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# Human Factors in Modelling Mixed Traffic of Traditional, Connected, and Automated Vehicles

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**Abstract:** Connected and automated vehicle technologies are widely expected to revolutionize transport systems, enhancing the mobility and quality of life while reducing the environmental impact. However, in the foreseeable future, connected and automated vehicles will have to co-exist with traditional vehicles, indicating a great research need of modelling mixed traffic flow. In few attempts of modelling mixed traffic flow recently, human factors are largely ignored, despite their critical roles in understanding traffic flow dynamics and effective operation and control of this mixed traffic flow. To properly investigate the role of human factors in mixed traffic, we have designed a series of experiments using a high-fidelity driving simulator. Complementary information is collected using questionnaires. This study can assist in developing accurate, realistic, and robust microscopic traffic flow models.

**Keywords:** Connected vehicles · Automated vehicles · Human factors · Advanced Driving simulator · Microscopic traffic flow models

## 1 Introduction

The connected and automated vehicle technologies have great potential as the solution to massive road transport issues. Experts predict that by the year 2030, connected and/or autonomous vehicles will be mainstream, fundamentally transforming the automobile industry and how humans travel [1]. Such prediction has been supported by numerous studies and research programs [2]. Some key contributions of connected and automated vehicles will be improving traffic safety, reducing emission, enhancing mobility by alleviating traffic congestion and improving overall traffic performance [3].

Connected vehicles are capable to communicate with nearby vehicles as well as external networks. The connectivity can be Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), and Vehicle-to-Everything (V2X, e.g. pedestrian and electronic devices). Obviously, when driving a connected vehicle a human driver is supposed to

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consider the information supplied through the connected system. Therefore, drivers' response to the information assistance becomes critical because it will affect the dynamics of the connected vehicles and thereby the traffic flow, as reflected in the driver assistance system (DAS) studies. Furthermore, it is reasonable to assume that there will be a transition in connected vehicle technology as well as in the penetration of connected vehicles. Also, drivers' adaptation to this new technology requires time [4]. Even a successful adaptation to this technology does not guarantee a full compliance to the system at all time. Thus, it is of utmost importance to: a) identify the human factors that significantly influence the operation of connected vehicles, both in terms of safety and efficiency; and b) incorporate these important human factors in developing traffic models. To date, only few researchers have attempted to incorporate these factors [5]. As such, more work is needed due to the emerging nature of the connected vehicle technologies.

Automated vehicles perform the driving tasks without any human intervention. This definition represents the fifth level of automation (level 5) as per vehicle automation classifications by the Society of Automotive Engineers (SAE) [6]. Although drivers do not need to perform the driving tasks, their role of supervisor-cum-operator is crucial [7]. Similar to connected vehicles, there will be a transition in the levels of automation and their penetration in the traffic stream. During this transition phase, depending on the level of automation, drivers need to monitor the driving environment and take over the vehicular control timely for various reasons. Previous studies reported that automation may lead to overreliance, erratic workload, skill degradation, and reduced situation awareness [8].

Meanwhile, traditional vehicles have been modelled extensively since more than 50 years ago. Specifically, microscopic traffic flow models that describe the flow at the individual vehicle level are broadly categorized as car-following models and lane changing models (refer to [9, 10] for a review on each of these models). Human factors are often disregarded in these models which has made them insufficient for explaining the complex interaction between the human driver and the traffic flow. Notably, reaction time is the only human factor that has been extensively used in the modelling.

It is clear from the above discussion that human factors will play an essential role in governing the dynamics of mixed traffic consisting of traditional, connected, and automated vehicles. Unfortunately, human factors are largely ignored both in traffic data collection and in traffic flow modelling. As a part of the on-going effort to model the mixed traffic, this paper presents a comprehensive discussion on the human factors and related issues important for data collection and modelling. In addition, this paper presents one of the first efforts in capturing the human factors for traditional and connected vehicles using driving simulator experiments.

The rest of the paper is organized as follows: Section 2 details the important human factors in modelling traditional, connected and automated vehicles; Section 3 describes a design of the experiments to incorporate the human factors in modelling mixed traffic; and Section 4 summarizes main conclusions and on-going research.

## 2 Important Human Factors in Modelling Traditional, Connected, and Automated Vehicles

### 2.1 Traditional Vehicles

Based on the literature, the human factors that govern the traditional vehicles dynamics in the traffic flow are depicted in the Fig. 1. Due to space limitation, the ensuing paragraphs detail only some of the important human factors and their impact on traffic flow.

