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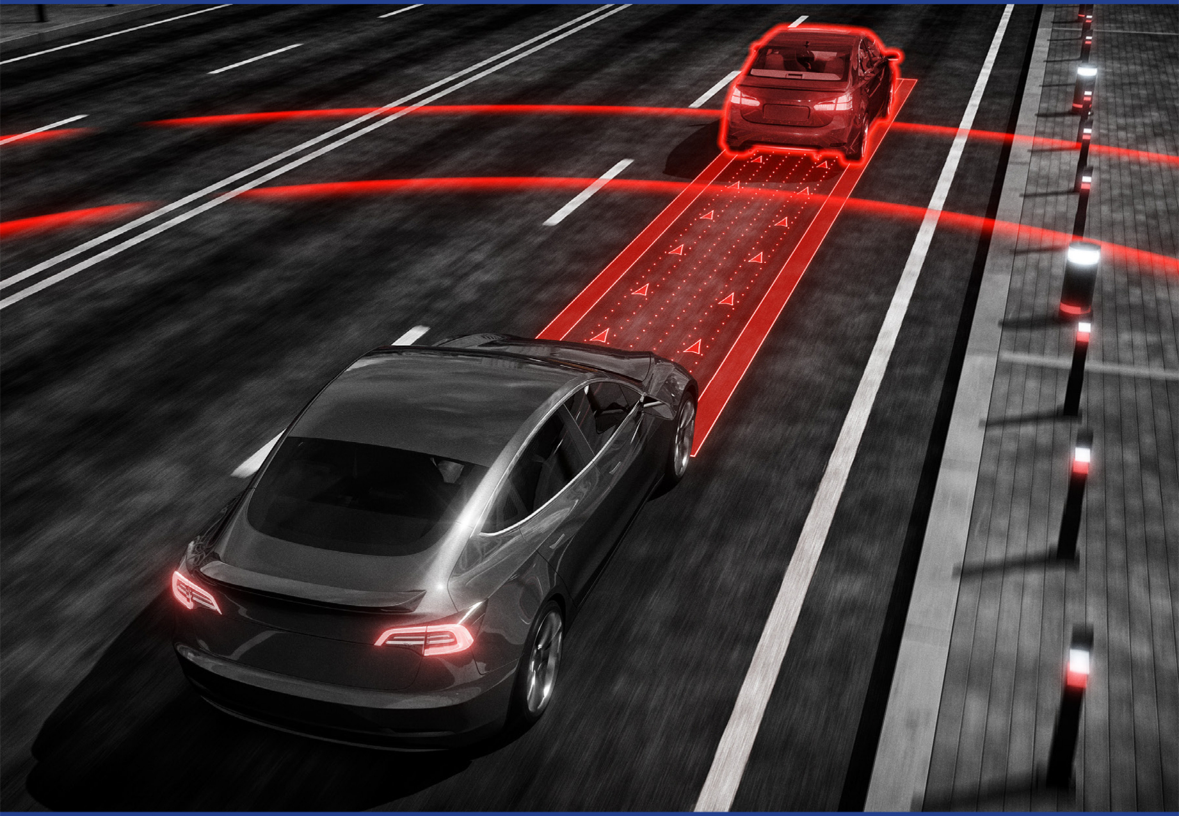
Driving Automation

A Human Factors Perspective



Mark S. Young
Neville A. Stanton

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Driving Automation

The technology behind self-driving cars is being heavily promulgated as the solution to a variety of transport problems including safety, congestion, and impact on the environment. This text examines the key role that human factors plays in driving forward future vehicle automation in a way that realizes the benefits while avoiding the pitfalls.

Driving Automation: A Human Factors Perspective addresses a range of issues related to vehicle automation beyond the 'can we' to 'how should we'. It covers important topics including mental workload and malleable attentional resources theory, effects of automation on driver performance, in-vehicle interface design, driver monitoring, eco-driving, responses to automation failure, and human-centred automation.

The text will be useful for graduate students and professionals in diverse areas such as ergonomics/human factors, automobile engineering, industrial engineering, mechanical engineering, and health and safety.

The Human Factors of Simulation and Assessment Series

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Ongoing advances in lower-cost technologies are supporting a substantive growth worldwide in the use of simulation and naturalistic performance assessment methods for research, training and operational purposes in domains such as road, rail, aviation, mining and healthcare. However, this has not been accompanied by a similar growth in the expertise required to develop and use such systems for evaluating human performance. Whether for research or practitioner purposes, many of the challenges in assessing operator performance, both using simulation and in natural environments, are common. What performance measures should be used, what technology can support the collection of these measures across the different designs, how can other methods and performance measures be integrated to complement objective data, how should behaviours be coded and the performance standards measured and defined? How can these approaches be used to support product development and training, and how can performance within these complex systems be validated? This series addresses a shortfall in knowledge and expertise by providing a unique and dedicated forum for researchers and experienced users of simulation and field-based assessment methods to share practical experiences and knowledge in sufficient depth to facilitate delivery of practical guidance.

