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8 ALLOCATION OF FUNCTION TO HUMANS AND AUTOMATION AND TRANSFER OF CONTROL

Author 1 Name: *Natasha Merat
Author 1 Department: Institute for Transport Studies,
Author 1 Mailing Address: University of Leeds, Leeds, U.K.
Author 1 Email: n.merat@its.leeds.ac.uk
Author 1 Telephone: +44 113 3436614

Author 2 Name: Tyron Louw
Author 2 Department: Institute for Transport Studies,
Author 2 Mailing Address: University of Leeds, Leeds, U.K.
Author 2 Email: t.l.louw@leeds.ac.uk
Author 2 Telephone: +44 113 3437882

8.1 Abstract

Following a short description of function allocation (FA), and its use in other domains, this Chapter provides a summary of the likely human factors challenges facing system engineers and designers currently developing and assigning different functionalities for automated vehicles. We argue that, historically, allocation of particular functions to a machine has been motivated by the wish to relieve the user of monotonous, repetitive or unsafe tasks, or for providing system capabilities that are faster, stronger or more capable than humans. However, such function allocation has traditionally been implemented in static environments, such as factory floors, where tasks can be initiated and stopped by the user, and there are no detrimental effects of delayed transfer of control between machines and humans. An example of a more time-critical transfer of FA is perhaps seen in aviation, although the protocols and training used in that domain have had the attention of more dedicated resources, some of which may indeed be relevant to road-based vehicles. The rationale for allocating more tasks to the vehicle, and increasing the likelihood of higher level of automated driving, is primarily based on the desire to

reduce the number of human-based errors and limitations, which are known to lead to crashes, and reduce road safety. Well-designed automated vehicles also promise to reduce transport-related emissions and congestion, and pledge increased productivity, by relieving the human from the monotonous and repetitive driving task, affording them the opportunity to perform other tasks. However, we provide evidence from studies which suggest that, due to the complex and dynamic nature of driving, and the continually fluid responsibility for tasks between the system and the user, there remain some fundamental challenges for system designers in this domain. For automated vehicles to deliver on their promises, and reduce transport-related crashes, it is imperative for engineers and designers to be aware of the unintended consequences of human interaction with, and expectations of, their (almost perfect) system. In addition to increasing the likelihood of new errors; inappropriate, untimely, or prolonged allocation of function to the system has been shown to lead to user confusion, distraction, fatigue, loss of skill, and complacency, which have ultimately led to problems with the transfer of control, when the technology reaches its limitations. Currently, many of these limitations are also largely defined by infrastructural shortcomings, which can appear quite suddenly, and unexpectedly, limiting the system's ability to function safely, and requiring humans to act as a backup. An important, and yet ill-understood, area of research in this context involves better ways of communicating system capability to the user, ensuring they have the correct mental model, which may in itself require regular updates. Keeping the driver vigilant during prolonged periods of system use, and understanding what sustains their ability to resume control from the machine, are other areas which require further knowledge in this context, as are considerations of how to manage failed transfer of control. We argue that; once more knowledge in these areas is acquired, manufacturers and authorities can work towards providing better training protocols for users, and developing better standards for Human Machine Interfaces, to ensure highly automated vehicles deliver on their aspired promises.

8.1.1 Keywords

Function Allocation, Dynamic Function Allocation, Transfer of Control in Automation, Vehicle Automation, Driver models and FA, mental model, complacency, situation awareness, fatigue

8.1.2 Key points (3-5)

- Traditional allocation of functions to machines has historically been used in static environments, which is challenging for the dynamic driving domain.
- As more functions are allocated to automated vehicles, it is important to understand the dynamic and fluid relationship that exists between humans and machines, especially in SAE L2-4 vehicles
- For highly automated vehicles to deliver the promise of reducing human error in road-related crashes, it is important that system designers are aware of the limitations and expectations of human users, to minimise the unexpected consequences of inappropriate function allocation.
- Safe and successful transfer of control from automated vehicles to humans requires better knowledge of how human attention and vigilance can be maintained during prolonged

periods of automation, and how factors such as fatigue, distraction and complacency can be mitigated and managed.

8.2 Introduction

Over its entire history, the motor vehicle has probably had its most fundamental structural change during the past 20 years, with the addition of many primary (active) and secondary (passive) safety systems, which have mostly been implemented due to the need to improve road safety, and reduce vehicle-related injuries and deaths (Peden et al., 2004). Examples of primary (active) safety systems include Electronic Stability Control, Automatic Emergency Braking, and Antilock Brakes, which help reduce the likelihood of crashes (Scanlon, Sherony, & Gabler, 2017; Page, Hermitte, & Cuny, 2011). Secondary (passive) safety systems include airbags, seatbelts and more advanced vehicle body engineering solutions, which mitigate the impact of crashes (Richter, Pape, Otte, & Krettek, 2005; Frampton & Lenard, 2009).

