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# Human-Machine Interaction for Vehicles: Review and Outlook

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# Contents

# Human-Machine Interaction for Vehicles: Review and Outlook

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ABSTRACT

Today's vehicles have myriad user interfaces, from those related to the moment-to-moment control of the vehicle, to those that allow the consumption of information and entertainment. The bulk of the research in this domain is related to manual driving. With recent advances in automated vehicles, there is an increased attention to user interactions as they relate to automated vehicles. In exploring human-machine interaction for both manual and automated driving, a key issue has been how to create safe in-vehicle interactions that assist the driver in completing the driving task, as well as to allow drivers to accomplish various non-driving tasks. In automated vehicles, human-machine interactions will increasingly allow users to reclaim their time, so that they can spend time on non-driving tasks. Given that it is unlikely that most vehicles will be fully automated in the near future, there are also significant efforts to understand how to help the driver switch between different modes of automation. This paper provides a review of these areas of research, as well as recommendations for future work.

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# 1

# Introduction

Road vehicles, from cars, to buses, to trucks, are an inseparable part of modern life. People use cars and buses to commute to work, go shopping, and visit vacation spots. They use trucks to transport goods over long distances, deliver packages to a customer's doorstep, and to provide a mobile base for electricians, plumbers, and first responders. It is not surprising then that industry, academia, and government have been spending a considerable amount of effort to create road vehicles that are safe, efficient, pleasant to drive, and can help us to effectively accomplish different tasks. Much of this effort is focused on problems such as how to design brakes that can halt the vehicle quickly, and how to design fuel-efficient engines. In this paper, we explore the efforts to design in-vehicle user interfaces.

User interfaces in vehicles have gone through a significant transformation since the invention of the automobile in 1886 by Karl Benz (Figure 1.1). Akamatsu and colleagues document this transformation (Akamatsu *et al.*, 2013): early vehicles only provided interfaces that allowed steering and braking; instrument clusters appeared in the 1920s; by the 1980s navigation systems began to appear in vehicles; and starting with the 1990s brought-in devices, primarily cell phones (and later

**Figure 1.1:** Human-machine interaction for vehicles has become more complicated over the years. On the left is the Benz's 1886 Patent Motorwagen, the world's first automobile (image by DaimlerChrysler AG, CC-BY-SA-3.0, via Wikimedia Commons). On the right is the interior of a 2017 Opel. The operator of the Benz interacted with the vehicle through inputs to control lateral and longitudinal position. The 2017 vehicle has myriad displays and inputs.

smartphones), became a major presence in vehicles. The drastic transformation of in-vehicle user interfaces is also documented by Kern and Schmidt who compared two vehicles from the same manufacturer, one from 1954 and another from 2007 – the newer vehicle had 113 in-vehicle devices, which is almost four times more than the older vehicle (Kern and Schmidt, 2009). In general, today's vehicles have myriad functions, and related user interfaces. These can be quite confusing to the driver – this is such a significant problem that since 2015 there is a website dedicated to explaining to consumers which safety technologies are available in their vehicles, and how to use these technologies, including how to use their user interfaces (www.mycardoeswhat.org).

In this paper we focus on discussing work related to modern in-vehicle user interfaces. The bulk of this work in the recent past and the present is related to manual driving – the case when the driver's primary task is the control of the vehicle, and all other activities in the vehicle, such as interacting with a navigation system, or communicating with remote conversants, are considered secondary tasks. In exploring user interfaces for manual driving a key issue has been assessing the effects of the interfaces on driving safety. Very frequently this is done in the context of an application, such as navigation, entertainment, or communication. In this paper we will review key findings from this line of work.

Yet another topic that has received attention is the user experience (UX) of in-vehicle user interfaces. This type of work is aimed both at the driver, as well as at passengers who have become more frequent subjects of exploration in recent times. This is especially true with the advent of automated vehicles, given that all occupants of highly automated vehicles will be passengers for at least part of the journey. And, with automated vehicles there is increasing attention to user interactions for work and play (Kun *et al.*, 2016). Given that it is unlikely that most vehicles will be fully automated in the near future, there are also significant efforts to understand how to help the driver switch between different modes of automation. This paper will review work in all of these areas, and it will provide recommendations for future research.

# 2

# Methods for Exploring Human-Machine Interaction for Driving

Up to the present time, manual driving has been the primary focus of the research, development, and regulation of in-vehicle user interfaces. The situation is now changing, because the automotive community is increasingly working on issues related to automated vehicles (Kun *et al.*, 2016). Still, manual driving is by far the dominant form of driving on today's roads. Calvert and colleagues estimate that the share of vehicles with automation will start to increase significantly from 2020 (Calvert *et al.*, 2017). However, their estimate is that in 2020 only about 5% of the vehicles on the road will have adaptive cruise control, and less than 1% will have both ACC and some form of lane keeping assistance. Furthermore, they expect that manually-driven vehicles will be present on roads for decades, even as the number of automated vehicles increases. Luettel and colleagues also make the argument that in the near future the use of automation might have to be limited to highly-structured environments (Luettel *et al.*, 2012). Thus, even for vehicles that are equipped with automation technology, manual operation will likely be required in order to handle driving in construction sites, and on road segments with poor lane markings. Due to the fact that manually-driven vehicles greatly outnumber vehicles with automation, and that this balance is expected to change only slowly, manual driving remains the focus of much of the research on human-machine interaction for vehicles.

In manual driving a human operator – the driver – is responsible for performing all of the real-time functions of the dynamic driving task. According to the widely-accepted J3016 standard of the Society of Automotive Engineers (SAE), these functions include controlling the longitudinal and lateral position of the vehicle, monitoring the environment, responding to objects and events, planning maneuvers, and enhancing conspicuity (SAE On-Road Automated Vehicle Standards Committee, 2016). Note that systems such as electronic stability control, or lane keeping assistance, might provide momentary support to the driver during manual driving. However, the SAE J3016 standard considers these to be brief interventions – the sustained effort of driving is the responsibility of the human operator.

As we explore the use of in-vehicle devices during manual driving, as well as automated driving, the most important issue is safety. After all, crashes, including those with fatalities, are far too common around the world. Our goal with in-vehicle devices should be to reduce the rate of crashes, and ideally to eliminate them. Thus, some of the questions we ask are "can the driver safely control their vehicle while operating this in-vehicle device?" and "how is safety affected by the driving context?" The first AutomotiveUI conference in 2009 was held in Essen, in the Ruhr region of Germany. In the early 1900s this region was a center of coal production. Albrecht Schmidt, the co-chair of the 2009 conference, drew an interesting parallel between the public perceptions of coal mining in the early 1900s, and those of driving in the early 2000s (Schmidt *et al.*, 2010). He pointed out that in the early 1900s coal mining was a difficult and dangerous job. Severe, and even fatal, injuries were a common occurrence, and the public accepted them as a necessary cost of conducting business. By 2009 mining had become significantly safer, and the public would not have accepted the unsafe conditions of early 1900s mines. However, argued Schmidt, even in the early $21^{st}$ century we do accept the stunningly high number of fatalities related to driving. According to data in the Fatality Analysis Reporting System (FARS), operated by the National Highway Traffic Safety Administration

(NHTSA), in 2014 there were over 32,000 fatalities in the US related to crashes (from drivers, to passengers, to pedestrians); NHTSA estimates that the number of fatalities climbed to over 37,000 in 2016 (National Highway Traffic Safety Administration, 2017a). Thus, approximately 1 in 10,000 inhabitants of the US can expect to perish in a crash-related incident annually. In the 28 countries of the European Union around 26,000 people (approximately 1 in 20,000) lost their lives in 2014 in traffic-related incidents (European Commission, 2016). In a 2002 article, Nantulya and Reich pointed out that in some developing countries the situation was even worse (Nantulya and Reich, 2002). And in 2012, road traffic injuries were the leading cause of death globally among people 15–24 year old (World Health Organization, 2015). In another 50 or 100 years, argued Schmidt, we might look back at these numbers and ask, how could we have allowed so many deaths on our roads?

Of course, there has been much progress in improving driving safety over the years; for example, as Sivak and Schoettle point out, over the 50-year period between 1958 and 2008, the fatality rate in the US decreased by 40% (Sivak and Schoettle, 2011). This decrease was likely due to a combination of factors, including the introduction of passive-safety measures (e.g. airbags), active-safety measures (e.g. anti-lock brakes), and policy changes (e.g. requiring child restraints). And, all over the world, there are national and international initiatives, such as Vision Zero (Tingvall and Haworth, 1999), that aim to completely eliminate traffic fatalities.

Yet, we know that human-machine interaction for vehicles can have a negative impact on safety. Much of the current and recent work in this field is related to the fact that drivers are often engaged with secondary tasks while driving. This engagement is driven both by the increase in built-in devices in modern vehicles (Kern and Schmidt, 2009), as well as with the increase in brought-in devices, which in 2018 means primarily smartphones. The well-known 100-car Naturalistic Driving Study reviewed causes of inattention for 9,125 cases of crashes, near-crashes, and incidents in passenger cars (Neale *et al.*, 2005). This review showed that in just over 670 of these cases drivers were engaged in a secondary task on a brought-in wireless device (most commonly a cell phone). Hanowski and colleagues found similar evidence for drivers of long-haul trucks, who also reached for cell phones, dialed numbers, and talked to remote conversants (Hanowski *et al.*, 2005). More recently Dingus and colleagues used the SHRP-2 database of naturalistic driving that followed drivers in their personal vehicles (Dingus *et al.*, 2015). They found that a crash is 3.6 times more likely when the driver is using a cell phone, compared to the case when the driver is focused on the primary driving task (Dingus *et al.*, 2016). Guo and colleagues found that cell phone use increases the odds ratio of a crash across all driver age groups (Guo *et al.*, 2016).

Thus, a significant impetus for research on automotive human-machine interaction has been the need to further improve driving safety. This safety-related research has two main thrusts. First, researchers have been working towards understanding the driving task, and the influences of various aspects of context on the safety of driving. Second, a great deal of effort has been put into improving the safety of specific tasks related to driving, and for specific users.

The exploration of human-machine interaction and driving very often uses Michon's 3-level hierarchy of driving (Michon, 1985). The highest level in the hierarchy is the *strategic* level, where the driver generates general plans, such as the desired trip destination. The next level is *maneuvering*, which is concerned with directing the vehicle such that the strategic goals are supported, for example by taking a turn at an intersection, or changing lanes in preparation for the turn at the intersection. The lowest level of the hierarchy is the *control* level, which is concerned with the constant lateral and longitudinal control of the vehicle. Drivers are in charge of all tasks, at three different levels of granularity: from strategic planning of the entire trip that lasts many minutes, to planning and executing maneuvers such as changing lanes, that last several seconds, and all the way down to millisecond-level control of the vehicle. Consequently, for manual driving the exploration of in-vehicle interfaces also focuses on all three of these levels. Much of our current understanding of how drivers interleave the primary driving task and possible secondary tasks is based on the work of Wickens (Wickens, 2002). He argues that humans use multiple mental resources to interact with their environment; for example visual and auditory inputs are handled by different resources, as are manual and verbal responses. This insight is important, because it means that not all concurrent tasks will have the same effect on drivers. For example, an auditory secondary task might have less impact on the ability of the driver to maintain lane position, than a visual task that requires frequent gazes away from the road.

The interaction of drivers with their vehicles, with in-vehicle devices, and the effects of context on driving are complex. Thus, we often use proxy measures to assess how interactions with an in-vehicle device might affect safety. For example, we can compare the driver's visual attention to the road with and without the presence of an in-vehicle device; if the presence of the device reduces the driver's visual attention to the road, we can conclude that using the device might increase the risk of a crash. This example also tells us what our studies need to focus on: we need an understanding of what drivers normally do when they are not distracted, and we also need to understand the mechanisms and effects of distraction when drivers are using an in-vehicle device.

When researchers explore automated driving, they often use the same methods that we will discuss below. This is not surprising, since very often researchers explore automated driving that is not fully automated, and thus the driver has a role to play. This role might be to observe the traffic situation, or it might be to take over driving responsibilities at the request of the automation. Either way, whenever there is a need to assess how well the driver can handle a driving-related task in a vehicle with automation, the same methods come into play as when exploring manual driving.

Now that we have outlined our problem space – manual driving, as well as automated driving, consisting of tasks at three hierarchical levels, where safety is a primary concern, and where the driver brings to bear multiple mental resources to safely maneuver their vehicle while engaging in secondary tasks – we can take a closer look at the work in this area.

## 2.1 Measures to assess manual driving

To experimentally assess the impact of interactions with in-vehicle devices, we most often use driving performance measures. These measures assess the performance of the driver on tasks related to the three levels of

Michon's hierarchy, most often on the lowest (control) level. In general, worse performance on any of these tasks indicates reduced driving safety.

Tightly related to performance measures are measures related to eye movement, which inform us about where the driver is looking while operating a vehicle. Obviously, the less the driver looks away from road, the safer the drive will be; however, it is not just the overall time spent looking at the road ahead that matters – details of visual behavior also play an important role in allowing for safe driving.

Driving is also evaluated from the perspective of cognitive or mental workload. While there is no generally agreed-upon definition for cognitive or mental workload (Mehler *et al.*, 2012b), we will use the working definition that it represents the portion of cognitive resources devoted to completing a set of tasks. This definition is close to that of Young and Stanton, who argue that "the mental workload of a task represents the level of attentional resources required to meet both objective and subjective performance criteria, which may be mediated by task demands, external support, and past experience" (Young and Stanton, 2001). We expect that the driving task will use certain cognitive resources; additionally, if the driver is engaged in a secondary task this will also require cognitive resources. If the totality of resources being used for driving and secondary tasks starts to exceed the available resources, the driver might not be able to safely control their vehicle. Researchers use performance-, physiological-, and subjective measures to assess the level of workload. These measures are used as relative measures, which allow us to compare the effects of two experimental conditions on driving. In contrast, we are always in search of "absolute" measures that can provide a relationship between the use of an in-vehicle device, and/or a particular driving context on the one hand, and crash risk on the other.

