Delta T_r$ up to 0.75 s seem to have little influence on efficiency, with downstream flow being about 2,250 vehicles per hour. Apparently, temporal anticipation is relatively accurate for reaction times up to 1.25 s. For large values of $\Delta T_r$, seriously deteriorated traffic flow efficiency occurred.

Figure 3, *d* and *e*, shows the influence of $\Delta T_r$ on the number of collisions and TTC between 0 s and 4 s (i.e., critical values). Both indicators show a similar effect: larger reaction times deteriorate safety. For $\Delta T_r = 1.25$ s, 1.1 collisions occurred on average, whereas $\Delta T_r = 1.5$ s produced five collisions on average. TTC values between 0 s and 4 s are also frequent for these values of $\Delta T_r$. For $\Delta T_r = 0.75$ s and $\Delta T_r = 1$ s, TTC values between 0 s and 4 s also occurred, but not often.

The influence of $\Delta v_0$ on the number of collisions was not present because with $\Delta T_r = 1$ s being used within these scenarios, no collisions are produced. The influence of $\Delta v_0$ on TTC is present, with smaller values of $\Delta v_0$ reducing the infrequent number of low TTC values at $\Delta T_r = 1$ s even further, namely from 143.57 at −50 km/h to 26.43 at −40 km/h. The strength of the disturbances thus affects safety.

Figure 3*f* shows the spatial distribution of small values of TTC up to 8 s for one scenario, with $\Delta v_0 = -50$ km/h and $\Delta T_r = 1.25$ s. From the distribution, it can be seen that because of the temporal anticipation, traffic remained relatively safe away from the incident. Near the incident, very critical TTC values occurred, and for this scenario, 1.1 collisions occurred on average. In the range of 1,000 m to 2,500 m, TTC values between 2 s and 8 s occurred. This result is because of jams that move upstream. These moving jams show strong decelerations because the large reaction times at the incident create very strong decelerations.

## Discussion of Results

What this experiment illustrates is that by simulating the findings of Hoogendoorn et al. (a speed reduction and reaction time increase caused by an incident on the other direction of the roadway) (*51*) with a regular car-following model, counterintuitive results may occur. The results indicate that increased reaction time does not necessarily create unsafe traffic, at least not if the assumption of Treiber et al. holds that temporal anticipation of drivers is usually able to compensate the reaction time sufficiently (*19*). Put simply, drivers have quite effective predictive abilities, and Treiber et al. provide fairly convincing arguments for it (*19*). The question is under which conditions this case remains and which determinants govern these predictive abilities.

However, if larger distractions are introduced, the results indicate that both efficiency and safety deteriorate. In that case, collisions occur in the simulation for particular values of $\Delta T_r$. In reality, secondary collisions certainly do take place (also in opposite driving directions). Nonetheless, the question again is which critical factors will govern the probability of accidents under a variety of conditions. Clearly, if researchers would be able to compute reaction time endogenously and sensitivity to stimuli with validated mental models, it would open up the possibility of actually predicting both safety and efficiency effects through simulation under conditions for which current models are not yet valid. These evaluations would further improve if researchers were better able to understand how drivers are able to make predictions and under which conditions these predictions may deteriorate.

## CONCLUSION AND OUTLOOK

In this paper, the authors discussed why it is imperative for the traffic flow simulation and theory community to start serious collaborations with peers in the fields of human factors and social psychology:

- Most of the microscopic models used today are not predictively valid to evaluate ex ante the effects of vehicle automation, because they lack explanatory models for the dynamics of critical parameters of human drivers, such as reaction time and sensitivity to stimuli.
- It is possible to simulate traffic by using findings from human factors studies and do what-if analyses, but one must be modest in drawing conclusions because of the many assumptions involved (in this case, the idea that drivers have pretty strong anticipatory abilities) and the limited knowledge of the circumstances under which these assumptions are still valid.

The authors also presented a modular agent-based design for the open-source simulation suite OTS that provides the objects and classes to integrate human factors gradually (as research efforts progress) into regular microsimulation modeling. The OTS framework is built on state-of-the-art open-source simulation libraries and offers much additional functionality related to visualization and network handling. Clearly, the work has just started, and in the past year and a half it has been a process of two steps forward, one step back. But with support from industry, progress is accelerating.

Given the societal importance of predicting the effects on safety and efficiency of vehicle automation, the authors sincerely hope that this paper will fuel the discussion on how both open- and closed-source simulation software can be adapted and made ready for the next generation of traffic simulation models that are needed for the coming decades.

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