In addition to these safety systems, today's vehicles incorporate features that provide drivers with higher levels of assistance with performing the driving task, guiding, warning and informing the driver, as well as taking over particular driving functions, which can replace drivers' actual physical control of the vehicle, for certain time periods. As more tasks are taken away from the driver, and controlled by the vehicle's various systems, a number of human factors implications need to be considered regarding this change of role, in order to fully understand the implication of these additional systems on drivers' behavior and performance, and the effect of any consequent changes on driver and road safety (see e.g., this Handbook, Chapters 1 & 2).

To understand whether, and how, such allocation of function(s) to the vehicle's various systems is likely to influence the driving task, this chapter begins by providing a short overview of Function Allocation (FA) between humans and machines, initially considered during human-machine interaction studies in other domains. We then set the scene by outlining the functions required by humans in a conventional driving task, using several well-established models in this context, before discussing how, when, and why different functions are allocated in an automated vehicle (AV). Specifically, we examine the rationale used by designers and engineers to allocate functions to each actor in an automated vehicle, followed by an overview of how, and when, drivers are informed about this allocation. Furthermore, we discuss what the consequences of such allocation of function might be on driver behavior and performance, how these may be managed, as well as the broader effect such consequences might have on road safety.

8.3 Defining Function Allocation

When considering the interaction and cooperation between humans and machines, function (or task) allocation simply considers whether, why, and how a function/task, or a series of related functions/tasks, are allocated to, and must be managed by the human, the machine, or a combination of the two, in order for a particular goal to be achieved (Bouzekri, Canny, Martinie, Palanque, & Gris, 2018). According to Hancock et al. (2017), FA is "*a process which examines a list of functions that the human-machine system needs to execute in order to achieve operational requirements, and determines whether the human, machine (i.e., automation), or some combination should implement each function*". Historically, this allocation of function has been fixed in nature, with the MABA-MABA ("Men Are Better At" - "Machines Are Better At") lists

(Price, 1985) revealing the assumption that either the human or the machine would be superior for a particular function. As initially outlined by Fitts et al. (1951; see Table 1), this allocation is partly determined by the ability of each actor to successfully achieve the required task, with humans being generally better at tasks requiring judgement, reasoning and improvisation, while machines are generally better at repetitive tasks, or those that require force, precision, and/or a quick response (de Winter & Hancock, 2015). However, although this type of FA continues to be considered (de Winter & Dodou, 2014), it has been widely criticized (Jordan, 1963; Fuld, 1993; Hancock & Scallen, 1996; Sheridan, 2000; Dekker & Woods, 2002), because it assumes that FA is static, and is considered acontextual, because it is insensitive to the influence of environmental variables (Scallen & Hancock, 2001). This view solidified as we began to understand the nature of work better, including its context and environment, while also appreciating that users of a system have different needs and information processing capabilities. Today, human factors investigations demonstrate that, for tasks requiring cooperation between machines and humans, although assigning the right function to the right actor is important, other factors must also be considered, to ensure safe and efficient task completion. These include the number of functions assigned, as well as the frequency and sequence of allocation of these functions. Also, it is essential that each actor assumes the appropriate *responsibility*, and *authority*, for taking control of, or assigning, a function.

Table 1 The original Fitts list (Fitts et al., 1951, p. 10)

Humans appear to surpass present-day machines in respect to the following:	Present-day machines appear to surpass humans in respect to the following:
1. Ability to detect a small amount of visual or acoustic energy 2. Ability to perceive patterns of light or sound 3. Ability to improvise and use flexible procedures 4. Ability to store very large amounts of information for long periods and to recall relevant facts at the appropriate time 5. Ability to reason inductively 6. Ability to exercise judgment	1. Ability to respond quickly to control signals and to apply great force smoothly and precisely 2. Ability to perform repetitive, routine tasks 3. Ability to store information briefly and then to erase it completely 4. Ability to reason deductively, including computational ability 5. Ability to handle highly complex operations, i.e. to do many different things at once.

8.3.1 *Allocating responsibility*

Flemisch, Heesen, Hesse, Kelsch, & Schieben (2012) suggest that by assuming responsibility for a task an actor becomes "*accountable for his actions*". With regards to humans, an awareness of this responsibility may be determined before they start a task, for example by reference to appropriate information and training about the task, or by the relay of suitable messages from the system during task completion, for instance, via relevant Human-Machine Interfaces (HMI). Assigning and assuming the right degree and type of responsibility is likely to reduce errors and confusion. The transfer of this responsibility between actors must also be achieved in a timely manner, and under the correct circumstances, in order to avoid or reduce task error. For example, safety may be affected if the human resumes responsibility for a task unnecessarily, when it is being well-controlled and managed by the system (Noy, Shinar & Horrey, 2018). Equally, passing responsibility back to the human by the system in a timely manner is important, to ensure that adequate mental and physical resources are available to assume such responsibility (Louw et al., 2015).

Therefore, it is important that system engineers consider this allocation of responsibility to the system and human carefully, communicating this information clearly, to ensure the user is aware of their role, versus that of the system. Any allocation of responsibility to the human is also done under the assumption that the human honors that responsibility, and that there is a minimal likelihood of misuse or abuse of the system's functionality, which would result in reductions of their own and others' safety. However, the automation must also be designed with the human's limitations in mind, to ensure that any likely failures can be appropriately managed by the user.