### 2.1.1 Performance measures of driving

The majority of driving performance measures assess the driver's abilities at the lowest level of Michon's hierarchy, that is their ability to control the lateral and longitudinal position of the vehicle with high temporal granularity. In this section we discuss a number of measures that are commonly used.

### Number of collisions

Ultimately, the most basic driving performance measure is the driver's ability to avoid a collision. This requires both lateral and longitudinal control. In driving simulator-based studies researchers can count the number of collisions during a simulated drive. As driving performance decreases, perhaps because there is a distracting in-vehicle device, the number of collisions increases. Nass and colleagues used this measure to explore spoken interactions between drivers and in-vehicle devices (Nass *et al.*, 2005). They found that matching the emotion of the driver and the device resulted in fewer collisions than mismatching the emotions. In a driving simulator-based experiment Chisholm and colleagues found that collisions were more likely when drivers engaged in a complicated task with a music player, than in cases when there was no interaction with the music player, or when the interactions were simple (Chisholm *et al.*, 2008). In another simulator-based study, Kass and colleagues found that drivers involved in cell phone conversations were involved in more collisions than drivers who were not distracted in this way (Kass *et al.*, 2007).

Yet, the number of collisions normalized by distance travelled is relatively low. For example, NTHSA reported that in 2015, on average, 1.04 fatal crashes occurred for every 100 million miles driven, while the rate of all crashes was 203 per 100 million miles driven (National Highway Traffic Safety Administration, 2017b). We are grateful for this low normalized number of crashes and fatalities on the road. (The total number of fatalities is still unacceptably high, since people drive a great deal.) But, the rate of collisions is low in most driving simulator experiments as well. This often makes collisions useless as a relative driving performance measure. For example, Iqbal and colleagues explored ways to mediate phone conversations while driving, and they found no effect of their mediation approach on the number of collisions between a simulated vehicle and other vehicles, pedestrians, and objects in the simulation (Iqbal *et al.*, 2011). Medenica and colleagues compared the effects of three navigation aids on driving (Medenica *et al.*, 2011); for each of the participants they analyzed thirteen 200-meter-long segments on 2-lane city streets, each with a turn at the beginning and end, with ambient traffic, and no unexpected events, and found no collisions. One reason why some studies (e.g. Nass *et al.*) found a larger number of collisions than others (e.g. Medenica *et al.*) could be the driving simulator used: Nass *et al.* used a PlayStation game, while Medenica *et al.* used a high-fidelity driving simulator which allows for more accurate control of the vehicle. Another reason that there are no (or very few) collisions in many studies is that there are simply no (or very few) opportunities for collisions; for example, studies where participants have to follow a lead vehicle with no other traffic present, or studies in which the participant's vehicle is the only one on the road.

Nevertheless, it is good practice to report the number of collisions in a driving simulator study, especially if it is reasonable to expect that collisions could happen (e.g. because there is ambient traffic). The number of collisions helps us to draw conclusions about the experimental conditions, as well as about the underlying tasks. For example, a small number of collisions might indicate that, while the tasks we are comparing might require different levels of driver attention, all of them are reasonable to complete while driving. On the other hand, a high number of collisions might simply indicate that the experimental environment does not match real-life driving well, and that the results should be interpreted with this in mind.

### Discrete lateral-control-related measures

It is reasonable to assume that if a driver is struggling to keep their car within the lane markings, there is an increased chance of a collision. This is the argument for using various discrete lateral control-related errors as a driving performance measures. For example, Iqbal *et al.* (2011) counted instances when the simulated vehicle crossed a lane marking on either side of the road in order to assess driving performance under different experimental conditions. Kass *et al.* (2007) distinguished between crossing the center lane marking, and the road side marking. Such a distinction is useful if the drivers can perceive a difference in the risk associated with the two types of lane-departures; for example, crossing the center lane marking might result in a collision, but crossing the road side marking might have no perceptible negative consequences in a simulator.

### Discrete reaction-time measures

Wickens' model of multiple resources argues that there are separate channels for ambient (peripheral) and focal vision. Horrey and Wickens found support for this aspect of the model in their exploration of in-vehicle devices (Horrey and Wickens, 2004). Their results show that drivers can maintain lane position while interacting with in-vehicle devices, because lane position maintenance relies on ambient vision, while the interaction relies on focal vision. However, when drivers are faced with two tasks that require focal vision, such as hazard monitoring and interactions with a device, they have less success. Further, in a meta-analysis of research on cell phone use while driving (Horrey and Wickens, 2006), Horrey and Wickens found that measures related to focal vision, such as the response time to a road event, are the ones that are primarily affected by cell phone use. In contrast, measures related to ambient vision, such as lane tracking, were affected less by cell phone use. This implies that discrete reaction-time measures, such as reacting to a braking lead vehicle, might be a better predictor of how safe an in-vehicle interaction is than measures related to lateral lane position. In their simulator-based study Chisholm *et al.* collected data on how quickly participants applied the brakes when a lead vehicle started braking (Chisholm *et al.*, 2008); they found that participants' reaction time increased with the complexity of the secondary task.

Wu and colleagues strove to go beyond simply measuring reaction time, and worked on a modeling of pedal applications that would explain different reaction times. They conducted a driving simulator-based study, in which participants responded to traffic signal changes (Wu *et al.*, 2015). The authors identified three classes of pedal application that resulted in correct application, and one class, pedal errors, that resulted in incorrect application. They found that drivers under 21 years of age were more likely to quickly put their foot on the appropriate pedal (accelerator or brake), than older drivers (ages 26 to 83). They also found that pedal applications were more likely to be slowed down by hesitation, or to be incorrect, when the signal appeared closer, indicating that driving context can have an impact on pedal application.

### Variability of lateral lane position

Collisions happen infrequently even in simulated driving. Similarly, in many experiments there are few lateral-control-related events to count, or reaction-time events to evaluate. However, even if such events are infrequent, we can continuously track the variability of lateral lane position of the vehicle. If the driver is not paying sufficient attention to the driving task, or if the totality of the driving task and some secondary task is very challenging, lane position variability might increase compared to those instances when the driver is fully focused on the primary task of driving. Importantly, as Allen *et al.* point out, increased standard deviation of lane position can increase the probability of lane departure, which can presumably result in an increased probability of collisions (Allen *et al.*, 1996).

In a driving simulator-based study Medenica and Kun showed that lane position variance is significantly higher when the driver operates a police radio manually, than when they operate it using a speech interface (Medenica and Kun, 2007). This makes sense intuitively: the manual interaction required the driver to look away from the road and onto the radio, and it required them to take their hand off the steering wheel. The combined result was increased lane position variability. In another simulator-based study Kun and colleagues found that lane position variance increases when the recognition rate of a speech interface decreases (Kun *et al.*, 2007): this might indicate that low recognition rate was distracting to the drivers and this affected their driving performance negatively. Variability of lane position has been used in a host of studies successfully identifying the effects of engagement in a secondary task on driving performance (Engström *et al.*, 2005; Horrey *et al.*, 2006; Kun *et al.*, 2007; Kun *et al.*, 2013b; Maciej and Vollrath, 2009; Salvucci *et al.*, 2007; Tsimhoni *et al.*, 2004), although others found counterintuitive results, where greater engagement in a secondary task resulted in reduced lane position variability (e.g. Angell *et al.*, 2006; Becic *et al.*, 2010; Peng *et al.*, 2013).

Of course, variability of lane position depends a great deal on the driving context, including road geometry. For example, lane position variability will be larger on a curvy road, where there is a constant need for steering, than on a straight road, where less steering is needed. Tsimhoni and Green compared driving performance on three curvy roads, each with a different curve radius (582 m, 291 m, and 194 m) (Tsimhoni and Green, 2001). They found that the standard deviation of lane position was 75% larger in the 194 m radius curves than on straight roads.

Note that, on straight road segments, some simulated vehicles will remain in their lane with hardly any steering required from the driver. In these cases, drivers who look away from the road, and/or manipulate in-vehicle devices, might appear to have excellent control of their vehicles. In order to make driving on straight segments more challenging, researchers sometimes include wind disturbance – for example Horrey *et al.* added wind turbulence (Horrey *et al.*, 2006), while van der Meulen *et al.* added a lateral wind disturbance that periodically changed direction (van der Meulen *et al.*, 2016).

If we wish to assess the impact of an in-vehicle device on driving under different reasonable circumstances, then the variability of lane position will be affected by more than just road curvature, and wind disturbance. For example, Kun and colleagues conducted an experiment in which one group of participants drove a simulated vehicle in a city environment while interacting with an in-vehicle device, while another group drove on a three-lane highway (Kun *et al.*, 2014). Both environments presented straight roads, but there were multiple differences between them, such as the number and width of lanes (one 3.2-meter-wide lane of traffic in each direction in the city vs. three 3.6 meter lanes on the highway), travel speed (40 mph city vs. 55 mph highway), ambient traffic direction (oncoming and following vs. travelling in the same direction), and the presence of parked vehicles on the side of the road (yes in the city vs. no on the highway). Kun *et al.* found that lane position variability was greater on the highway than in the city, presumably because drivers were not as concerned with lateral threats on the highway, and thus they did not try as hard to reduce lane position variability. Horrey and Wickens found that lane position variability increased from an urban environment, to straight highway roads, to curvy highway roads (Horrey and Wickens, 2004).

Variability of lane position can be affected by other factors as well. For example, participants might drive close to the center of the lane for much of a road segment, but move the vehicle to one side in preparation for a turn at the end of that road segment. This movement in preparation for the turn will increase the lane position variability for the entire segment, but it does not indicate poor driving performance. Similarly, participants might choose different lateral positions for their vehicles depending on lane markings: for example, on road segments without markings they might move closer to the outer edge of the road, and on segments with lane markings they might move closer to the road center. These movements do not indicate poor driving performance, but they can contribute to an increased value of calculated variability of lane position. And of course, if we introduce unexpected events, such as a pedestrian stepping out between parked vehicles (e.g. Medenica and Kun, 2007), our participants might swerve to avoid a collision. The swerving can greatly increase lane position variability, but obviously does not indicate poor driving.

#### Variability of steering wheel angle

Drivers maintain the vehicle's lane position by manipulating the steering wheel. However, while lane position variability might indicate how well a driver is able to control the vehicle, the variability of steering wheel angle might indicate the effort that is needed to maintain good lane position performance. For example, on a road with both left- and right curves, steering wheel angle variability will be high because the driver has to turn the wheel one way and then the other in order to maintain satisfactory lane position.

Steering wheel angle is readily available on real vehicles, and not just simulated ones. For example, in an on-road study Solovey and colleagues recorded steering wheel positions from the controller area network (CAN) bus of the vehicle, and used this data in different workload classification algorithms (Solovey *et al.*, 2014).

#### Evaluating performance at higher levels of Michon's hierarchy

In the preceding paragraphs, we discussed measures that are related to the lowest level of Michon's hierarchy – the control level. Relatively little work has been done on evaluating performance at higher levels of this hierarchy. At the maneuvering level Iqbal *et al.* (2011) report on turning errors in their study on mediating phone conversations while driving: they found that their mediation approach reduced the instances where drivers made a turning error, compared to the case without mediation. Kim and Dey also report on turning errors in an exploration of an augmented reality (AR) navigation aid: they found that their AR navigation aid reduces the incidence of turning errors, and especially so for older drivers (Kim and Dey, 2009). Bolton and colleagues similarly explored turning errors with an AR navigation aid, and found that drivers made fewer turning errors when they saw landmarks enclosed in a box, than in the case when they saw conventional distance-to-turn information (Bolton *et al.*, 2015).

### 2.1.2 Eye movement measures of driving

Driving is a visual-manual task, and eye movement measures provide information about the driver's visual behavior during this task. As we discuss eye movement measures we rely on definitions found in the book by Holmquist and colleagues (Holmqvist *et al.*, 2011). Thus, we define areas of interest (AOIs) as "regions in the stimulus that [we] are interested gathering data about," such as the road, or an in-vehicle device. Also, a glance is "one visit to an AOI, from entry to exit."

#### Percent dwell time (PDT)

Percent dwell time is the relative amount of time spent looking at an area of interest. It is a common measure to assess how much visual attention the driver is paying to driving, particularly the road ahead, and to other in-vehicle tasks. The higher the visual attention to the road ahead, the more likely it is that the driver can safely control the vehicle. A number of efforts have used PDT to the road ahead, as well as to different in-vehicle devices, to assess how distracting those devices might be to the driver, (e.g. Horrey *et al.*, 2006; Maciej and Vollrath, 2009; Medenica *et al.*, 2011; van der Meulen *et al.*, 2016; Wang *et al.*, 2010). However, as we pointed out in the discussion about discrete reaction time measures, a reduction in PDT on the road ahead will not always result in significant performance effects. Horrey and Wickens argue against using PDT, or lane keeping performance measures, in isolation as a measure of driving safety; instead, the two should be looked at in conjunction (Horrey *et al.*, 2006).