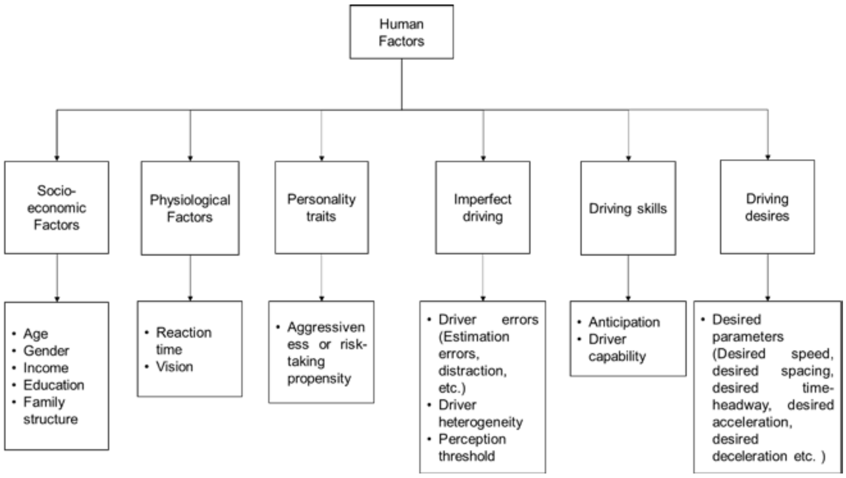


**Fig. 1.** Human factors critical for modelling traditional vehicles [12, 13]

**Socio-economic Characteristics**. These factors refer to a combination of economic and sociological experiences and realities that influence the personality, attitude, and lifestyle of a driver. The main factors are age, income, gender, occupation, education, family background/ structure and etc. The effect of socio-economic factors has been widely studied in various fields such as traffic safety [13] and driver compliance [14]. However, limited research studies have considered these factors in traffic flow modelling.

**Reaction time.** It is the duration between when a stimulus is observed by the driver and when the driver responses to that stimulus. Some examples of stimulus are sudden acceleration/deceleration of the leading vehicle, a lane changing vehicle ahead, and red traffic light. More specifically, the reaction time has four major psychologic aspects: sensing, perceiving, deciding, and performing an action [15]. Further, the reaction time varies among drivers depending on various factors such as driver's age, gender, driving experience, driving intensity [16], and driver alertness [17].

To describe the stimulus-response relationship such as in the case of car-following, reaction time is an important parameter. Driver reaction time causes traffic instabilities characterized by traffic waves [12], and also reflects inter-driver heterogeneity, i.e.

every driver has a different reaction time [18].Therefore, it is included in many microscopic traffic models (refer [9] for details of these models).

**Aggressiveness or risk-taking propensity**. Aggressive driving behavior usually neglects other person's right or safety and is intended to hurt/ harm another person, either other drivers or pedestrians [19]. Aggressive driving behavior has different forms varying from mild aggressiveness such as flashing lights, honking, tailgating, blocking other drivers, verbal threat, and non-verbal gestures, to extreme aggressiveness such as unsafe lane-changing, speeding, and car ramming [20]. From the modelling perspective, Gasser et al. [21] proposed a car-following model with variable reaction times and aggressiveness of driver and reported that more aggressiveness has a stabilizing effect on the traffic flow characteristics. Moreover, researchers have incorporated risk-taking in some car-following models by considering its psychological and cognitive aspects [22].

**Distraction.** It pertains to the cognitive and decision-making errors and is caused by the failure of psychological mechanism of attention [23]. Distraction poses serious traffic safety issues [24]. In addition, it impacts braking behavior [25], reaction time [26], and car-following behavior [27]. Recently, Lint et al. [28] have incorporated driver distraction as a parameter to estimate the resultant desired speed and reaction time.

**Estimation errors.** These errors also pertain to cognitive and decision-making errors and are caused by the unsuccessful attempt of situation assessment [23]. The most common estimation errors are the inaccurate estimation of the spacing between the driver and the preceding vehicle and the relative velocity. Research related to considering estimation errors in microscopic traffic modelling is also limited. Synthesis of the literature revealed that only one study has attempted to model the estimation errors [12]. This study demonstrates that while small errors have minor impact on traffic waves, large errors may have drastic effects and even lead to crashes.