Part of the designers' challenge is ensuring that users have the correct *mental model* of system functionality (Sarter & Woods, 1995; see also, this Handbook, Chapter 3) so that their responsibility for every stage of task completion is clear. Research shows that the ability to assume responsibility for a particular task, or a series of related tasks, also relies on users' expectation, training, and experience (Flemisch et al., 2012). This responsibly may also shift, be interrupted, or neglected, if the user is engaged in other, competing, tasks, which may or may not be related to the user's primary goal outcome. For example, in a recent driving simulator study, we investigated driver response to "silent" failures in SAE L2 and 3 automated driving, where automation failure during a simulator drive was not preceded by a take-over warning (Louw et al., 2019). This is an example of when automation hands responsibility of the function back to the driver, due to an unexpected/unknown failure, perhaps because the system encounters a scenario not anticipated by its designer, such as absence/obstruction of lane markings used for keeping the vehicle in its lane. Drivers completed two drives in a counterbalanced order. In one drive, they were required to monitor the road and driving environment during automation, where attention to the road was maintained by asking them to read the words on a series of road-based Variable Message Signs (VMS, L2). For the other condition (L3), drivers performed an additional non-driving related task (NDRT) during automation, the visual search-based Arrows task (see Jamson & Merat, 2005). This task was presented on a screen near the gear shift, obliging drivers to look down and away from the road. The VMS task was also required in this drive, which meant that drivers divided their attention between the road, the VMS, and the NDRT.

When considering performance, results showed that, after the silent failure, a significantly higher number of lane excursions were observed during the NDRT drive (L3), and participants took longer to take over control. Participants also had a more erratic pattern of eye movements after silent automation failure in the NDRT drive, presumably because they were attempting to gather the most useful visual information from the road ahead and the dash-based HMI, which contained information about automation status (on/off). This example of a fluid, and un-signalized, shift of task control between machine and human, illustrates the detrimental effects of unclear responsibilities, especially if the driver's attention is directed away from the forward road, and if the accompanying HMI is confusing, rather than assisting, the driver.

One main reason for striving towards clearer allocation of responsibility for each actor, is to ensure that the source of any possible errors during task engagement can be rapidly identified. Therefore, the main human factors challenge here is not only for system designers to assign the correct responsibility to each actor, but also for humans to be aware, and capable, of honoring this responsibility, through to completion of the task. Of course, problems arise when this allocation is unreasonable, or when sustained commitment by the human is not possible, for example, when fatigue and distraction creep in.

8.3.2 *Allocating authority to take responsibility for a function*

In addition to the allocation of the correct level and type of responsibility to each actor, when humans and machines are cooperating, successful and safe accomplishment of tasks must also consider the *rights* of each actor in assuming a function, or allocating authority for the function to the other actor. Flemisch et al. (2012) describe this "authority" as what each actor is, or is not, *"allowed"* to do. Here, it is assumed that the authority to take over a function, or allocate it to the other actor, must be closely linked to the capabilities of either actor, and will be partly related to the MABA-MABA list (Fitts et al., 1951; Price, 1985). For systems, this authority to manage the task or take over from the human must be accompanied by a guarantee that the system can function in all foreseeable scenarios. From a human factors perspective, the consideration for functions that can be shared between humans and machines is that, following prolonged assignment of function responsibility to the system, humans will likely suffer from certain limitations, which can affect goal completion, especially if there is a system failure. The likelihood of these limitations arising must, therefore, be taken into consideration, when deciding whether to give humans the authority to take control of a function. Examples of such limitations include: (i) reduced attention to, and monitoring of, the function (Carsten et al., 2012; Körber, Cingel, Zimmermann, & Bengler, 2015); which leads to (ii) loss of situation awareness towards the system and surroundings, diminishing ability to resume responsibility and control (if required) (Sarter & Woods, 1995; this Handbook, Chapter 7), as well as (iii) onset of drowsiness/fatigue (Goode, 2003), and (iv) loss of skill to complete the function, due to prolonged non-use (Hampton, 2016). Therefore, system designers must decide whether or not an agent should be given the authority to assume and/or assign control of a particular function, when a task is being performed adequately by the other agent. Here, it seems sensible that the human should be given less authority following longer periods of system functionality.

A key challenge in this context is understanding how humans can remain vigilant and engaged during prolonged periods of automation use, sustaining the ability to successfully resume responsibility of the function (for instance, due to failures). A consideration of how this vigilance and capability of humans can be determined by the system is also important, as is the ethical consequences of incorrect FA, or authority to assume control. For example, should an appropriately functioning system cede control to an impaired driver, if asked to do so?

Having provided a generic overview of FA, and summarized the implications of allocating responsibility and authority to each agent in complex scenarios involving human-machine interactions, it is now important to understand how this general overview relates specifically to the interaction of humans with higher levels of vehicle automation. This is especially important when considering functions that are currently *shared* between the human and vehicle, where responsibility and authority are assigned to/assumed by either agent. Before considering this FA in automated vehicles, the next section provides a brief overview of models developed for describing the driver's role during manual control of driving, and describes how these roles are likely to change as a result of allocating functions to the vehicle.