### Total glance duration, and individual glance duration and frequency

Glance duration and frequency has been explored in a number of studies, and has shown that drivers might tactically adapt to the demands of different roads, and change how they interact with an in-vehicle device. Tsimhoni *et al.* explored address entry using a keyboard while driving on straight and curvy roads (Tsimhoni *et al.*, 2004). They found that the total glance duration to complete the address entry task did not change between straight and curvy roads; however, on curvy roads drivers cast a larger number of shorter glances at the keyboard and display, while on straight roads they cast a smaller number of longer glances. Kun *et al.* found that drivers cast longer glances at an in-vehicle device on the highway than on city roads, although they did not find evidence that the number of glances changed between the two environments (Kun *et al.*, 2014). This result is in agreement with the findings of Victor *et al.*; they also found that mean glance duration away from the road was shorter when driving conditions were more difficult, but found no evidence that gaze frequency changes with the change in driving conditions (Victor *et al.*, 2005).

### Gaze dispersion measures

Victor and colleagues asked: which eye-movement measures are sensitive to changes in the driving task and to changes in a secondary in-vehicle task (Victor *et al.*, 2005)? They undertook an extensive data collection effort in which participants engaged in visual and in auditory tasks, and data was collected both in simulators and on the road. Victor *et al.* found that increased demand on the driving task, and on the secondary task have the same effect: they increase the time participants spend visually focusing on a narrow area of the road ahead, in contrast to scanning the left and right side of the road. This result can be expressed using a new measure they called percent road center. Similarly, Wang *et al.* found that the standard deviation of horizontal gaze position is a sensitive measure for assessing the level of cognitive demand of a secondary task in a vehicle (Wang *et al.*, 2014).

### Occlusion

Researchers use the occlusion technique to simulate a reduction in visual attention to the road. This technique employs a system that has two states. In one state, the participant can see the real or simulated outside world. In the other state, their vision of the world is occluded, for example by a head-worn device. The occluded state is the default. The participant can force the system to remove the occlusion, for example by pushing a button. The system then transitions to the unocclued state, and remains in that state for a period of time, after which it returns to the default, occluded state. In seminal work Senders *et al.* found that more complex roads, and/or faster driving, required drivers to spend more time looking at the road (Senders *et al.*, 1967). In a simulator experiment Tsimhoni and Green assessed the visual demand of driving in curves using the occlusion method (Tsimhoni and Green, 1999). Their participants wore occlusion glasses while driving on curvy roads of different curvature, and pressed a button to allow them to see the road for 0.5 seconds at a time. The more demanding the driving task, the more frequently participants pressed the button to be able to see the road. Both of these experiments (Senders *et al.*, 1967; Tsimhoni and Green, 1999) used occlusion time: that is the time drivers can spend without looking at the road and still drive within some safety limits. More recently Kujala *et al.* argued that occlusion time is not an adequate measure for realistic scenarios, because in such scenarios drivers can control their vehicle's speed, which in turn affects occlusion time (slower driving allows drivers to spend relatively less time looking at the road than fast driving) (Kujala *et al.*, 2016). Thus, Kujala *et al.* proposed using occlusion distance to assess the attentional demands of driving – this is the distance that the driver feels comfortable travelling without seeing the road.

### 2.1.3 Physiological measures of driving

A wide variety of physiological measures have been used to estimate the cognitive state of a human who is engaged in various types of tasks (Kramer, 1991), and this is often done from the perspective of Wickens' multiple resources theory (Wickens, 2002). Here we review three measures that are frequently used to investigate human-machine interactions in vehicles: electro-dermal activity, heart-rate-related measures, and pupil diameter.

#### Measures related to electro-dermal activity and cardio-vascular activity

Many studies combine data from electro-dermal activity (primarily skin conductance) and electro-cardiograms (which provides information such as heart rate, heart rate variability, and inter-beat interval). Thus, we will combine the discussion of such data.

In one of the best-known papers that deal with physiological sensing in the car, Healey and Picard explored the use of physiological measurements to assess the driver's stress (Healey and Picard, 2005). For 24 drivers operating a vehicle on roads in the Boston area, they collected four types of measurements: electrocardiogram (EKG); electromyogram (EMG) with electrodes placed on the shoulder; skin conductivity on the palm of the left hand and on the sole of the left foot; and chest cavity expansion, which is a measure of respiratory activity. They argue that of these four types of measurements, skin conductivity and heart rate measures are best correlated to driver stress. Engström and colleagues found that skin conductance increased, and inter-beat interval decreased, when drivers were engaged in a manual-visual task, both in a simulator and in a real vehicle (Engström *et al.*, 2005). In an on-road study Mehler and colleagues assessed the workload experienced by drivers who were also engaged in a verbal secondary task (Mehler *et al.*, 2012a). They found that skin conductance and heart rate increased with increased task difficulty. Schneegass and colleagues collected skin conductance and electrocardiogram data (as well as driving context data) in an on-road study with 10 participants – their data is publicly available, representing a resource for the research community (Schneegass *et al.*, 2013).

Note that these types of measures work best when we want to observe changes over relatively long periods of time. For example, Healey and Picard found that 100 second windows worked well in processing skin conductance and heart-rate-related signals. A related issue is that, as Mehler et al. warn, skin conductance has a somewhat long recovery period – thus, studies might need to present tasks in order of increasing workload, or allow long-enough recovery periods.

Also note that most (reliable) sensors for electro-dermal activity and heart-rate are intrusive, as they need to be attached to the subject. This mostly limits their use to the development phase of an in-vehicle interface.

### Pupil diameter

Numerous studies have shown that pupil diameter increases with an increased utilization of mental resources – Beatty provides a thorough, although dated, review of many such studies (Beatty, 1982). This effect can also be used effectively to assess workload in driving simulator studies where the driver is engaged in spoken secondary tasks (Heeman *et al.*, 2013; Kun *et al.*, 2013a; Palinko *et al.*, 2010). A strength of this method is that it is capable of tracking both longer-term changes (that occur over several minutes), and rapid changes that occur on the order of a second or less.

However, studies that rely on pupil diameter must carefully account for changes due to the pupillary light reflex (Kun *et al.*, 2012; Palinko and Kun, 2012; Pfleging *et al.*, 2016a), as well as other effects such as emotional arousal (Wang *et al.*, 2013). This is especially important because changes in pupil diameter due to the pupillary light reflex can easily be an order of magnitude larger than changes due to variations in the use of mental resources. In part because of the pupillary light reflex, but also due to a number of other issues, pupil diameter measurements are noisy. Thus, researchers commonly present stimuli to participants repeatedly, and average the pupillary response.

### 2.1.4 Subjective measures of driving

Sinclair defines subjective measures as the results of methods that "use the people involved in the system that you wish to study as a measuring instrument" (Sinclair, 1995). For our purposes, the system is a vehicle, or more specifically some user interface related to the vehicle. We use subjective measures to assess how difficult some non-driving task is, and how much it might reduce the ability of the driver to control their vehicle.

Probably the most common subjective measure used to assess driver interactions with in-vehicle devices is the NASA Task Load Index (NASA-TLX) test (Hart and Staveland, 1988). NASA-TLX provides a quantitative estimate of the subjective experience of workload for participants in an experiment. NASA-TLX can in fact provide a single numerical value to assess the subjectively experienced workload of a given task. Pauzié introduced the Driving Activity Load Index (DALI), which is a modified version of the NASA-TLX, specifically targeting the driving domain (Pauzié, 2008).

While measures such as NASA-TLX are relatively simple to administer, researchers often also include even simpler measures. One common tool when comparing interactions with two (or more) different devices, is a questionnaire that instructs participants to rank-order the interactions according to some criterion, such as level of distraction from driving, or their willingness to engage in the interaction (e.g. (Medenica *et al.*, 2011)). Such simple approaches can be useful in testing a research hypothesis – for example, we might hypothesize that drivers are more willing to interact with one particular in-vehicle device, or that another device might be perceived as more distracting, and the rank-ordering will provide an evaluation of such a hypothesis.

Another tool is a questionnaire that instructs participants to indicate their level of agreement with one or more statements that address a hypothesis in an experiment. For example, we might ask participants to indicate their level of agreement with the statement "Interactions with the device distracted me from the driving task." Participants indicate their level of agreement on a multi-point scale – a 5-point scale is often used, where possible responses are "highly agree," "agree," "neutral," "disagree," and "highly disagree." Such questionnaires are called Likert-type questions. Note that this tool is often described as a Likert scale. However, as Clason and Dormody point out, a Likert scale is a set of questions, where responses are coded numerically and combined into a composite score (Clason and Dormody, 1994). The composite score is treated as an interval measure (Boone Jr and Boone, 2012), as defined in Stevens' classification of scales of measurement (Stevens, 1946). In contrast, Likert-type questions are treated as ordinal data, since the differences between ratings do not translate into identical intervals, and statistics such as the average are not good representations of participant responses (for example, the average of "highly agree" and "highly disagree" should not be treated as "neutral"). The majority of publications exploring interactions with in-vehicle devices use Likert-type questions (e.g. (Medenica *et al.*, 2011)) and not Likert scales.

As we use subjective measures in which we ask participants to express their opinions, we must be careful to avoid, or at least discuss the possibility of, participant response bias. This bias was clearly demonstrated in the work Dell and colleagues (Dell *et al.*, 2012). The authors asked participants to rank-order two technological artifacts. The artifacts were identical, but the participants were told that the interviewer developed one, but not the other artifact. The authors found that participants were about 2.5 times more likely to prefer the artifact that they believed was developed by the interviewer.

### 2.1.5 Performance on a secondary task

Drivers routinely engage in secondary tasks, such as changing radio channels, operating hands-free phones, and interacting with navigation aids. Performance on a secondary task can provide evidence about the status of the driver's mental resources: in many cases, as these resources are depleted, secondary task performance will worsen.

The secondary task is often a probe task, which is designed specifically to help us assess the driver's mental state. An ISO (International Organization for Standardization) standard probe task is the Detection Response Task (DRT) (ISO, 2016); the driver has to react to visual or tactile stimuli presented at random intervals, and equipment tracks the reaction times and the number of missed stimuli. Slow reaction times, and/or many missed stimuli are an indication of depleted cognitive resources.

## 2.2 Data sources to assess manual driving

In 2013 the US Federal Highway Administration (FHWA) organized a workshop to explore the use of different datasets in driving research (Romo *et al.*, 2014). In exploring manual driving, researchers conduct experiments in different settings, and collect different types of data. These include survey data, as well as data from simulators, test tracks, and from road studies. At the FHWA workshop Chrysler pointed out (Romo *et al.*, 2014) that we can order these types of data based on the level of control over experimental variables – surveys provide the highest level of control, followed by simulators, test track experiments, and finally on-road studies. High level of control is desirable because it provides high internal validity: control gives us confidence that our results are due to differences in treatments and not some other factor that we failed to account for. However, the high level of control comes at a cost, because it can reduce external validity – after all, some of the controls we impose make the in-vehicle tasks less realistic, and thus the conclusions of our study might not predict what will happen in real driving.

Burnett makes a similar argument to that of Chrysler; he also discusses the relationship between the experimental setting and the types of tasks that participants engage in, as well as the evaluation methods that are employed with a given experimental setting (Burnett, 2009). For example, he points out that experiments often include both a driving task and some secondary task. However, in on-road studies, secondary task engagement depends on the motivation of the driver, while in simulator-based experiments, it is to a large extent manipulated by the experimenter.

### 2.2.1 Simulators

Much of the work in exploring in-vehicle human-machine interaction has used simulated environments (e.g. (Allen *et al.*, 1996; Becic *et*

**Figure 2.1:** Driving simulators: University of New Hampshire (top left), Texas Transportation Institute (top right), University of Washington (bottom left, image by Linda Boyle), Liberty Mutual Research Institute for Safety (bottom right).

*al.*, 2010; Chisholm *et al.*, 2008; Engström *et al.*, 2005; Heeman *et al.*, 2013; Horrey and Wickens, 2004; Horrey *et al.*, 2006; Iqbal *et al.*, 2011; Kim and Dey, 2009; Kun *et al.*, 2007; Kun *et al.*, 2014; Kun *et al.*, 2013b; Medenica and Kun, 2007; Medenica *et al.*, 2011; Nass *et al.*, 2005; Palinko *et al.*, 2010; Salvucci *et al.*, 2007; Tsimhoni and Green, 1999; Tsimhoni *et al.*, 2004; Victor *et al.*, 2005)), and the use of driving simulators has dramatically increased over the years (Boyle and Lee, 2010). Several representative simulator setups are shown in Figure 2.1.

Driving simulators have two key characteristics which make them advantageous for driving studies. First, they are safe environments for experiments, regardless of road geometry, traffic situation, or distractions from brought-in devices. Second, in driving simulator studies we expose multiple participants to identical conditions – this is in contrast to naturalistic studies, where we observe driving on real roads, and every event can be unique (Boyle and Lee, 2010). Additionally, the cost of high-fidelity simulation is dropping, making these tools affordable to a wider range of researchers than before (Boyle and Lee, 2010; Burnett, 2009).

Still, different simulators provide different levels of driving realism, and might be appropriate for different experiments. In fact, sometimes these environments can be rather simple in order to focus on a particular aspect of the manual-visual task of driving, such as tracking. For example, in their seminal work on the effects of cell phone conversation on driving performance, Strayer and Johnston employed a pursuit tracking task; participants used a joystick to move the cursor on a computer screen such that it is aligned with a moving target (Strayer and Johnston, 2001). The experiment tested the hypothesis that cell phone conversations with a remote conversant divert the attention of the driver from the manual-visual task of driving to the verbal communication task. In spite of the simplicity of the experimental task, the article successfully provided support for the authors' hypothesis.