**Driver Heterogeneity.** This is defined as the differences in the driving behavior under homogeneous conditions (similar roadway, traffic and weather conditions). It can be classified into two groups: inter-driver heterogeneity and intra-driver heterogeneity. The former illustrates heterogeneity across different drivers, i.e. different drivers have different driving behaviors for the same stimulus and the later describes heterogeneity within the same driver's driving behavior, i.e. the same driver can respond differently for the same stimuli at different times or locations. Both types of heterogeneities have been clearly observed in the real traffic [29]. So far, a few attempts have been made to incorporate driver heterogeneity in traffic models [29]. Driver heterogeneity can lead to a better understanding of traffic flow phenomena such as stop-and-go oscillations, capacity drop, traffic hysteresis flow distribution across lanes, and lane changing maneuvers [30–32]. Moreover, driver heterogeneity also attributes to model calibration errors [12].

**Anticipation.** Drivers frequently inspect the surrounding traffic situation and anticipate the emerging traffic situation. Driver's such capability is known as anticipation, which can be broadly categorized as temporal anticipation and spatial anticipation (also known as multi-anticipation )[12]. The former is related to the driver's ability to predict the traffic situation for the next few time intervals and the later describes the driver's ability to take into account several vehicles ahead in decision making. Multi-anticipation has been incorporated in various car-following models and its stabilizing effect on traffic flow has been reported [33].

**Perception threshold.** It is defined as the minimum value of the stimulus drivers can perceive and react to [34]. The concept of speed-based and spacing based thresholds was first reported by Michales [35]. Psycho-physiological car-following models (or action point models) consider both local traffic and drivers' perception thresholds in contrast to most traffic flow models where drivers are assumed to respond continuously to an exogenous stimuli, irrespective of how small in the magnitude. Wiedemann [34] is an example of this type of model. Recently, Hoogendoorn et al. [36] presented a data-driven action point model.

**Driver capability.** This term was first introduced by Ray Fuller in the Task-Capability Interface (TCI) model, which explains driver behavior through the interaction of driver capability and task demand [37]. Capability of a driver is limited by constitutional characteristics (such as knowledge and skills developed through education and training) and biological capabilities (such as perceptual acuity, reaction time and visual acuity). Furthermore, sensation seeking and distraction are also found to affect driver capability. Previous studies have discovered a correlation between driver capability and time headway selection [38]. Most recently, Saifuzzaman et al. [39] reported that incorporating TCI model into existing car-following models improves the model's performance.

## 2.2 Connected Vehicles

**Human factors related to the deployment of connected vehicles.** The most critical human factor for the success of connected vehicles is driver behavioral adaptation. It is defined as "*any change of driver, traveler, and travel behaviors that occurs following user interaction with a change to the road-vehicle-user system, in addition to those behaviors specifically and immediately targeted by the initiators of the change*" [40]. Furthermore, the degree of behavioral adaptation according to the 'Qualitative model of behavioral adaption' is the amount of trust a driver has in the system (wherein trust includes 'reliability' and 'competence' of the system), which is determined by the system characteristics such as feedback timing (immediate vs. delayed), amount of usage (amount of exposure) and persistence [41].

Although, drivers' behavioral adaptation to DAS is a widely acknowledged phenomenon, the human centered factors plausible to explain behavioral adaptation are not well established [42]. Behavioral adaptation to connected vehicle technology is possible only if drivers comply with the information provided by the system. Zero compliance will result in zero adaptation. Likewise, degree of compliance will directly influence the degree of behavioral adaptation. In light of this, we propose that drivers' compliance is the sole human factor that governs behavioral adaptation. All the other human factors impact behavioral adaptation through their impact on drivers' compliance.

*Driver's compliance.* Drivers' compliance to the information is crucial for the success of the connected vehicles. For example, in relation with variable speed limit system, Hellinga and Mandelzys [43] revealed that safety is positively correlated and travel time is negatively correlated with compliance. Some of the factors that affect driver's compliance are: individual factors such as attitude, subjective norm, habit, distraction, inattention, mindfulness, awareness [44]; situational factors such as traffic conditions, familiarity of road, neighboring vehicle's behavior [45]; and other factors such as the type and presentation of advisory information [45].

For simplicity, we categorize the human factors influencing driver compliance (or the degree of compliance) into four groups, namely, (i) personality traits, (ii) affective, cognitive and psychomotor functions, (iii) acceptance and trust, and (iv) socio-economic characteristics. Some of these factors may be correlated. A field test for examining the freeway merging assistance systems for connected vehicles concluded that the compliance rate is higher for older drivers and is independent of gender [46]. Note that, a full driver compliance (100% compliance) is highly unlikely due to these human factors. Therefore, it is imperative to carry out a comprehensive analysis of human factor impact on the effectiveness of any information assistance system through field or driving simulator experiments prior to its large-scale deployment.