8.4 Defining the driving task: How automation changes Function Allocation

Models of driver behavior, originally developed for manual control of the vehicle, generally consider three main categories of driver responsibility and control, for achieving the driving task (Hollnagel and Woods, 2005; Michon, 1985). The first category involves a physical (perceptual-motor) engagement with the vehicle controls, to manage the appropriate lateral and longitudinal position of the vehicle in the intended driving lane (maintained via moment-to-moment steering, brake/accelerator control). The next category of control by the human involves tactical functions, such as negotiating intersections, or detecting and avoiding obstacles, and changing lane accordingly, which also relies on perceptual-motor engagement. Finally, strategic control involves higher levels of (cognitive) engagement, for tasks such as navigation and route planning. As outlined in Merat et al. (2018), in manual driving, some level of monitoring is required by the driver, for each of these levels of control (see Figure 1, and SAE (2016a, b)). However, as these functions are (either progressively, intermittently, or completely) assumed by the vehicle's automated driving system (L1-L5), the role of the driver will change from that of an *active controller* of individual functions that operate the vehicle during a designated journey, to one that *monitors* and supervises some of these functions, while perhaps continuing to engage in, and be responsible for, others.

However, it has long been shown that humans are not especially effective at supervising or monitoring a system for long periods (Mackworth, 1948; this Handbook, Chapter 21) and that as the length of such monitoring increases, human factors problems arise, which can lead to reduced safety. Examples from aviation show that this is due to issues such as user distraction (Endsley & Garland, 2000; Loukopoulos, Dismukes, & Barshi, 2001; this Handbook, Chapter 9), fatigue (Goode, 2003; this Handbook, Chapter 9), over-trust of system capabilities - followed by user complacency (Parasuraman and Riley, 1997; this Handbook, Chapter 4), loss of skill

(Hampton, 2016; this handbook, Chapter 10), and degraded situation awareness (Salmon et al., 2016; this Handbook, Chapters 7, 13). Some of these errors are thought to be exacerbated by lack of suitable feedback from the system via its HMI (Lee & Seppelt, 2009). Here, we distinguish between monitoring of systems controlled by the human, where the perceptual-motor (physical) link is still preserved in manual driving (as shown in Figure 1), compared to where an automated system's performance is monitored without this physical link. Indeed, there is also a need to describe precisely what monitoring refers to in this context. While "monitoring" is considered synonymous with "checking" and "observing" a system's performance, it is not simply a case of verifying that some level of physical/perceptual-motor/cognitive engagement is maintained with the system (such as establishing whether eyes are on the road and hands are on the steering wheel). Instead, as Victor et al. (2018) highlight, an additional cognitive element (an element beyond paying attention) may also be required as part of such monitoring, to ensure the user is capable of "*understanding in the mind the need for action control*".

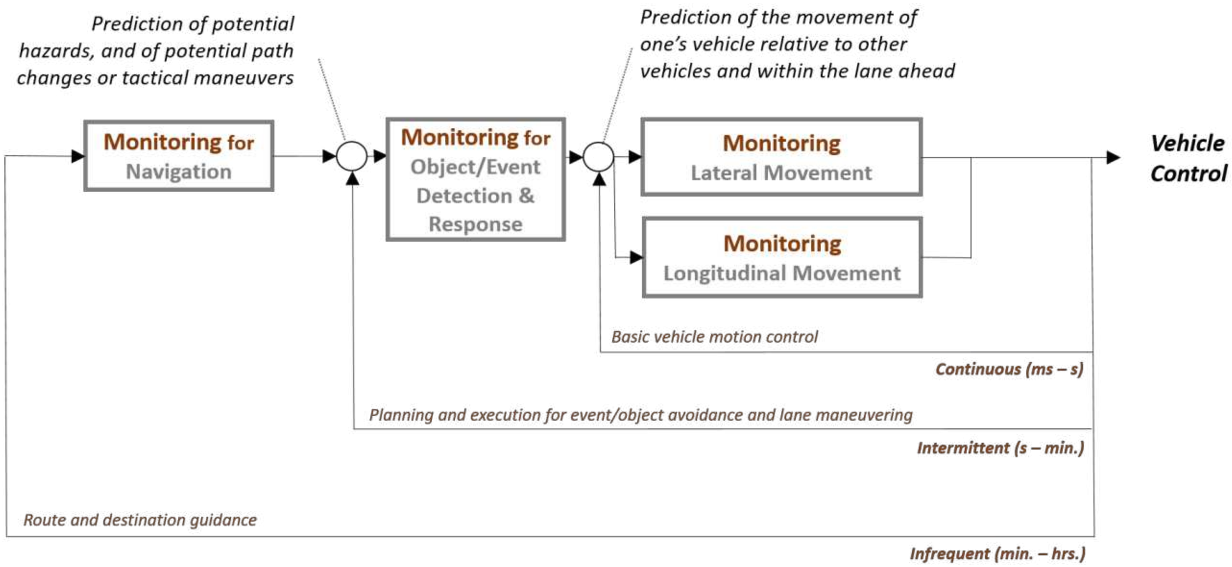

Figure 1 – Drivers' monitoring role in manual control of the driving task (Merat et al., 2019; based on Michon's model, 1985; Copyright © 2019 Springer. Reprinted with Permission of Springer Publications)