In general, we need to be careful when drawing conclusions based on results from driving simulator studies. After all, simulators and real driving differ in many aspects, perhaps most importantly in the level of perceived and actual risk to the wellbeing of the participants and people around them. However, driving simulator studies can be very useful in predicting on-road behavior. For example, Lew *et al.* (Lew *et al.*, 2005) found that simulator experiments are predictive of future driving performance of patients with brain injuries. Wang and colleagues conducted a study in which participants interacted with an in-vehicle information system while operating either a simulated or a real vehicle (Wang *et al.*, 2010). They found that visual attention and task performance measures were very similar in the two environments, while this was not the case for driving performance measures, such as the standard deviation of lane position. Reed and Green instructed participants to complete a phone task under two conditions: in an instrumented vehicle on the road, and in a simulated vehicle (Reed and Green, 1999). On the road they observed decrements in performance due to the engagement in the secondary phone task; they found that a driving simulator can also capture these decrements, even though the absolute values of the different performance measures might be different on the road and in the simulator.

### 2.2.2 Test tracks

Test tracks are environments where we can experiment with real cars while we retain control over variables such as traffic and road geometry. The work of Lee and colleagues provides an example for the utility of test tracks (Lee *et al.*, 2016). The authors explored the negative effects of drowsiness on driving performance. The experiment assessed the effects of night-shift work on measures of drowsiness and driving performance. In this case a simulator study could have easily provided safety: drowsy drivers cannot hurt themselves, or others, in simulated crashes. However, using a simulator to explore drowsy driving would reduce the external validity of the results: after all, it seems reasonable to assume that drivers would be less concerned with their safety in a simulator, and would thus respond to drowsiness differently. Conducting the experiment on a test track is a reasonable compromise: the driving is real, and should thus result in realistic driver behaviors, yet there are no other drivers to endanger, and the experimenter is charged with keeping the participant safe. Similarly, Noble and colleagues conducted a test track study to explore in-vehicle displays to guide drivers through stop-sign-controlled intersections (Noble *et al.*, 2016), while Tidwell *et al.* conducted a test track study to explore the effectiveness of collision warnings for drivers of heavy vehicles (Tidwell *et al.*, 2015). In both studies, the realism of driving a vehicle was an important factor in assessing how drivers will react to in-vehicle audio-visual instructions or warnings. This realism meant that participants experienced the actual dynamics of a vehicle (and not just a simulation), and that they perceived the possibility of a crash.

Figure 2.2 shows the test track at the Texas Transportation Institute, which was created on the site of an old airfield. The track has long straight sections, and allows for testing vehicles which travel at highway speeds.

### 2.2.3 Road studies

On-road experiments offer realism at the cost of giving up control over many aspects of driving context. Furthermore, researchers must be extremely careful not to expose participants in on-road experiments to


**Figure 2.2:** The Texas Transportation Institute test track is located on an old airfield. This picture shows the test track when it was set up for a study exploring how sponsored changeable message signs might affect driver distraction, and road visibility.

unsafe situations, which limits their ability to test different scenarios. On-road studies include naturalistic studies where one or many vehicles are equipped with instruments and driver activity and context are tracked (Belyusar *et al.*, 2016; Dingus *et al.*, 2016; Dingus *et al.*, 2015; Fröhlich *et al.*, 2011; Guo *et al.*, 2016; Hanowski *et al.*, 2005; Miller and Kun, 2013; Neale *et al.*, 2005). In recent work Belyusar and colleagues explored drivers' gazes on roadside billboards (Belyusar *et al.*, 2016). Their work addresses a question that would be difficult, if not impossible, to adequately address in a driving simulator study. One reason is that in a driving simulator drivers might be more inclined to look away from the road since there would be no threat of physical harm to them or others. A more mundane concern is that driving simulators have relatively low-resolution displays, which would not match the visual detail of a real roadside billboard; thus drivers would not be able to make out details of the billboard from the same distance as they would in a road study. Wilfinger and colleagues designed a mobile phone-based tool that allows collecting data during road studies, including information from the vehicle's OBD-II port, such as acceleration and RPM readings, as well as environmental data from the phone, such as light and sound levels (Wilfinger *et al.*, 2013).

We can also consider epidemiological studies to be on-road studies – these studies use real-world data to relate some aspect of the driving context (such as the age, gender, or occupation of the driver, the equipment of the vehicle, or road geometry), and outcomes such as crashes or injuries. For example, exploring data from the Quebec province of Canada, a study revealed that between 2000 and 2008 there were 849 collisions involving an emergency vehicle in that province, and that 40% of these collisions were due to distraction or inattention (Pignatelli *et al.*, 2014).

## 2.3 Data sources to assess automated driving

Interactions related to automated vehicles are often explored in simulators (Koo *et al.*, 2015; Merat *et al.*, 2014; Mok *et al.*, 2015; Mok *et al.*, 2017; van der Meulen *et al.*, 2016), however a number of studies have used on-road vehicles. Seppelt and colleagues explore in-vehicle

**Figure 2.3:** The RADDS platform at Stanford was used to explore automated driving — the vehicle's steering wheel is on the right, and the driver is hidden from the participant by a partition. This setup encourages participants to imagine, or even believe, that the car is moving under the control of a machine agent.

interaction challenges in a naturalistic study of Tesla drivers (Seppelt *et al.*, 2017). Llaneras *et al.* used test-bed vehicles on a closed track to explore driver behaviors when using both ACC and lane-centering (Llaneras *et al.*, 2013). Biondi and colleagues conducted an on-road study in which 10 participants drove a vehicle that was equipped with both ACC and a lane keeping assistant system (Biondi *et al.*, 2017).

Researchers who do not have access to real vehicles with automation features turn to other options. Thus, the RRADS platform (Figure 2.3) (Baltodano *et al.*, 2015b; Baltodano *et al.*, 2015a), as well as the newer Marionette platform (Wang *et al.*, 2017), use a Wizard-of-Oz setup, in which the human driver is hidden from the participant by a partition. In a simpler setup, Krome *et al.* experimented with passengers who were chauffeured by a researcher (Figure 2.4) (Krome *et al.*, 2016). Their argument is that we need to understand the commuting experience of a passenger, and this can be done without pretending that they are riding in an automated vehicle.

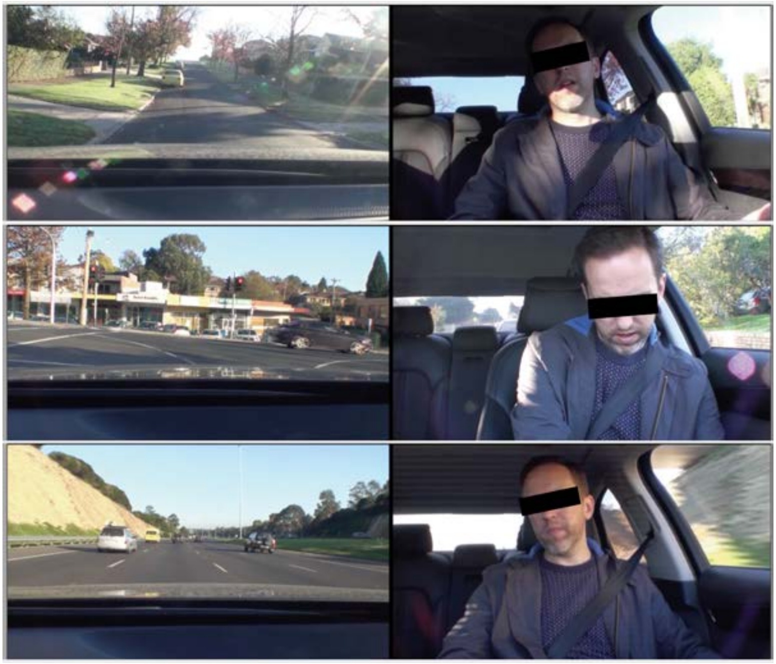

**Figure 2.4:** Krome conducted an experiment with passengers driven to work and back to learn about passenger behaviors that might be relevant for future automated vehicles. Images by Sven Krome.

Another innovative approach to finding data sources is that of Brown and Laurier (Brown and Laurier, 2017) – in their research exploring social interactions on the road, the authors used videos posted online about people's experiences with automated vehicles. While such videos provide only a limited insight into real driving, they can provide valuable lessons – for example, the authors found evidence that the actions of automated vehicles can lead to confusion for human drivers in surrounding vehicles.

## 2.4 Participant populations

Even a cursory review of papers in various human-machine interaction-related publications reveals that too often the majority of participants in studies are young, male college students (Barkhuus and Rode, 2007).

Furthermore, given that most papers originate in western countries, the participant population is further narrowed. However, driving is affected by many participant characteristics, such as gender, age, cognitive impairment, and culture. For example, D'Ambrosio and colleagues explored perceived self-regulation for older drivers, and found that older women report to be more likely than older men to avoid driving at night, or on highways, or in heavy traffic (D'Ambrosio *et al.*, 2008). Reimer *et al.* report that in a driving simulator study individuals diagnosed with high functioning autism shifted their visual attention away from the road when they had to deal with a secondary task in addition to driving (Reimer *et al.*, 2013). Wang *et al.* report on differences between Swedish and Chinese drivers in the type of auditory warnings they might find useful; the authors relate their results to the driving cultures of the two countries (Wang *et al.*, 2016). And Jeon and colleagues report that drivers in Austria, Korea, and the USA differ in their concerns about vehicle-to-vehicle (V2V) communications, with Korean and US drivers most concerned about safety, while Austrian drivers most concerned about privacy and data security (Jeon *et al.*, 2012). Thus, careful examination of in-vehicle human-machine interaction has to take into account different participant populations.

## 2.5 Standardization efforts and guides

Standardization of methods can help members of a research community to replicate and compare results between studies. In his 2012 AutomotiveUI conference keynote address, Paul Green made a strong argument for the need for a standards document to address the definitions of various measures used by this research community (Green, 2012). This document is now available as SAE J2944 Recommended Practice, Operational Definitions of Driving Performance Measures and Statistics (SAE, 2015). Green's keynote also lists a number of other relevant ISO and US Department of Transportation (US DOT) documents (Green, 2012).

# 3

# Focus Areas in Research on Human-Machine Interaction for Manual Driving

Over the last several decades manual driving research has primarily focused on three general areas. The first one is safety – extensive work has been done to understand the driving task, how this task interacts with other in-vehicle tasks, and how driving can be made safer. The second area is that of developing new or improved user interfaces for in-vehicle devices, such as speech-based or gesture-based interfaces. Finally, the third area is that of in-vehicle applications, which means bringing new or improved functionality into the vehicle, for example in the form of new types of entertainment, or new tools for completing a task that is related to driving. And since safety is always of the highest priority in driving, ultimately new interfaces and applications must also be explored through the lens of safety. In addition to safety, new user interfaces, and in-vehicle applications, in this section we will also discuss increasingly important work on user experience (UX), and passengers.

## 3.1 HMI and driving safety

The work related to driving safety has three major thrusts. One is to improve our understanding of the driving task, and how humans can successfully perform it. The second is to understand the effects of secondary in-vehicle tasks on driving safety. Finally, the third one is to improve driving safety for specific users, or for specific applications.

### 3.1.1 Understanding manual driving

How do people complete the manual-visual task of driving? What are the components of this task, and how are they supported by driver capabilities and resources? How does attention influence driving, and which distractions can be detrimental to the driving task? These are some of the questions that researchers have asked over the years as they try to understand driving. Many of the examples discussed in section 2 address these questions.

### 3.1.2 Understanding the effects of secondary tasks

Interaction with in-vehicle devices is a significant safety concern, especially with the proliferation of brought-in devices. In one of the first studies to explore in-vehicle interactions with a brought-in music player, Salvucci and colleagues found that interactions with the device, such as selecting media, affected both lateral and longitudinal measures of driving performance (Salvucci *et al.*, 2007). Kun and colleagues explored how interactions with a music player affect visual behavior and lane keeping in different driving environments (Kun *et al.*, 2014). They found that drivers made shorter glances at the music player in a city environment, than on a highway, perhaps because they felt that long glances away from the road are more risky in the city than on the highway.

### 3.1.3 Improving safety

Researchers and practitioners who are engaged in exploring and developing in-vehicle user interfaces have focused on improving driving safety in two ways. First, a great deal of effort has been put into improving safety for different applications, interaction modalities, and users. Brumby and colleagues found that speech interaction can lead to safer driving than manual-visual interaction (Figure 3.1), but that drivers who are in a hurry to complete a task might choose the faster but less safe manual-visual interaction (Brumby *et al.*, 2011). Janssen *et al.* experimented with using audio cues to inform a remote conversant about how busy

**Figure 3.1:** Manual-visual interaction with a mobile phone in the experiment by Brumby and colleagues (Brumby *et al.*, 2011) (photo by Duncan Brumby).

the driver is at a given time, with the hope that this understanding will bring about changes in dialogue behavior and ultimately safer driving; their results indicate that in many cases this approach can be expected to have modest positive effects (Janssen *et al.*, 2014).

The availability of new technologies has encouraged researchers and developers to explore creating new approaches to improving safety. For example, Steinberger and colleagues proposed using in-vehicle games (gamification) to improve safety (Steinberger *et al.*, 2015). One of their concepts is shown in Figure 3.2 – here the proposed system would use augmented reality to display an item that the driver's vehicle is transporting. The driver needs to leave enough room for the virtual item, such that it does not hit a lead vehicle. The safety benefit is an increased following distance.