**Connected vehicles' impact on human driving behavior.** Limited research has been conducted using driving simulators or connected vehicle test beds (field tests) to investigate how connected technology influences driver behavior. For instance, using driving simulator experiments, Chang et al. [47] found a significant reduction in driver perception-reaction time while analyzing the rear-end collision warning systems of a connected bus system.

Evidently, connected vehicles will be equipped with devices similar to DAS to receive, process, and then display the kinematic information (position, velocity, acceleration, recommended speed, space-headway, etc.) disseminated by the neighboring vehicles and/or roadside units. During the development stage of connected vehicles, findings from DAS based studies may provide valuable references to understand the potential impact of this new technology on driver's performance. Over the past two decades the impact of different types of DAS (such as vehicle dynamics stabilization systems, information warning, and comfort systems) on driver's performance have been studied in detail. Some intriguing findings are, for example, DAS has the potential of reducing driver errors (e.g. perception, anticipation, and distraction), increasing driving comfort and improving traffic flow [48]. In particular, many studies investigated the impact of DAS on time headway either in field or simulator studies. Almost all the studies reported a decrease in the occurrence of potentially unsafe headways [49, 50]. Furthermore, a shorter reaction time is reported when any anticipatory information was available through DAS [49]. Other positive aspects of DAS are safe speed adaptation [49], collision avoidance [51], and better route selection [52]. Connected vehicle technology is more advanced compared to DAS because it will not only communicate with the surrounding vehicles, but also with the infrastructure and with all other related technologies. Connectivity will help the driver by providing real time and advanced information related to safe and efficient driving. Therefore, it is reasonable to anticipate that the impact of connectivity on human driving behavior should be more profound than that of DAS in terms of improving safety, comfort and efficiency.

### 2.3 Automated vehicles

Major human factors associated with automated vehicles are driver inattention and distraction, situational awareness, overreliance and trust, skill degradation, and motion sickness. Driver inattention and distraction pertain to passive fatigue [53], reduced driver vigilance [54], engagement in secondary activities [55], and etc. Concerns have been raised that automated driving may lead to impoverished situation awareness [55]. In addition, over-reliance on the automation can cause negative behavioral adaptation effects and can be detrimental to safe driving [56]. Skottke et al. [57] reported carry-over effects of highly automated convoy driving such as shorter time headways and increased variability of lateral position in a manual driving task subsequent to brief periods of highly-automated driving . Researchers have argued that re-engaging the driver or shared control has the potential to reduce the detrimental impact of automated driving [8], such as time-dependent takeover of vehicle control by the driver (Level 3 automation). The major issues investigated by the previous studies are the time frame required by the driver to regain the control [58] and after-effects of takeover [59].

## 3 Driving Simulator Experiment Design

A significant challenge in investigating issues relating to connected and automated vehicles is the lack of field data because these vehicles are not yet operating on a scale suitable for naturalistic research. To overcome this challenge, many researchers choose numerical experiments. While using numerical methods is a reasonable compromise in this circumstance, there is a high risk of oversimplification because an important component, human behavior in the connected environment, is not accounted for. Motivated by the current research needs and limitations of the previous studies, this study seeks to carefully and innovatively design driving simulator experiments to collect vital empirical data. The simulator experiments have been conducted with the CARRS-Q Advanced Driving Simulator at QUT [27]. Two critical factors are considered in order to represent the connected environment realistically in the simulator experiments: design of driving aids and design of connectivity

**Design of driving aids.** It involves the type of information disseminated and how the disseminated information is presented. Some important factors that have been considered in this research while designing the driving aids are: the content of the aids, the type of the messages, the position of the display, and the duration and frequency of the displayed messages. The content of the driving aids are divided into three categories: a) continuous information, which is available all the time to the drivers (for example, speed of the preceding vehicle); b) on-time event-based information, which is available only at the onset of an event (for example, warning about speed violation); and c) advanced event-based information, which is provided a few seconds earlier of encountering the actual event (for example, advisory information about congestion ahead). Two types of message presentation are reported in the literature: auditory and imagery messages. Both of these types are incorporated in this study based on needs. For example, the event based information is displayed with a sound to draw driver's attention on those messages. All these messages are carefully presented on the windscreen without obstructing the field of driver view. The design of the driving aids is a crucial part of this study as it has a direct effect on the driving behaviour. All the above-mentioned factors affect the workload of the driver to some extent as the driver needs to understand the presented information, relate it with the driving context and finally act upon it. Hence the information load should be considered judiciously in order to get the optimum benefit from the connected vehicle technology.