Therefore, as more functionality is taken over by the automated system, and the role of the driver changes to that of a supervisor of these functions, there is a need for additional *aides* in the vehicle, to help the human controller with their altered role. These include interfaces that offer intuitive and accurate information about the automated system's functionality, informing the driver of likely changes in this functionality. This information should also be timely, provided with adequate notice, and should not surprise, distract or overload the user (see also, this Handbook, Chapter 15). Drivers may also need assistance in managing the function that is being transferred back from the automated system, since skill degradation and reduced situation awareness are known to accompany such FA to the vehicle (Endsley, 2017), especially after longer periods of system use (Trösterer et al., 2016). Here, driver monitoring systems will be a useful addition to the vehicle (this Handbook, Chapter 11), to ensure that drivers are vigilant, and capable of honoring their responsibilities (this Handbook, Chapter 10). Figure 2, illustrates the effect of these changes on the driver's role, altering the original models of driver behavior, developed for conventional driving. As more and more functions are allocated to systems, the driver's physical control of the vehicle decreases. Depending on the level of automation engaged, drivers' reliance on good warning and communication from the different HMI will increase. To ensure there is a suitable degree of monitoring of this HMI, and that important information and warnings are not missed by the driver, an informative and accurate driver monitoring system, which manages the human-HMI-vehicle link is required. In addition to acquiring more accurate data about driver state for such DMS, future research must consider opportunities for informative and intuitive HMI for highly automated vehicles (Carsten & Martens, 2018). This knowledge can also be used to inform extensive, and regular, training of the human driver, to ensure they have a good understanding and mental model of system capabilities and limitations.

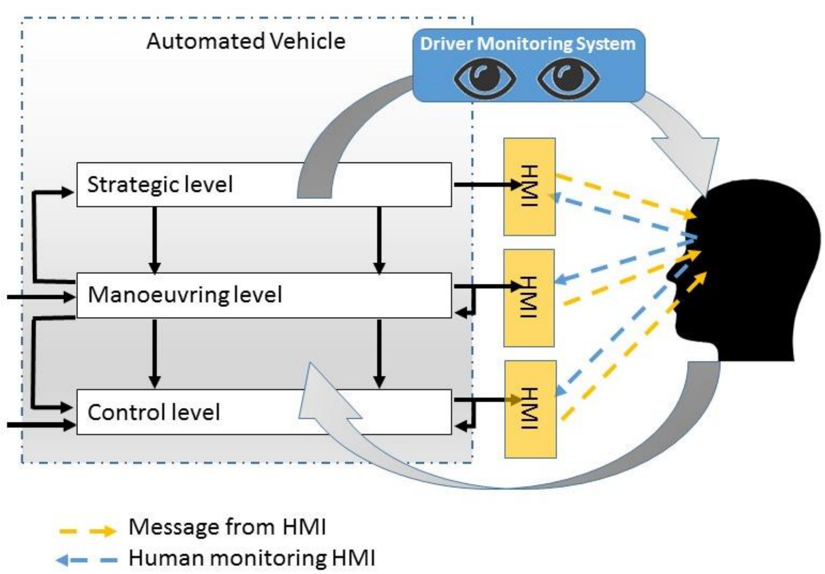

Figure 2 – A proposed model showing the changing position and role of the human due to the introduction of automated functions in the driving task

8.5 The *can* and *why* of allocating functions

Whether a function *can* be performed by an agent, and therefore allocated, has traditionally been considered simply by assessing strengths and weaknesses, or capabilities, of each agent (Hollnagel & Bye, 2000). However, even if there is a good argument that an individual function *can* be allocated, it does not necessarily provide compelling justification or guidance for *why* a function should be allocated, *when* it is suitable for this allocation to take place, and *who* should be responsible for this allocation. Some regard of how different functions interact with each other, and their effect on human performance, is also important, where it can be argued that the sum effect on performance is not equal to all of its parts.

As discussed above, when considering the allocation of functions between humans and machines, it is important to establish *what* task is being allocated (i.e. the nature of the task/function), as well as the *degree* of involvement in task management for each agent (i.e. how is responsibility assumed or shared between agents). However, as part of this discussion, it is also essential to establish whether or not a function *can* be allocated (i.e. can the machine perform the function/task, at least as well as, or better than, the human?). There are also safety, ethical and moral issues when deciding whether a function *should* be allocated, that go beyond the system's technical capabilities. This is also linked to how much authority a designer gives the system for taking responsibility of the task. Here, it seems essential for engineers and system designers to have a good appreciation of the unintended consequences on humans of this FA, which, as outlined above (and further below), may lead to user confusion, distraction, fatigue, loss of skill, or complacency. These unintended consequences are also closely tied to system failures, which may occur due to unforeseen technological limitations (not yet known by designers), or an unintentionally lax testing protocol, as well as user (mis) understanding of system capabilities.