Furthermore, standardization efforts and guides attempt to provide designers with design practices that lead to safe in-vehicle interactions. For example, in the realm of assessing distractions, the ISO standardized the Detection Response Task (DRT) (ISO, 2016), as well as the Simulated Lane Change Task (LCT) (ISO, 2010), both of which are widely used by researchers. The US National Highway Traffic Safety Administration (NHTSA) has issued guidelines for evaluating the distractions caused by built-in electronic devices in vehicles (National

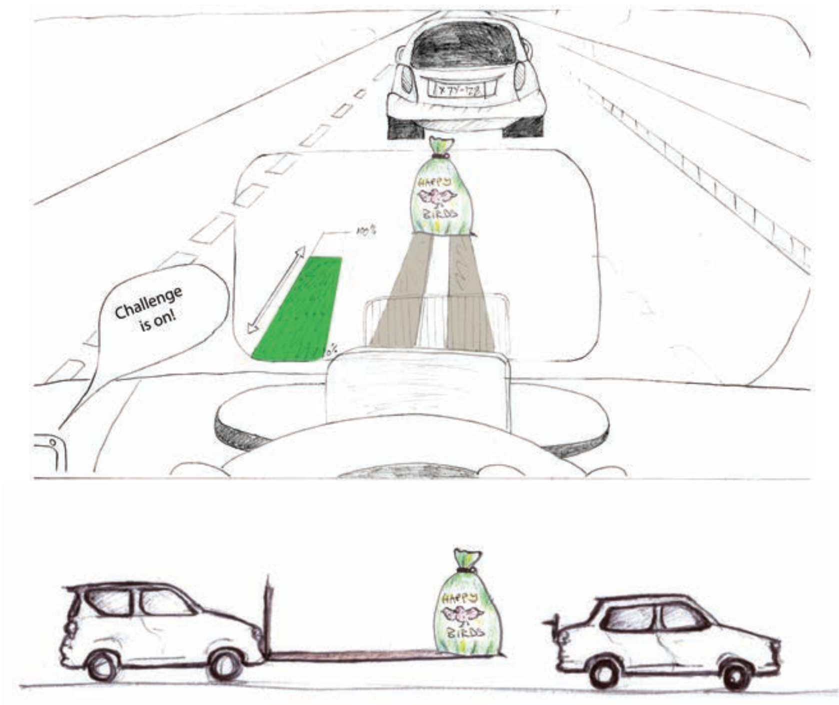


**Figure 3.2:** Gamification for safety (image by Ronald Schroeter and Verena Lindner): the system displays a virtual item in front of the car, and this item needs to fit in the space between the driver's car and the one they are following. To fit the item the driver has to leave adequate room between the vehicles, which is the intended safety benefit of the game.

Highway Traffic Safety Administration, 2012), as well brought-in devices (National Highway Traffic Safety Administration, 2016c). NHTSA also issued a human factors guidance document (Campbell *et al.*, 2016), which covers a wide range of topics, from visual interfaces, to haptic interfaces, to auditory interfaces, to system integration issues. This document also includes valuable references to a host of relevant standards.

## 3.2 In-vehicle interaction techniques

As technological tools have become available, researchers and developers have been eager to put them to test in providing novel interaction modalities in the vehicle.


**Figure 3.3:** Project54 created a unique voice actuated computer system which integrated the control of in-cruiser devices such as lights and siren, radar, and video (Kun *et al.*, 2004; Kun *et al.*, 2003). The system also allowed performing voice driven data queries.

### 3.2.1 Speech interaction

In-vehicle speech interaction has received a great deal of attention, because of its promise to allow the driver to focus their visual resources on the driving task. The Project54 system (Figure 3.3) integrated devices in first responder vehicles into a single system that could be operated using a speech interface (Kun *et al.*, 2004; Kun *et al.*, 2003). The system provided a user-initiative dialogue system – the user had to initiate actions by pressing and holding a push-to-talk button, issuing a voice command from a pre-coded grammar, and finally releasing the button. Others also explored speech interfaces for first responders. For example, in a driving simulator-based study by Mitsopoulos-Rubins *et al.* police officers rated speech interfaces as easier to use than manual-visual interfaces (Mitsopoulos-Rubens *et al.*, 2013).

Speech interfaces are gaining prominence in the consumer world – in 2018 many new vehicles provide a voice interface to various functions, and smartphones also respond to voice commands in vehicles. Most systems still implement user-initiative dialogues – the system rarely, if ever, makes an utterance without being prompted. However, modern systems use natural speech interaction and users are not required to memorize a set of commands (Large *et al.*, 2017). Lo and Green review some recently developed in-vehicle speech systems, as well as relevant standards, and suggest tools for design and testing (Lo and Green, 2013).

Speech is not only used in dialogue-based systems. Jeon and colleagues explored the use of enhanced auditory menu cues (Jeon *et al.*, 2015): “spearcons” which are sped-up speech cues, and “spindex” which are speech-based index cues (in this case the pronunciation of the first letter of an item). In a driving simulator study, participants were given a secondary song-selection task. The list of songs was presented either only visually, or both visually and with auditory cues. The use of auditory cues improved both the driving performance and the selection speed, compared to using only the visual presentation.

Of course, in-vehicle speech interaction must be designed with care – the work of Kun and colleagues showed that low speech recognition accuracy could detract from driving performance (Kun *et al.*, 2007). More recently, Sokol *et al.* compared user perceptions of noise-robust and noise-sensitive in-vehicle speech systems (Sokol *et al.*, 2017). The authors found indications that a noise-robust speech recognizer would lead to higher satisfaction, and perceived usefulness, even if users had a clear explanation for the degradation of performance for the noise-sensitive system. And while voice interfaces might help drivers keep their eyes on the road, Mehler and colleagues point out that voice interfaces are actually multi-modal interfaces; they require drivers to look away from the road, push buttons, and think about questions and responses (Mehler *et al.*, 2016).

### 3.2.2 Gesture input

Another technology that has received considerable attention for in-vehicle user interfaces is gesture-based input. Gestures can be mid-air gestures, performed without contact with an object, as well as gestures in contact with an object, such as with a touch screen. We expect that mid-air gestures are easier to perform than manipulations of buttons, levers, or other physical objects, in part because gestures do not require the driver to use vision to locate the object to be manipulated (Ohn-Bar *et al.*, 2012). Ohn-Bar *et al.* demonstrated the feasibility of a vision-based system to detect hand gestures by the driver or front-seat passenger with very high accuracy (Ohn-Bar *et al.*, 2012). Rümelin *et al.* conducted an on-road (Wizard-of-Oz) experiment where drivers had to point at objects outside the vehicle (such as buildings) (Rümelin *et al.*, 2013). Drivers found pointing to be a desirable interaction technique while driving.

Eren and colleagues explored the visual demands of ten gestures that could be performed as shortcuts on in-vehicle touchscreens (Eren *et al.*, 2015), such as a star, or a square. The authors used four criteria to assess the ease of using a gesture: accuracy of correctly performing the gesture, number of glances at the touchscreen, total length of time looking at the touchscreen, and the NASA-TLX score of performing a gesture. The authors recommend four gestures as a gesture set for use in vehicles. Of the ten tested gestures, these four were most accurately executed, they were rated the least difficult, and they required the least amount of visual attention.

### 3.2.3 Ambient light displays

Wickens argues that ambient and focal vision represent different mental resources, and that they support time-sharing (Wickens, 2002). Ambient light displays are an attempt to take advantage of these separate resources, and provide information to the driver in visual form. They engage the driver's ambient vision, allowing the driver's focal vision to attend to the outside world, as well as to gauges, buttons, and other visual targets in the vehicle.

Researchers at the University of Oldenburg have explored a number of potential uses of ambient light displays in vehicles (Figure 3.4). Matviienko *et al.* found that ambient light shows promise in navigation applications (Matviienko *et al.*, 2016). Löcken *et al.* experimented with using ambient light to help a driver decide if and when to change lanes – the ambient light provided information about the distance to a vehicle that was approaching in another lane (Löcken *et al.*, 2015). And in an

**Figure 3.4:** Ambient light display (purple light on the left) in the driving simulator at the University of Oldenburg (image by Maleah Maxie).

experiment with a real vehicle, Hipp and colleagues found that ambient light can be useful in supporting the driver as they reverse into a parking spot (Hipp *et al.*, 2016).

### 3.2.4 Augmented reality

Several groups have experimented with augmented reality using different technology approaches. One approach used in driving simulator-based studies is to present augmented-reality content directly on the simulator displays, by manipulating the output of the simulation (Kim and Dey, 2009; Medenica *et al.*, 2011). Other approaches include using a head-up display (Bolton *et al.*, 2015), using a head-down display (Fröhlich *et al.*, 2011), and using augmented reality glasses such as Microsoft's HoloLens (Kun *et al.*, 2017) – two examples are shown in Figure 3.5. Augmented reality is similar to ambient lights in that it might be able to display information in the periphery of the driver's visual field. This is not the case for all augmented reality devices – for example Microsoft's first-generation HoloLens has a narrow field of display (around 40° wide), thus any item it displays will be somewhat close to the driver's visual focus.

Augmented reality also holds the promise of being able to alter the way drivers see their environment, which could be used to gamify the


**Figure 3.5:** Researchers at the University of Nottingham used a head-up display (HUD) as an augmented reality display, and provided navigation instructions to drivers in a simulator. The left image shows the view through the HUD with the arrow pointing to a landmark (image by Gary Burnett). Researchers at the University of New Hampshire (UNH) used Microsoft HoloLens augmented reality glasses in a driving simulator-based experiment in which the driver communicated with a remote conversant. The right image shows a UNH researcher with HoloLens in the simulator.

driving task (Steinberger *et al.*, 2015), or provide useful information to them, such as navigation instructions (Bolton *et al.*, 2015; Fröhlich *et al.*, 2011; Medenica *et al.*, 2011).

### 3.2.5 Haptic feedback

Researchers have also explored the use of haptic devices in vehicles. For example, Asif and Boll used a haptic belt to provide navigation instructions to drivers (Asif and Boll, 2010). However, as Campbell and colleagues note, we cannot assume that vibrotactile messages will always be perceived as directional (Campbell *et al.*, 2016). Furthermore, the authors warn that different body parts have different levels of sensitivity to the displacement and frequency of vibrotactile elements, and that there are individual differences between people in their perception of vibrotactile inputs, at least in part because of differences in body composition and attire.

## 3.3 Applications

Arguably, one of the most prolific areas of research in recent years has been the exploration of in-vehicle applications. This work encompasses bringing a functionality to the vehicle, or improving on an existing one.

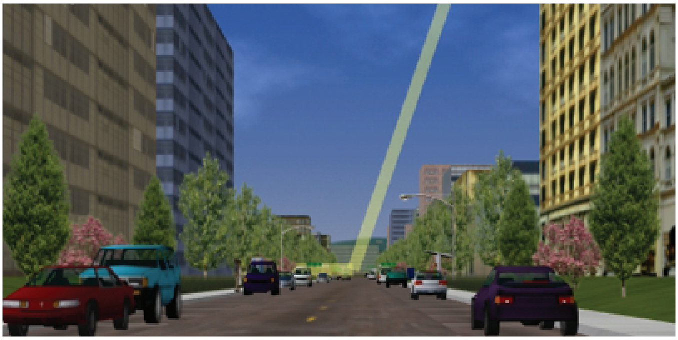

**Figure 3.6:** AR navigation simulated by drawing lines on the projection screen in a simulator (Medenica *et al.*, 2011).

The primary focus is on consumers, but work has also been done on applications for special groups, such as first responders (Kun *et al.*, 2003; Mitsopoulos-Rubens *et al.*, 2013). Here are the major application types that have been explored, with some examples:

- **Navigation.** Perhaps the most wide-spread in-vehicle application is the use of mapping software to provide navigation instructions for the driver. Brown and Laurier created video recordings of 14 drivers using GPS systems (Brown and Laurier, 2012). They documented five so-called "troubles" with the GPS systems, and argue that drivers (and passengers) must actively process the GPS instructions, and use them in combination with their own understanding of the driving context. Medenica *et al.* found that augmented reality (AR) navigation aids (Figure 3.6) can increase the time drivers spend looking at the road ahead, compared to head-down navigation aids (Medenica *et al.*, 2011). Bolton and colleagues found that using landmarks in AR navigation aids can lead to better navigational performance, as well as higher driver satisfaction, compared to using distance-to-turn instructions (Bolton *et al.*, 2015).

- **Communication.** Drivers engage in communication with remote conversants, and this can create dangerous situations (Neale *et al.*, 2005). This issue has been explored in detail, including by Charlton, who found that drivers who were engaged in voice-only communication with a remote conversant performed worse at the driving task than drivers who spoke to a passenger, or those who were not engaged in communication (Charlton, 2009). Additionally, he found that passengers often slow down the spoken dialogue when driving difficulty increases. He also found that it is possible to get similar discourse patterns by including warning tones in the conversation between a driver and a remote conversant. Kun and colleagues explored video calling, and found that in some situations drivers might decide that it is safe to look at an LCD screen that shows the video of a remote conversant (Kun and Medenica, 2012). However, in a separate experiment when drivers used augmented reality (AR) glasses, they did not look at the remote conversant (Kun *et al.*, 2017); it is possible that this is because the visual field of the AR glasses is small, and looking at the remote conversant would have required drivers to turn their head away from the road.

- **Entertainment and infotainment.** We know that drivers engage in activities such as playing games or consuming information in the vehicle. Alt and colleagues propose taking advantage of the frequent pauses in driving that are caused by red lights in cities, and allowing drivers to consume infotainment during these pauses (Alt *et al.*, 2010). To make this approach successful we need to also know how to create the small chunks of media such that drivers will want to consume them – for this problem Rosario and colleagues propose using text summarization techniques (Rosario *et al.*, 2011).
- **Information.** While consumers can successfully complete the driving task without engaging with any secondary tasks, some professionals need to engage in secondary tasks as part of completing a job. A prominent such group of professionals are first responders (Kun *et al.*, 2015). Thus, one aspect of the Project54 system discussed above was that it enabled using speech commands to query remote databases and to receive spoken feedback about the query results (Miller and Kun, 2013).