**Design of connectivity.** In the connected environment, the information is received and transferred by the connected vehicles using V2V and V2I communications. The effectiveness of the information dissemination depends on the penetration and distribution of connected vehicles in the traffic and the distribution of roadside units along the road. Communication impairment is a critical issue that is inevitable in the real-world. Hence, in this experiment, both the perfect communication and communication impairments are included to mimic the connected environment more realistically. In the perfect communication, the flow of information is uninterrupted, whereas no information dissemination (communication loss) or a delay in information dissemination (communication delay) are the characteristics of the communication impairments.

**The Experiment.** Two scenarios are covered within the scope of this research: baseline (with no connectivity, i.e., traditional vehicles) and connected environment (with both V2V and V2I communications). In the baseline scenario, each participant is asked to drive the vehicle as they normally do with a traditional vehicle (without driving aids). In the connected scenario, information assistance is provided to the participant on the windscreen using the driving aid. Figure 2 is an example, a snapshot of the windscreen when a participant is driving in the connected environment. Each participant needs to complete three driving tasks: car-following (free flow and braking events), lane changing (both mandatory and discretionary), and merging.

A noteworthy feature of connectivity in this research (especially compared with the present DAS) is that the information on some critical events is provided in advance to the driver (about 3-5 seconds before the occurrence of that event). It is assumed that the connected technology should be smart enough to predict these critical events in advance. For example, when two or more connected vehicles are in front of the driver, the connected vehicle technology should predict and inform the driver in advance about the next braking event of the preceding vehicle. Similarly, it should also be able to inform the drivers about lane closure or traffic state at downstream locations. These advanced information will assist the drivers in tactical decision-making. The experiment design involves all these events. Moreover, to make the experiment more realistic, the connected scenario also incorporates the communication impairments.

**Questionnaire Survey Design.** To obtain more information related to human factors, pre-drive and post-drive questionnaire surveys have been carried out to understand how human drivers influence, and are influenced by the connected environment. The pre-drive survey involves questions pertaining to socio-demographic information, driving experience, and driving behavior (based on driving anger expression inventory [60]). After each scenario drive participants have to complete NASA Task Load Index (NASA-TLX) [61]. This is to comprehend the required human cost (workload during the experiment) represented by the subscales corresponding to the mental, physical, and temporal demands, frustration, effort, and performance. Finally, the post-drive survey is designed to understand how human factors such as user-acceptance, trust in the technology, and sensation-seeking contribute towards driver's compliance/non-compliance to the information aid.

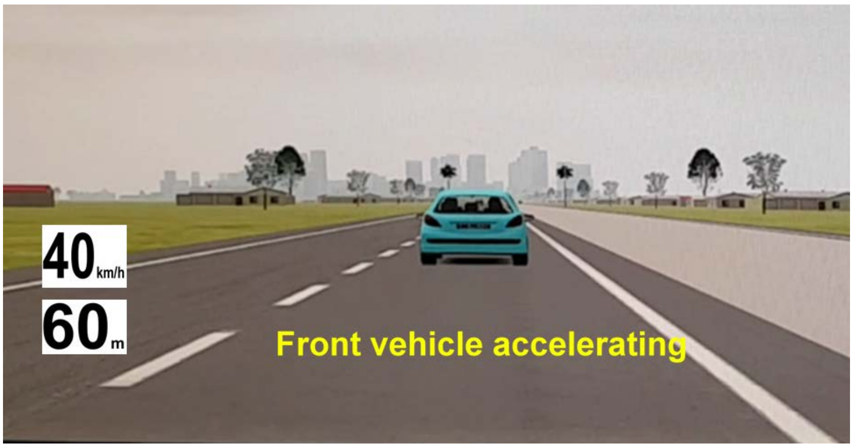


**Fig. 2.** A visual description of driving aids on the wind screen (Note that 40 km/h and 30 m represent the front vehicle's speed and spacing to the front vehicle, respectively).

## 4 Conclusion

This paper focuses on human factors and their importance for the success of connected and automated vehicles. Furthermore, the paper presents a detail discussion on critical human factors that need to be incorporated in microscopic traffic flow models, especially for traditional and connected vehicles. In addition, this paper also presents the design of a driving simulator experiments for traditional and connected vehicles. Data collected from this driving simulator experiment can assist in developing more accurate, realistic, and robust microscopic traffic flow models, which are important tools for understanding characteristics of mixed traffic flow consisting of traditional, connected, and automated vehicles, and for developing effective operation and control strategies for mixed traffic flow. Such effort is ongoing.

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