In the case of vehicle automation, the manufacturers' motivations, and rationale, for FA is partly motivated by the challenges facing our congested and polluted cities, and a desire to reduce transport-related emissions, and increase throughput, while also enhancing driver comfort, and improving road safety. However, based on our understanding of how automation affects human performance, the aspiration to increase road safety by removing "the human element" is currently a growing irony. For example, the "out of the loop" problems associated with a lack of engagement in the driving task (Merat et al., 2018), especially when sparse and uncomplicated road conditions provide drivers with a false sense of security about system capabilities, are leading to real-world crashes (Vlasic & Boudette, 2016; Silverstein, 2019; Stewart, 2019).

Another important motivation for allocation of more functions to the system, which in turn increases the level of vehicle automation, is the desire to release humans from the monotonous aspects of the driving task, providing freedom for engagement in other (more productive) tasks. This freedom to attend to other tasks is linked to economic benefits, estimated to be worth tens of billions of dollars (Leech, Whelan, Bhaiji, Hawes & Scharring, 2015). Again, if not planned and implemented well, this task substitution, can lead to the same human factors problems outlined above, in addition to an eventual loss of skill, with prolonged system engagement (Carsten, Lai, Barnard, Jamson & Merat, 2012).

Different approaches have been used for categorizing the capabilities of automated driving systems. For example, original categorization of levels of automation, proposed by control engineers, typically accounts for the locus of control (human or automation) and how information is presented to the human (c.f. Sheridan & Verplank, 1978). There are also more driving-specific levels of automation, which describe, at each level of automation, what aspects of the primary driving task are performed by the human or the system (SAE, 2016a). Finally, when considered within a human factors context, systems can also be classified based on their correspondence to models of human information processing, such as sensory perception, working memory, decision making, and response selection (Parasuraman, Sheridan, & Wickens, 2000; this Handbook, Chapter 21).

While each of these approaches has a particular application, and implies some pre-determined FA, the main failure of such categorization is that, for the most part, they focus on the capabilities of systems, rather than that of their users. They also fail to identify the influence of system and human on one another, when the two have to work together, as is currently the case for vehicle automation. Therefore, while simply considering a vehicle's ability based on its stated levels of automation would be a desirable solution, it does not represent the ideal approach for determining appropriate FA.

Here, it can be argued that the MABA-MABA type lists (Price, 1985; see Table 1) represent the skills and abilities of machines and humans in *the best-case* scenarios. However, in reality, these abilities cannot be maintained in perpetuity. For example, systems will have specified Operational Design Domains (ODD), which will determine whether, where and when they reach their limitations. Due to shortcomings in technological advances, this limitation is not an issue that will be resolved in the near future, even though substantial developments are being achieved in this context, on a daily basis, with both automotive companies, tier 1 suppliers, and big and small newcomers in the market investing heavily in this area. However, widespread penetration of vehicles with Level 5 (SAE, 2016a) automated driving capability, for all road types and environments, is not likely for some decades, before which humans will still be involved in, and responsible for, different aspects of the driving task.

The continuous nature of driving, and the constantly changing environment in which it is performed means that the moment-to-moment driving tasks and responsibilities will also change. Consequently, the allocation of responsibility for some functions/tasks will need to transfer between the automated vehicle and the human driver, depending on the capability of the system, and the particular driving environment. To illustrate, using an example from limited ODD, an automated vehicle may be able to operate at L2 in most areas, at L3 in some areas, and at L4 in only a few areas. If this vehicle moves from an area where it can function at L4, to one where it can function at L2, the human is required to be aware of this change, and start monitoring system and road environment for L2 functionality. However, if the vehicle moves from an L4 area to an L0 area, this change in ODD would require a fundamental shift in the human driver's responsibilities, which will not only require monitoring the road and vehicle, but also resuming lateral and longitudinal control of the vehicle. This transition may also involve the responsibility for obstacle detection and avoidance. Therefore, functional capability alone is not adequate, with different (and changing) environmental settings also playing a role in this relationship. The need for dynamic allocation of responsibility and authority between human and machines is therefore necessary for some functions, until the system can satisfactorily perform in all possible driving conditions. Here, one ideal solution for system functionality is its ability to *recognize* its own limitations, as the environment changes, informing the human, in sufficient time (Figure 2). System functionality should therefore only be available for the correct environmental setting, and otherwise, not operational.

Another consideration in this context is that the hardware and software utilized in automated driving systems can change rapidly and frequently. For example, some OEMs allow “over-the-air” download updates of automated driving software (Barry, 2018). This type of, instant, change may alter the vehicle’s behavior in certain scenarios, also changing system capability, for example, by activating latent hardware, which may enable new features. The nature of this update creates problems with "type approval" of vehicles, as well as presenting significant human factors challenges. For example, this approach requires users to update their mental model of the functionality of the system, which presents a higher risk of mode confusion. These issues can be of concern for driver training, especially novices, since research on training in other domains, such as aviation, has shown that some novice pilots are biased towards trusting automation over their own judgement (Parasuraman & Riley, 1997). Casner and Hutchings (2019) argue that, for successful use of new automated systems in the driving domain, a comparable level of consideration, to that used in aviation, should be given to the training protocols developed for human drivers, to ensure they are familiar with the capabilities of the system, appreciate their own capabilities and limitations, as well as having a good understanding of the “human-automation team”.