- **Eco-driving.** Driving behaviors, such as travel speed and acceleration after stops, might differ a great deal between drivers, and even between different trips for the same driver. These differences in behavior have a large impact on fuel consumption. Gonder and colleagues found that even modest behavior changes, such as a reduction in travel speed on the highway, can reduce fuel consumption by 10% (Gonder *et al.*, 2011). This can translate into significant financial savings for individuals, and societies, as well as into significant reductions in $CO_2$ emissions. Thus, a number of researchers are exploring user interaction techniques that would help drivers make the necessary behavioral changes (Meschtscherjakov *et al.*, 2009). Of course, the use of (hybrid-) electric vehicles can greatly reduce fuel consumption and $CO_2$ emissions, but drivers are often concerned about the range of such a vehicle, and a number of researchers are thus engaged in designing user interactions that address this concern (Loehmann *et al.*, 2014; Neumann and Krems, 2016).

## 3.4 User Experience (UX)

In his seminal book entitled "The Design of Everyday Things," Don Norman argues that designers must pay attention to the experience of interacting with their product (Norman, 2013). Norman is one of the first to have used the term "user experience," or simply UX. He argues that UX is critical in enabling people to successfully use a product, as well as to want to use the product again. Some aspects of UX can be found in many publications that deal with in-vehicle user interactions – for example, researchers often ask participants to state their preference with respect to several possible interaction styles (Medenica *et al.*, 2011), or to assess how likely they might be to use a type of interaction in their own vehicle (Kun and Medenica, 2012; Kun *et al.*, 2017). However, UX is usually not the primary focus of these efforts. For researchers who wish to include UX in their work, Obrist *et al.* provide a primer on how this can be done in mobile environments (Obrist *et al.*, 2010). Meschtscherjakov *et al.* provide one example of a detailed evaluation of measures of UX, combined with measures of driving safety (Meschtscherjakov *et al.*, 2015). The authors created a prototype system that uses ambient light to provide feedback to the driver about vehicle speed. In evaluating the prototype, the authors assessed the effect of the prototype on vehicle speed, and also assessed UX variables such as participant perceptions of usefulness, ease-of-use, and safety of the system.

## 3.5 Passengers

Passengers are not frequently the subjects of exploration of human-computer interaction in manually driven vehicles. However, research with passenger participants has a number of important benefits. First, it can improve the riding experience of passengers, which can make a vehicle more desirable. Second, it can help create an environment that provides for the information and entertainment needs of the passenger, without distracting the driver. Third, it can create an environment in which the passenger can effectively support the driver (Meschtscherjakov *et al.*, 2017). Finally, with the advent of automated vehicles, all of us will be passengers, at least some of the time (we will address this in the next section of this paper). Thus, what we learn about in-vehicle human-computer interaction for passengers can prove to be quite useful when we design interfaces for automated vehicles.

Wilfinger and colleagues at the Contextual Interfaces lab at the University of Salzburg focused on passengers in the rear seat in an experiment that involved 20 families (Wilfinger *et al.*, 2011). It is interesting to note that passengers in the rear seat are often children. The authors argue that in designing user interactions for the rear seat it is important to focus on experiences – understanding the experiences can guide designers to deploy desirable technological solutions, in contrast to pursuing technological solutions simply because we can.

Meschtscherjakov and colleagues recently reported on a sequence of studies from the Salzburg group that focused on passengers (Meschtscherjakov *et al.*, 2017). They report on five research activities that explore the experience of passengers in vehicles. One of these activities was the prototyping of the active corners interaction concept (Figure 3.7). Active corners allows passengers, and the driver, to ex-

**Figure 3.7:** Meschtscherjakov and colleagues explored the experiences of passengers in vehicles (Meschtscherjakov *et al.*, 2017). This image shows the active corners concept, which enables sending information from one tablet to another (image by Alexander Meschtscherjakov). The concept maps the physical location of each user to one corner of each tablet. This helps users select the recipient of the information they wish to share.

change information. The concept helps the user select the recipient of the information by mapping the physical location of the driver and passengers to the four corners of a tablet. The authors highlight the scarcity of research on this topic, and argue that improving user experience in vehicles can best be done if all occupants are taken into account, including passengers.

## 3.6 What is next?

Much of the work discussed in this section is ongoing. The most important question underlying all of this research is: how do we keep all road users safe? We do not know the complete answer to this question. At the same time, the vehicle is quickly becoming a place for work and play. This is due to the advances of technology which make it possible to work and play in mobile environments, and people's accompanying expectations of being able to work and play in any environment. However,


**Figure 3.8:** Google car on display in the Computer History Museum, San Francisco.

the available in-vehicle user interfaces often do not effectively allow drivers to work and play while keeping themselves, and other road users, safe. Thus, work continues on this front, both attempting to provide functionality to drivers safely, and attempting to reduce drivers' access to functionality when it is not safe for them to engage with it.

The most significant aspect of future work in developing in-vehicle user interfaces is the fact that vehicle automation is gaining ground, from vehicles with cruise control, to those that attempt to completely eliminate the need for a human driver, such as the Google car (Figure 3.8). This is the topic of the next section.

# 4

# Focus Areas in Human-Machine Interaction for Automated Driving

Isaac Asimov's "Caves of Steel" is a 1950s science fiction novel that describes Earth about 1,000 years from now (Asimov, 2011). In this imagined world, people dislike and fear robots. Consequently, the protagonist drives a car manually, just like we would drive a car today – there is no automation in place. While there is no telling what will happen 1,000 years from today, current trends in the automobile industry make it likely that in the coming years and decades we will enjoy rides in vehicles that take over more and more driving tasks, until they become fully autonomous (Luettel *et al.*, 2012).

There are a number of factors that make automated driving desirable (Bengler *et al.*, 2014; Koopman and Wagner, 2017; Kun *et al.*, 2016; National Highway Traffic Safety Administration, 2016b; Riener *et al.*, 2016; Shladover, 2009; Stanton and Marsden, 1996), and we will address three of them. First, automation, and ultimately complete autonomy, is expected to make driving significantly safer than it is today. One goal might be to make driving as safe as air travel: Koopman and Wagner call this the ultra-dependability safety target (Koopman and Wagner, 2017). In addition to safety, automation can help transform vehicles into places of work and play, such that drivers and passengers can re-claim the time they spend travelling (Kun *et al.*, 2016). Furthermore, automation holds out the promise of greater accessibility to transportation options for a wide range of people, from the elderly, to people with disabilities (Pierce *et al.*, 2016). In order to achieve these lofty goals, human-machine interaction with automated vehicles will have to build the trust of users, and we will also need frameworks for resolving the legal issues related to HMI for automated vehicles.

## 4.1 Automated vehicles and safety

The following subsections will explore the roles of human-machine interaction for automated vehicles in improving driving safety.

### 4.1.1 Assisting the driver: Warnings, and nudges

Vehicle automation systems use sensors to perceive the world around the vehicle, computing devices to set goals on how to proceed in this world, and actuators to accomplish the goals (Luettel *et al.*, 2012). The sensors can be onboard the vehicle, or they can be part of other vehicles or the infrastructure surrounding the vehicle (Bengler *et al.*, 2014). Utilizing these remote sensors will be possible if Vehicle-to-Vehicle (V2V) communication is standardized, for example as proposed in 2016 by NHTSA (National Highway Traffic Safety Administration, 2016a), and if at a later date Vehicle-to-Infrastructure (V2I) communication is standardized (Geller, 2015). The remote sensors can provide information about the location, speed, and direction of travel of other vehicles on the road.

Autonomous vehicles will rely on the perception-computation-actuation loop to control the vehicle without human intervention. Yet, even without fully closing this automation loop and excluding the human driver, the same sensors, and computing devices that would be used for autonomous driving, can be used to provide parking assistance, collisions warnings, and lane departure warnings to the driver. Collision warnings often take the form of auditory signals that indicate the presence of an obstacle, but they can also provide video of the area behind or in front of the vehicle (Bengler *et al.*, 2014). For collision warning, Lee and colleagues found evidence that an auditory-visual warning system can be very effective, both for distracted and non-distracted drivers (Lee *et al.*, 2002). Similarly, Tidwell *et al.* found that both auditory-only and audio-visual forward collision warnings are useful in alerting drivers of heavy vehicles (Tidwell *et al.*, 2015). Noble and colleagues also found that the combination of a visual display and an auditory alert is useful in guiding drivers through stop-sign-controlled intersections (Noble *et al.*, 2016). Note that such warnings can be realized using future V2V and/or V2I technology. In general, warnings must be designed carefully to avoid temporal conflicts between different warnings, as well as to avoid nuisance warnings – these are false-positives where the system warns the driver about a non-existent threat (Marshall *et al.*, 2007).

Going a step further toward closing the automation loop, the system can also introduce lane keeping assistance, to nudge the vehicle away from a trajectory that would lead to a lane departure. This partial automation uses sensors, computers, and actuators, but only under limited circumstances. Navarro and colleagues found such nudging can be more effective than a simple lane departure warning (Navarro *et al.*, 2007).

Technologies that fully close the automation loop, but only affect driving under extreme circumstances, include electronic stability control, and antilock brakes. These technologies commonly do not have a user interface – they operate when they are needed as "background automation" (Kyriakidis *et al.*, 2017). Another technology that fully closes the automation loop is automatic braking. Automatic braking can stop the vehicle when the system detects an imminent collision, either with an object in front of the vehicle, or one that is approaching on a collision course. Automatic braking is sometimes combined with a warning system: the driver is first warned, and if they do not react, the automation applies the brakes. Police-reported crash data indicates that forward collision warning alone, as well as in combination with automatic braking, can reduce rear-end collisions (Cicchino, 2017). Of course, automatic braking does not require a user interface – after all, such action happens because the automation determined that the driver will not react in time. Yet, an explanation of what is happening might be useful – Koo *et al.* found evidence that providing an explanation of how and why a car is reacting to an obstacle ahead could lead to better driving performance (Koo *et al.*, 2015).

### 4.1.2 Designing interfaces for systems with sustained automation

The first widely-deployed vehicular automation technology was cruise control (CC), invented in 1945 (Merat and Lee, 2012). Once engaged, CC maintains a desired vehicle speed, however the driver is responsible for slowing down to avoid crashing into obstacles, such as slow moving lead vehicles. By the late 1990s vehicles were also equipped with adaptive cruise control (ACC), which can automatically slow down the vehicle to match the speed of a slower lead vehicle (Jones, 2001). In a few vehicles on the market in 2018, ACC can match the speed limit on the road segment where the vehicle is travelling.

Both CC and ACC require drivers to set the desired speed, and ACC might additionally require drivers to set the acceptable gap between their vehicle and a lead vehicle. The gap setting might be confusing to drivers: in a study with 103 participants Wu and Boyle asked owners of ACC-equipped vehicles a series of questions, and found that around 24% of ACC owners found the gap setting confusing, while only around 17% found the speed setting to be confusing (Wu and Boyle, 2015). The study did not pinpoint the cause of the confusion; thus more work is needed in this respect.

Wu and Boyle also found that some drivers use ACC when they are engaged in secondary tasks, such as manipulating the radio, or making a phone call with a hands-free headset (Wu and Boyle, 2015). For designers of ACC-related user interfaces, such as warnings, it is important to understand who these users might be, and how to design interfaces that allow them to drive safely. In a simulator study Xiong *et al.* propose that risky behavior with ACC is related to drivers' mental model of ACC operation (Xiong *et al.*, 2012). The authors applied the model proposed by Rudin-Brown and Parker (Rudin-Brown and Parker, 2004), and divided drivers into two groups. One group consisted of drivers who believe that, to a large extent, their own decisions and efforts control their behaviors – these drivers are said to have an internal locus of control (LOC). The other group was that of drivers with an

**Figure 4.1:** Researchers from the Netherlands Organisation for Applied Scientific Research (TNO) demonstrated collaborative adaptive cruise control (CACC) at AutomotiveUI 2013. This image shows two of the three TNO vehicles that were at the conference. The three vehicles formed a single column, with a lead vehicle, and two following vehicles. The lead vehicle was fully controlled by a human driver. In the other two vehicles, the driver controlled the lateral position of the vehicle, but the longitudinal position was controlled by the CACC system.

external LOC, who believe that external circumstances guide their behaviors. Xiong *et al.* found that drivers with an external LOC tend to engage in risky behaviors more frequently than drivers with an internal LOC.

If V2V and/or V2I communication is implemented, various cooperative systems become possible, including cooperative adaptive cruise control (CACC – see Figure 4.1), and platooning (Shladover, 2009). Just like ACC, CACC controls the longitudinal position of the vehicle, but it eliminates the need to measure the velocity of the lead vehicle, relying instead on data provided by that lead vehicle, through a V2V communications link. This idea can be expanded to an entire platoon of vehicles, all travelling at the same speed at very short following distances. The benefits are important: platoons are safe, they also make better use of highway real-estate than single vehicles travelling at longer following distances, and they improve fuel efficiency (Shladover, 2009). Friedrichs and colleagues conducted a test-track study to evaluate a prototype user interface that supports truck drivers in platooning (Friedrichs *et al.*, 2016a). Their results indicate that the design shows promise in being accepted and in helping to improve drivers' situational awareness. In a driving simulator experiment this group also confirmed that visual interface design can influence the level of trust in the platooning system (Friedrichs *et al.*, 2016b). Hjälmdahl and colleagues also found that the human-machine interface is important in platooning systems in order to reduce drivers' workload, and increase their level of trust in the system (Hjälmdahl *et al.*, 2017).

One concern for platooning systems is that it might require drivers to perform some monitoring tasks – for example to monitor the system for requests to transfer control from the automation to the driver. The expectation is that drivers would be quite poor at such a task (see e.g. (Hancock, 2015)). Interestingly, Heikoop *et al.* found that during simulated platooning, drivers performed very well on a monitoring task (Heikoop *et al.*, 2017). Note that the monitoring task involved looking at the open road, which might have been an engaging task, which is perhaps why drivers performed unexpectedly well. This result underscores the idea that what and how drivers are expected to do (including human-machine interaction) will affect their performance.

Automation technology also helps drivers maintain lateral control of vehicles. For example, the 2010 Lincoln MKS, investigated by Reimer *et al.* (Reimer *et al.*, 2016), can be equipped with a parking assist feature. Parking assist automates lateral control (steering), and requires the driver to provide longitudinal control (accelerator, brake). Reimer and colleagues found that, compared to manual parking, the automation reduced subjects' anticipatory heart rate. Since anticipatory heart rate is a measure of stress, the results indicate that the automation reduced the stress of parking in this experiment.

There has been significant effort in combining lateral and longitudinal control for automated driving, notably in Tesla's production vehicles. Endsley describes her personal experiences with a Tesla vehicle, and notes that the user interface design can result in mode confusion for the driver (Endsley, 2017).

### 4.1.3 Transferring control to the driver

As of 2018, the consensus opinion is that, for the foreseeable future, automated vehicles will need to transfer control to a human driver more or less often. This problem of how to transfer control is a significant area of research, because we do not yet know how to ensure that the human driver will be able to safely take back control of the vehicle after automated driving.

One important question is how long it will take drivers to successfully resume control of an automated vehicle. Mok and colleagues placed participants in a simulated vehicle that drove under automated control for 10 minutes, during which time the participants watched a video. After 10 minutes the participants were given a warning that they had to rapidly assume manual control of the vehicle. The researchers wanted to know how much time participants needed from the onset of the warning to take over manual control such that they could safely maneuver the vehicle between a set of cones placed in a curve. They found that the minimum time for takeover in this scenario was between 2 and 5 seconds (Mok *et al.*, 2015). Mok and colleagues repeated the experiment but instead of asking participants to passively watch a video, they asked them to play a game (Mok *et al.*, 2017). The active distraction increased the minimum takeover time to between 5 and 8 seconds.

The performance criterion set by Mok and colleagues (can the driver avoid crashing into cones on a curve?) is quite appropriate – as we argued earlier, the critical driving performance measure is how well the driver can avoid crashes. Yet, this is also a measure that is similar to performance measures such as number of crashes, or various discrete measures of lateral or longitudinal control. This means that it does not provide a measure of how the driver's ability to manually control the vehicle changes over time after a warning is issued; furthermore, in scenarios where we do not observe any crashes into cones we might over-estimate the ability of the driver to handle all other driving challenges, such as unexpected actions by different road occupants. To evaluate how driving performance might change over time after a driver takes over manual control of a vehicle, Merat and colleagues (2014) used standard deviation of lane position (as well as a measure of visual attention to the road ahead). They found that it took about 40 seconds for the lateral control of the vehicle to stabilize after transfer of control from high automation to manual driving.

Van der Meulen *et al.* compared the times it took drivers to take control of a vehicle for two scenarios: in one scenario participants began in a parked vehicle and were then instructed to start following a lead vehicle, while in another they had to take over control after their vehicle was controlled by automation (van der Meulen *et al.*, 2016). In both cases participants operated the vehicle on a straight road with no distractions. In this simple environment, the authors found that in both cases the mean takeover time was around 2–2.5 seconds.

Schroeter and Steinberger proposed using augmented reality to introduce games in automated vehicles with the goal of maintaining the driver's situational awareness; they hypothesize that this can lead to shorter takeover times (Schroeter and Steinberger, 2016).

### 4.1.4 Interacting with other road users

Automated vehicles will interact with other road users, including other automated vehicles, as well as human-driven vehicles, pedestrians, and bicyclists. These interactions have significant safety implications. Rothenbücher and colleagues explored how pedestrians might treat a vehicle that appears to have no driver: will they step in front of it at a pedestrian crosswalk (Rothenbücher *et al.*, 2016)? In the study the vehicle was actually driven by an experimenter, but this person wore a costume that made them look like they were part of the driver's seat. The authors found that most pedestrians managed the interaction smoothly, trusting that what they believed to be an automated vehicle would let them cross the street safely.

Haeuslschmid *et al.* propose using the outside of the windshield for providing directions (Figure 4.2), as well as advertisement to pedestrians (Haeuslschmid *et al.*, 2016). The same mechanism might be useful in providing information to pedestrians who are attempting to cross the street in front of an automated vehicle.

On the road, drivers interact with other road participants in part through the motions of their vehicles. Thus, in the Rothenbücher study

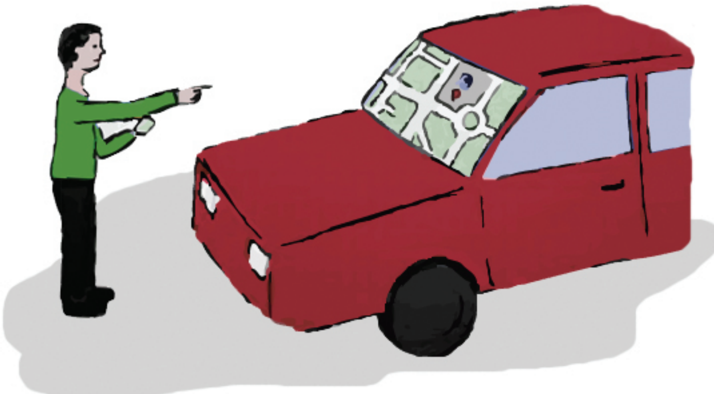

**Figure 4.2:** Haeuslschmid and colleagues proposed the idea of using the windshield to provide directions and advertising messages to pedestrians (image by Renate Haeuslschmid). This image demonstrates the idea that the interaction might include input from the pedestrian, for example to enter a desired destination on a map.

pedestrians saw a vehicle stop at the cross walk, and understood this to communicate that the car is inviting them to cross the road. Risto *et al.* explored a variety of what they call "vehicle movement gestures" and argue that these are vehicle motions that communicate different messages to other road users (Risto *et al.*, 2017). The authors argue that automated vehicles will have to understand such gestures to work well with human road users (drivers, bicyclists, and pedestrians). Brown and Laurier reviewed online videos about the use of automated vehicles, and their interactions with other road users (Brown and Laurier, 2017). They found that as of 2017 vehicle automation often cannot properly understand the "vehicle movement gestures" of vehicles controlled by humans, and vice versa.

### 4.1.5 Safety concerns: atrophying skills, and mode confusion

While automated vehicles are likely to improve safety in many ways, there are at least two areas where researchers have expressed safety concerns. One of these is the potential loss of skill: as drivers rely more on automation, they might become less skilled drivers. Casner and colleagues found that pilots' skills atrophy with extended use of automation (Casner *et al.*, 2014). It is possible that this negative effect would be present in drivers too (Casner *et al.*, 2016; Stanton and Marsden, 1996). And, perhaps it would be even more pronounced than in pilots, given that drivers receive much less training than pilots do.

Another concern is that of mode confusion. Writing in 1996, Stanton and Marsden warned that the design of user interfaces can lead to mode confusion in automated vehicles. In reporting on her experiences with Tesla automation features, Endsley indicates that she had indeed experienced mode confusion (Endsley, 2017). It is worth noting that the different standards that have been used to categorize levels of automation (National Highway Traffic Safety Administration, 2013; SAE On-Road Automated Vehicle Standards Committee, 2016) do not easily translate into a system to describe and model mode confusion.

## 4.2 Reclaiming time

According to the US Census Bureau, in 2009 workers in the US spent an average of 25 minutes a day commuting to work, and over 75% complete this trip driving alone in their automobile (McKenzie and Rapino, 2011). Assuming that the trip back from work also takes around 25 minutes, millions of people spend nearly an hour of each working day in a vehicle. If they commuted in an automated vehicle, they could reclaim this time for relaxation, play, and work (Kun *et al.*, 2016).

However, for an automated vehicle to be transformed into a place of work and play, we have to create user interfaces that allow for work and play to take place. These interfaces will be constrained less with the need to keep the driver's attention to the road, and more with the physical characteristics of the vehicle, such as its size, motion, and the seating arrangement. Constraints will also include network speed, the on-board computing power, and quality of sensor readings. Importantly, interfaces will have to be created such that they reduce the likelihood of motion sickness, which could result from people looking away from the outside world.

The design of interfaces for work and play in automated vehicles can be informed by studies such as the one conducted by Large *et al.* – the authors observed six participants who undertook driving simulator-based journeys on five consecutive days (Large *et al.*, 2018). Each journey included both manual driving and highly-automated driving. Participants were told that during the highly-automated portions of the simulated trips, they need not monitor the system. Thus, during these portions of the journey, they engaged in activities, such as reading, web browsing, and watching videos.

The design of interfaces for automated vehicles will also benefit from improved understanding of how passengers behave in manually-driven vehicles, since in automated vehicles all of us will become passengers, at least for some of the time. Pfleging and colleagues conducted an online survey to find out which activities people would like to undertake while travelling in automated vehicles (Pfleging *et al.*, 2016b). Their results indicate that these activities would be similar to the activities of today's passengers travelling in manually-driven vehicles.

Yet, future automated vehicles will likely provide exciting opportunities for novel interactions, beyond those that today's passengers practice. Unfortunately, they will likely also present accompanying drawbacks and risks. One interesting opportunity will be to design interactions with other people in the vehicle, and even with people in other vehicles. Schroeter *et al.* (Schroeter *et al.*, 2012) explored one example of the latter, albeit in the realm of manual driving; the authors experimented with allowing drivers to assign badges to other road users as a way of providing feedback about their road behavior.

As for drawbacks and risks, perhaps the most important one is motion sickness. As Diets and Bos point out, when the passenger is engaged in a non-driving task, they might see motions that are different from the motions sensed by their vestibular system (Diels and Bos, 2016). This visual-vestibular conflict can result in motion sickness. The authors propose design guidelines to reduce this effect; for example, they recommend placing visual displays such that the passenger's peripheral vision can receive motion cues from the outside world.

Given that our future interfaces might allow for interactions that involve personal data (from bank accounts, to health data, to data about personal relationships) the interfaces will also present challenges in data security and privacy (Smith, 2017). The design of interfaces should also take into account possible new ways to intrude on the time and attention of vehicle occupants. After all, in vehicles with high automation, where the human operator no longer needs to be in charge of the moment-to-moment control of the vehicle, the designer of the interface does not need to worry (as much) about taking the occupants' attention away from the road. This opens up the possibility of introducing a significant amount of advertisements in the vehicle; as Krumm points out, advertising might be the killer app in ubiquitous computing systems (which include highly automated vehicles) (Krumm, 2011). This raises the issue of privacy – what does the car know about its occupants, and how does it share it with advertisers?

## 4.3 Expanding access to transportation

The majority of today's designs of automated vehicles are geared towards adults who do not suffer from major health issues. These designs assume that users can see and manipulate displays, and that they can issue verbal commands and hear auditory feedback. Yet, for people with a range of disabilities, some or all of these assumptions do not hold – for example, Pierce and colleagues provide a review of how different disabilities affect the transportation-related user needs of affected populations (Pierce *et al.*, 2016). Thus, many user interface designs explored today would not allow people with disabilities to use automated vehicles.

Access to transportation options is a significant problem for many people, from those with disabilities related to vision or hearing, to wounded veterans, to the elderly who have reduced mobility. A 2003 study conducted by the US Department of Transportation found that in the US 6 million people with disabilities had difficulty finding the transportation options that they needed (Bureau of Transportation Statistics, 2003). Improving this situation will require advances on multiple fronts, and one of those is the design of user interfaces to allow people with disabilities to interact with automated vehicles. These interactions should include entering destinations and preferred routes, issuing new commands and status queries during a trip, and receiving feedback about vehicle actions and status throughout the trip. The interface must meet three requirements. First, it has to be accurate. Accuracy means, in part, that the interface must allow the user to reliably set the vehicle on a desired path (including a destination and possibly waypoints, or other characteristics of the road), or it must provide clear feedback why this is not possible (e.g. because of a blocked road). Accuracy expectations will be high: it is likely that, unless the vehicle performs according to user expectations every time, it will not be accepted by users. After all, today's manually driven vehicles meet this high expectation of accuracy, and self-driving vehicles will likely be held to this high standard.

Another related requirement is for the interface to be trustworthy. In fact, trust is a central concern in the design of in-vehicle user interfaces for self-driving vehicles (Riener *et al.*, 2016) – this is the topic of the next subsection. Accuracy will greatly influence trustworthiness, but so will user interface design decisions, such as the clarity of feedback. Finally, users should like the system, because this will make it more likely that they will actually use it. If the system is cumbersome to use, or if it evokes negative emotions, then users might avoid using it.

## 4.4 Trust

Lee and See argue that trust is an "example of the important influence of affect and emotions on human-technology interaction" (Lee and See, 2004). The authors argue that trust will affect reliance on automation when the human operator is faced with uncertainty and complexity in operating a device that "make an exhaustive evaluation of options impractical." This can certainly be the situation in traffic: an automated vehicle has to make control decisions based on a complex context, that is full of uncertainty. Furthermore, the control decisions are based on complex algorithms. It follows then, that human acceptance of vehicle automation will be affected by trust.