In sum, the key point to consider here is that, while a function may be allocated in good faith for a particular system, or in a particular context, as soon as that context changes, the reallocation of a function may actually cause more harm than good, if it is not properly understood or implemented by its user. It is therefore important to fully appreciate these aspects of the technology's fallibility and propensity to change rapidly, when deciding who does what, and when, and also how the authority for resuming this responsibility is determined. At the moment, the rapid implementation of automation in driving means that humans are left to do the tasks that machines are either not yet, or perhaps ever, able to achieve, a concept known as the *leftover approach* (Bailey, 1989). As Chapanis (1970) aptly argues, it is our job as human factors researchers/engineering psychologists to ensure that these tasks are manageable within human capabilities.

8.6 The consequences of inappropriate Function Allocation

As system designers assign functions to humans or machines, in addition to considering the capabilities of each, they must also reflect on how the number of functions, and the timing of FA to the human, affects performance, with factors such as user impairment (distraction and fatigue) (Horberry, Anderson, Regan, Triggs, & Brown, 2006; Brown, 1994), under/overload (Hancock & Warm, 1989), and skill degradation (FAA - Federal Aviation Administration, 2013; Louw et al., 2017a) a few of the unintended consequences of inappropriate FA (Lee, Wickens, Liu, & Boyle, 2017).

A long history of driver behavior research has demonstrated that (apart from the very young/inexperienced and the very old) humans are generally competent drivers, with around 2 fatal crashes, per 100 million miles driven (Tefft, 2017). However, up to 90% of road vehicle accidents are thought to be caused by human error (Treat et al., 1977). Indeed, as highlighted above, this accountability of humans in crashes is one of the many rationales for introducing automated functions in vehicles. However, it has also been aptly argued that, if automation is not designed with the human in mind, replacing humans with automation does not necessarily remove the error, but simply *changes* it, "*To the extent that a system is made less vulnerable to operator error through the application of automation, it is made more vulnerable to designer error*" (Parasuraman and Riley, 1997).

In today's 24/7 hyper-connected society, drivers are still as, if not more, susceptible to fatigue, distraction (Gary, Lakhiani, Defazio, Masden, & Song, 2018; this Handbook, Chapter 9) and loss of awareness than they were when so many driving functions were not automated even 10 years ago (Endsley, 2017; this Handbook, Chapter 7). As long as drivers have some safety-critical role, the effects of these limitations on performance and safety will remain and are likely to be magnified in some cases, by the addition of automation. Moreover, the introduction of automation exposes "new" human factors limitations, based on the requirement by humans to interact, arbitrate, communicate, and cooperate with a system that has been developed without consideration of humans' need for continued training in this context. For example, if drivers have to constantly update their mental model of the automated driving system, *errant mental models* (Saffarian, de Winter, & Happee, 2012) or inappropriate communication could develop, giving rise to *mode confusion* (Sarter & Woods, 1995), especially if a vehicle has multiple modes of operation or levels of automation that have narrowly defined ODDs.

The extent to which users *trust* a system is also an important factor when considering FA (e.g., this Handbook, Chapter 4). When assigning a task or function to a machine, it is important that systems can help users develop the appropriate (well calibrated) level of trust in, or reliance on, the machine, where it performs the task they believe it will perform. However, in their interaction with the machine, users may either not trust the system enough (*distrust*) or trust it too much (*over trust*). *Distrust* can lead to users perceiving the automation as imperfect, resulting in *disuse* of the system (Parasuraman & Riley, 1997). Disuse can occur if the system is too susceptible to being incorrectly configured, if the procedure for operating it is too convoluted (Carsten & Martens, 2018), or if there is rate of high false alarms (Parasuraman & Riley, 1997). Distrust can also occur if a system does not adequately communicate its behavior or intention to its users, resulting in *automation induced surprises* (De Boer & Dekker, 2017) or misclassification of system errors (Wickens, Clegg, Vieane, & Sebok, 2015), and thus unsafe, or inappropriate, attempts to intervene (Louw et al., 2019).

On the other hand, *over trust,* sometimes referred to as *complacency* or *automation bias*, occurs when users trust a system more than is warranted, and is exacerbated when users rarely encounter failures (Bainbridge, 1983; Moray, 2003; Parasuraman & Manzey, 20l0). One of the consequences of complacency is *out-of-the-loop* behavior, where users are no longer actively attending to/monitoring or controlling the process, or significantly reduce their monitoring of the system (Merat et al., 2018). This leads to users with reduced *situation awareness* (Ma & Kaber, 2005) during automated driving, and an increased likelihood of *skill loss* in manual control, as a consequence of long-term automation use (Trösterer et al., 2016; Ward, 2000). Of course, these issues may also arise in compliant drivers (i.e., drivers who are monitoring their L2 vehicle). Therefore, the primary concern of inappropriate allocation of tasks is that errors and risks are not detected and dealt with, either by the human or the system, compromising safety. Safety is also affected if there is inappropriate intervention by the human. For instance, if the efficient operation of the system is unnecessarily interrupted by the human resuming control of steering, disturbing the safe trajectory of the vehicle, resulting in a collision. This would also be of concern if the human is incapacitated (e.g. due to fatigue or intoxication). Research needs to establish the risk of the above occurring in the context of when, and how, drivers will have to interact with the system.