Körber and colleagues found that introductory information about the automation in a vehicle can affect trust (Körber *et al.*, 2018). Furthermore, the authors found that the resulting level of trust has an effect on how quickly drivers react to a request for taking back control from the automation. Participants with higher trust in the automation took about 1.2 seconds longer to take back control of the vehicle. This delay resulted in a 0.9-second reduction in the time-to-collision with the obstacle that was the reason for the request to take back control. Thus, the authors show that the way we introduce the capabilities of the automation system can help users calibrate their level of trust appropriately, and avoid overtrust and distrust, which is the terminology used by Lee and See (Lee and See, 2004).

Public opinion on automated driving indicates that researchers and developers must take this issue very seriously. This is underscored by the results of online surveys that Schoettle and Sivak conducted in six countries: US, UK, Australia, China, India and Japan (Schoettle and Sivak, 2014a; Schoettle and Sivak, 2014b). Over 500 participants provided responses in each of the six countries. Participant responses indicate that the public has positive expectations for automated vehicles – for example, majorities in all six countries expect that this technology will improve driving safety by reducing the number and the severity of crashes. However, large majorities in all six countries also have at least some concern with issues such as equipment failure, and interacting with human-driven cars. Of course, part of the issue here is the underlying reliability of the technology: if automated vehicles perform well, users will trust them. However, automated vehicles will also have to interact with users, both inside and outside the vehicle, in such a way as to build and maintain the trust of the public.

This building of trust using improved human-machine interaction was explored by Yan *et al.* in a simulator-based study (Yan *et al.*, 2017). The authors evaluated an adaptive lane-change assistance system, and found a relationship between the effectiveness of the human-machine interaction and trust: better human-machine interaction led to increased trust.

Beggiato *et al.* show that trust in ACC develops over time, as do acceptance of the system, and self-reported measures of learning of system functions (Beggiato *et al.*, 2015). One of the self-reported measures of learning was the agreement with the statement “I understand what the displayed ACC messages mean,” which is a measure of how well drivers understand the human-machine interaction of operating the ACC. The message of this work is important, and it echoes one of the arguments put forth by Lee and See (Lee and See, 2004): trust is a dynamic concept and it evolves over time, in part as a function of human-machine interaction.

### 4.5 Legal issues

As of 2018, the laws governing the testing, deployment, and eventual widespread use of higher levels of automation in vehicles (when the driver is disengaged from the driving task for extended periods of time), are still under development worldwide. Greenblatt reviews a number of issues in this realm, focusing on the driving task itself – how to make it safe, and who is responsible if there is a crash (Greenblatt, 2016). Others have also explored the issue of crashes, especially the moral question of how an automated vehicle should choose between multiple undesirable outcomes; for example, given only two options, should the automated vehicle hit a wall and injure its own passengers, or hit pedestrians crossing the road and injure them (Frison *et al.*, 2016; Rahwan *et al.*, 2016)? Nyholm and Smids persuasively argue that such questions are not analogous to the classic trolley car problem, where a person has to make a split-second decision, and chose which people will live and which ones will be run over by a runaway trolley car (Nyholm and Smids, 2016). The authors argue that one of multiple differences is in the decision-making situation. In the trolley car problem a single human agent has to make a split-second decision about only two possible choices. In contrast, an automated vehicle preparing for a crash will implement prospective decisions of multiple stakeholders, and it will consider many possible outcomes, each of which will have some probability of occurrence. This element of probabilistic outcomes is also explored by Frison *et al.* in their trolley car-like experiment with automated vehicles (Frison *et al.*, 2016).

And while the legal questions pertaining to the driving task faced by automated vehicles continue to be considered by researchers, practitioners, and lawmakers, Inners and Kun explore legal questions related to human-machine interaction in automated vehicles (Inners and Kun, 2017). Their primary focus is on vehicles that we can expect in the near term, where the driver will have a role to play in the driving task, at least from time to time. The authors provide an overview of the legal landscape that automated vehicles (will) operate under in the US, including jurisdiction levels, liability laws, the regulation of equipment, and driver licensing. The authors then make the argument that several aspects of the design of human-machine interaction in automated vehicles might be regulated. Regulation might mean the standardization of some features of the in-vehicle interfaces, in order to avoid confusing drivers when they switch between automated vehicles. Also, we might need to standardize the behaviors that automated vehicles exhibit; this could be done to avoid confusing human drivers of manually-driven vehicles who will share the road with automated vehicles (c.f. Brown and Laurier, 2017). Furthermore, we might need rules about software updates of interfaces, because the updates can introduce changes that can confuse drivers.

## 4.6 What is next?

Automated vehicles are making rapid progress, but there is a great deal of work left for researchers, developers, as well as regulators. One exciting challenge in this realm, as discussed by Kun, Boll, and Schmidt, is how automated vehicles will change the meaning of mobility (Kun *et al.*, 2016). One aspect of this change is in the granularity of control that is necessary to operate a vehicle. The driver of a manually controlled vehicle exercises control in sub-second time intervals. For automated vehicles the commands would be less frequent – in terms of Michon's hierarchy (Michon, 1985), a highly automated vehicle might require input from the user only at the strategic (highest) level. Flemisch and colleagues explored vehicles that are more likely to appear in the near term: those that can operate with high levels of automation for some period of time, but also need driver intervention during other times. For such vehicles, the authors suggest implementing shared control between the human driver and the automation, where the level of human control can vary depending on context (Flemisch *et al.*, 2014). When the context is such that the automation can perform the driving task well, the driver might only issue commands at the middle level of Michon's hierarchy: maneuvering. If the context is too difficult for the automation, the driver would assume all control responsibilities.

Looking further into the future, the passenger travelling in a fully automated (that is autonomous) vehicle might simply have to enter a desired destination. In fact, our future vehicles might become similar to the clairvoyant elevators in the science fiction novel "The Hitchhiker's Guide to the Galaxy" by Douglas Adams – these elevators know which floor you wish to go to even before you do, thus eliminating the need to wait for an elevator (Adams, 2009). As the work of Krumm and Horvitz shows, our vehicles might soon be able to predict quite accurately where we wish to go at any given moment (Krumm and Horvitz, 2006). Here one challenge for designing user interactions will be to let the user still feel in control.

Yet another exciting area for research is how to allow children to use automated vehicles. Here, questions for user interactions abound. Who tells the vehicle where to go – the parent, the teacher, the child? How does the vehicle make sure the children are securely buckled? What happens if anything goes wrong – who intervenes and how? Similar issues might arise if we want to use automated vehicles to expand transportation options for elderly people (Dickerson *et al.*, 2017) and people with disabilities.

In a 2016 blog post, Yoav Hollander discussed the question of how to intervene if something goes wrong with an automated system (Hollander, 2016). He argues that we can expect to see the rise of mostly-autonomous systems, which will perform perfectly in almost any situation, but that will infrequently encounter situations they just cannot solve. One such case might be an automated vehicle that has its path blocked by a tree that fell on the roadway. A child (or a person with a disability) might not be able to manage such a situation. Hollander argues that there might be a need for a new profession to deal with these types of cases: operator of mostly autonomous systems. For designers of automotive user interfaces this would mean creating interfaces that allow remote operation of the vehicle, as well as appropriate remote communication with the occupants of the vehicle.

Remote operation might also be very interesting in the transportation industry. We can expect that platooning trucks will appear on our roads in the coming years. But do we need a driver in each of the trucks? Consider the following scenario. A company has a truck that is capable of platooning. In other words, the truck can follow another truck travelling in front of it at a very short distance. The truck's automation controls both the lateral and the longitudinal position of the truck in the platoon, and no human intervention is needed. However, platooning only works on some highway segments (e.g. platoons can travel in designated lanes where other vehicles are excluded for safety purposes). Other than on these highway segments, the truck must be driven by a human. Furthermore, the truck can be remotely operated to join, or to leave, a platoon. With such a truck, the company can hire a local driver to move the truck from a warehouse to a meeting point on the highway. Here, the local driver leaves, and a remote driver takes over. The remote driver controls the truck as it joins a platoon headed towards its destination. Once the truck reaches the meeting point closest to its destination, a remote driver takes control, pulls the truck out of the platoon and parks it. Then a local driver boards the truck and drives it to the destination. One of the technologies that would enable such a scenario is the user interface to allow remote control of the truck.

Inside the vehicle, we can expect dramatic changes with the advent of automation. One technology that has the potential to help make the vehicle a place for work and play is augmented reality (AR). AR (implemented on the windshield (Häuslschmid *et al.*, 2015), or with AR glasses (Kun *et al.*, 2017)) might help us make the best use of the limited space that is available in the vehicle cockpit, without requiring keyboards, displays, and other interaction devices that could be difficult to manipulate, and that might present dangerous flying objects in the case of a collision. One important question is whether AR can be implemented in vehicles without leading to motion sickness in users, since motion sickness can be caused by conflicts between signals from the visual and vestibular systems (Sivak and Schoettle, 2015). AR will provide visual signals, but these might not be congruent with the signals of the vestibular system which respond to the motions of the vehicle. It is also possible that virtual reality (VR) displays will play a role in future vehicles, however here the issues with motion sickness will be even more prominent, as the user will not have any direct visual feedback from the physical world in which the vehicle is moving (McGill *et al.*, 2017).

Another interesting set of questions regarding user interactions will be related to brand experience in automated vehicles. At the inaugural AutomotiveUI conference in 2009, Gert Volker Hildebrand, who was General Manager of Mini Design in the BMW Group, talked about designing the interior of a Mini vehicle, and pointed out how the designers strive to tie the brand experience in a new vehicle to that in an older model[1]. On the other hand, we might experience automated vehicles quite differently than today's vehicles, because they might be part of smaller or larger vehicle-sharing networks (Burns *et al.*, 2013; Schoettle and Sivak, 2015). Consequently, user interface design for automated vehicles might become similar to interior design for buildings. In buildings, the same office space might be rented to a jewelry store, a bank, or a child care facility, and the occupant will determine the interior design. Similarly, different commercial vehicle-sharing networks, or taxi services, might rely on the same underlying automated vehicle technology, but they might wish to differentiate themselves from each other in part by the design of the interior of the vehicle, including the user interactions that are available to riders.

Everyone who embarks on exploring in-vehicle user interfaces, for manually-driven or automated vehicles, should work towards understanding the context of driving. Who uses the vehicle, for what purpose, and under what circumstances? As Dourish and Bell argue, "cultural phenomena are prior, not consequent to design" (Dourish and Bell, 2011). Yet, we still do not know enough about the cultural practices that cars fit into, and this is especially true of automated vehicles. A place to start building an understanding of what vehicles are used for today is the work of John Krumm, based on 2009 National Household Travel Survey (Krumm, 2012). Krumm provides statistics for trip distances and durations, as well as statistics for popular destinations and destination sequences. It is also instructive to read the account of Genevive Bell, a cultural anthropologist, of working towards understanding cars as sites of human activity and cultural practices (Bell, 2011). Bell stresses that cars are "contested space when it comes to new technology" and that we

[1]See the concept video presented by Gert Volker Hildebrand at https://www.youtube.com/watch?v=aSWr_Craqos

need to understand this space in order to design interfaces for vehicles. Pettersson and Ju also make this argument, saying that automated vehicles operate in the same physical space that we inhabit, and thus they have to "be culturally situated and adapted" (Pettersson and Ju, 2017). It is important to note that technically similar vehicles are used by multiple groups of users: consumers, professionals whose focus is on driving, such as truck drivers and bus drivers, and professionals who also have to focus on other tasks beyond driving, such as first responders (Kun *et al.*, 2015), as well as installation and repair technicians. Much of the existing work on understanding the driving context has involved consumers, but there is less work exploring other populations.

The above list of issues is not exhaustive. However, it is important to remember one issue that will clearly be important as we design user interfaces for automated vehicles, especially in the short term, before vehicles are truly autonomous and do not need human intervention. This issue is that automation has been introduced in other realms of human activity, and the results are not always as we would expect (and like) them to be. This is the message that Casner and colleagues make (Casner *et al.*, 2016), and they draw parallels to the aviation industry where we have encountered some of the effects of automation that might appear in automated vehicles. These unwanted effects include putting too much trust in the automation, as well as ignoring alarms that are perceived to simply be a nuisance instead of warning of a genuine danger. User interface designers have a central role to play in reducing, and ideally eliminating, these negative effects.

# 5

# Conclusion

Driving is a defining characteristic of modern life. Millions of people commute to work each day in a car or a bus. Trucks transport goods on our roads, and first responders reach those in need by driving to them, lights flashing. Driving plays a positive role in the world, as it is a key element of our economic activity, our security, and our social lives. Thus, much work is done to make driving efficient, and to allow drivers and passengers to spend time their vehicles comfortably, and even productively. Yet tragically, a large number of people die each year in driving-related events worldwide. In the US, the number of people who die in crashes is over 30,000 annually. In the EU, the number is very similar. It is no surprise then, that a great deal of effort is expended on understanding how people drive, and how best to allow drivers to *safely* control their vehicles, even as they possibly interact with other devices, such as mobile phones. In this document, we reviewed some of the key areas of this broad effort, both in the realm of manually driven vehicles, and in the realm of vehicles with automation. We have also discussed some potentially fruitful areas for continued exploration of in-vehicle user interfaces.

One of the key questions for automotive user interface research and development is what role automation will play in future vehicles. Will we have a significant number of automated vehicles on the road in the near future? If so, what does “near future” mean? Or, will people insist on retaining control and reject automation? We do not know the answer to these questions yet. However, it seems likely that people will embrace automation, because the benefits are significant, and our technology is making dramatic progress towards enabling automated driving. Manual driving might persist for many years to come, but eventually it is likely to be relegated to the role of entertainment, just like horseback riding transformed from a mode of transportation to a pastime. Thus, in addition to working on important issues related to manually driven vehicles which dominate the roads in 2018, researchers and developers in the automotive user interface domain should devote increasing efforts to creating user interfaces for automated driving.

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