8.7 Transfer of Function Allocation in Automated Vehicles

One of the unique characteristics of allocating functions for automated driving systems, and in particular L1-L3 (SAE, 2016a), is that driving is a continuous task, which means that if the allocation changes, the human driver must resume manual vehicle control (with little or no warning), in order to maintain an appropriate level of task performance. This type of failure is perhaps dissimilar to some control room tasks, which are serialized and, therefore, can be stopped and restarted when the allocation changes, avoiding a deleterious impact on overall task performance. The driving environment can also be more complex than, for example, aviation, with the chance of an error being more catastrophic on a congested road. With fluid or dynamic allocation of functions (Byrne & Parasuraman, 1996; Hancock & Scallen, 1996), there are inevitably situations in which drivers will have to either resume manual control or cede control to the automated driving system. For example, if a driver, who is using an L2 automated driving system, is not monitoring the road environment appropriately, the automated driving system may request the driver to resume manual control, although recent research in this context has illustrated that safe resumption of control by drivers is not always possible (Louw et al., 2017b; Zhang et al., 2019) or, if possible, is not always initiated (Victor et al., 2018).

For safe resumption of control, drivers must have enough information about the vehicle's operation and the surrounding traffic situation, and there must be a clear means of communication between the two actors. However, despite intense work on trying to understand and solve this example of a "hand-over" in recent years (c.f. Merat & Jamson, 2009; Gold, Damböck, Lorenz, Bengler, 2013; Merat, Jamson, Lai, Daly & Carsten, 2014; Louw, Merat & Jamson, 2015; Zeeb, Buchner, Schrauf, 2015; Madigan et al., 2017; Louw et al., 2017a; Zhang et al., 2019; Mole et al., 2019; McDonald et al., 2019; Morando, Victor, Bengler, & Dozza, 2019; Gonçalves, Louw, Madigan, & Merat, 2019), a widely applicable solution is not yet available. This is due to the complex set of scenarios present in the driving environment which can lead to hand-overs, making it difficult to specify the correct timing, location, modality, legibility, and sequence of the information that must be presented by the vehicle's HMI, and managed by the driver. The value of this guidance also interacts with the drivers' own expectations, mental models, experience and capabilities. Therefore, when considering whether to create a machine to perform a function, it is important to establish whether a driver can reasonably be expected to intervene in time, appropriately, and safely. In this consideration, it should also be clear to the designer what the expectations are of the driver, what a successful response is, how this is measured, and whether these expectations and assessment methods apply uniformly across different situations. A fluid allocation of functions, therefore, requires engineers and designers to balance the benefits of introducing automation carefully against the risk of errors accompanying allocation switching.

Aside from the particular hand-over problems discussed above, there are a number of other factors that should be considered when allocating functions that will be controlled simultaneously by the human and automation, for example, in an L2 automated driving system.

These include the likelihood that drivers will misuse or abuse the automated driving system, whether they are flexible enough to adapt to dynamically changing roles and responsibilities during different journey types, and whether they actually want to have joint responsibility for the task or function. Further, there may be training requirements for users to learn to operate the automated driving system, depending on its design characteristics, which could bring additional costs, research needs, and barriers to automated driving system rollout. For example, it may be possible for a car dealership to train the driver of a newly-purchased vehicle, but this is not realistic for users of a rental car. As the introduction of such systems is relatively rapid, new and more agile methods of driver training, examination, and driver licensing need to be developed, which is especially relevant given situations where drivers may need to operate new, borrowed, or rental cars equipped with systems they may be unfamiliar with. Finally, a move to more standardized HMI must be considered (Carsten & Martens, 2018; this Handbook, Chapter 18).

8.8 Summary and Conclusions

Automated vehicles with some SAE L2 and L3 functionality are already available to consumers in the developed world, and manufacturers and researchers are currently testing human interaction with higher levels of automation (see for example: https://www.l3pilot.eu, http://agelab.mit.edu/avt). As the frequency and duration of drivers' use of automation systems increases, designers must be aware of the concomitant human factors challenges, especially if occasional system limitations require human intervention and control.

This Chapter highlights the challenges that still exist with respect to function allocation for a dynamic task such as driving, and provides some possible mid-term solutions for system engineers. In an era where such systems are not yet 100% capable of replacing the human in all road environments, and at all times, it is important for system engineers to be aware of the possible unintended consequences of their developed systems, ensuring that the responsibility of each agent in this human-automation relationship is clear throughout a drive, and that suitable mitigation processes are in place for managing system and human limitations. The journey towards achieving fully self-sufficient automated vehicles, safe to be used in all infrastructures, requires human factors specialists and engineers to work together to provide the knowledge needed for suitable training, communication, and interaction protocols, better Human Machine Interfaces, and more advanced driver monitoring systems.

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