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For my Dad, who always drove.

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Preface

Predicting the future is a dangerous game; fans of science fiction affectionately chuckle at optimistic visions in movies such as Back to the Future (specifically, part two of the trilogy). Released in 1989, the movie transports Marty McFly and Doc Emmett Brown forward in time to 21st October 2015, where we are blessed with nuclear fusion-powered flying cars.

That date has long passed and we are still waiting for our flying cars. Ironically, if we go further back in time, we stumble across another vision of the future that may yet prove to be more prophetic. In 1953, Isaac Asimov's short story Sally[1] was published. Set in 2057, the eponymous Sally is an 'automatobile', a fully autonomous vehicle with her own intelligence and, even, personality (albeit, as it turns out, slightly malevolent). First introduced in 2015 (there is that year again), automatobiles were originally made to serve the less able and the privileged (a theme echoed in Chapter 8 of this book – except the privileged bit). But by the time of the story they are the only vehicles on the road, thanks to the fact that they are patently safer than the 'hand-driven' cars.

Granted, the 2015 prediction now looks mildly optimistic – but only mildly so, as that was the year when the first fully driverless trip took place on public roads, to the benefit of a blind passenger. Meanwhile, component technologies that automate sub-tasks of driving became widely available around the same time (think adaptive cruise control, lane-keeping assist, and automatic emergency braking). Come 2045, when Sally herself was built, the commonplace sight of autonomous cars on our roads is a highly plausible scenario.

We realise the hypocrisy in that last sentence as we too, now, slip into the game of predicting the future. But we console ourselves in the company of other commentators, who variously anticipate self-driving technology to be on the market in anything from a few years to a few decades (see Chapter 1). And, to be honest, we have played the game before. Back in 1996, in the early days of our research together in this field, one of our first papers on the topic (Young & Stanton, 1997) quoted a press piece of the time which anticipated a concept vehicle of 100 years hence:

> …designers and engineers have combined forces to come up with the car they envisage we will be driving 100 years from now, "Concept 2096."

> Concept 2096 is like no other car we know – it has no wheels (it moves on a moving rubber base); it has no gasoline (it runs on electrical power beamed to it from a satellite); and it has no windows (due to its most notable distinction – it has no driver, only passengers). An onboard computer receives and processes navigation information – the car drives itself.
>
> (Young & Stanton, 1997, p. 325).

At that time, we were concerned with the effects of adaptive cruise control and lane centring – the early progenitors of vehicle automation – on driver mental workload and performance (see Chapters 3–7). Since then, we have spent a lot of time examining the human factors of in-car technology – what has, over the years, variously been called in-vehicle information systems or advanced driver assistance systems (though we discuss the nuances of such terminology in Chapter 1). In keeping with shifts in global priorities, this interest migrated towards using the technology to support independent mobility for older drivers (Chapter 8) as well as encouraging more eco-driving styles (Chapter 9). The common thread throughout all of this work is the human-centred application of automation to optimise driver performance.

This book represents a digest of the research that we have been involved with during that time, updated to incorporate the latest human factors literature. You will find at the end of each chapter a list of key references which form the source material for that chapter. Although some of this research was conducted several years ago now, we have brought it together in this book because the issues are still very current – if anything, even more so with the push towards connected and autonomous vehicles. As we have already noted above, self-driving cars may be just around the metaphorical corner, or they may be much further away yet (depending on who you talk to). But nobody can argue that we are entering a period of transition between humans in control and automation in control. The key question is about the duration of that transition, and what happens to the person in the driving seat in the meantime?

Despite the excitement surrounding the technology, it is crucial that we get the human factors right, lest we bump into similar problems as encountered with automation in aviation (see Chapter 2). We have already seen early signs of this going wrong with some high-profile accidents involving automated vehicles (also covered in Chapter 2). It would not be too much of a spoiler for the book ahead to suggest that these accidents result from a mismatch of expectations about the relative capabilities of human and machine.

Driving automation will undoubtedly result in benefits for safety, performance, and the environment – eventually. And one day, the technology will be ready to fully assume control of our cars and we can sit back as genuine passengers. Our reckoning is more in line with that of Asimov, as we believe we will have to wait several years – possibly even decades – for that day to arrive. Until then, humans and automation will increasingly share control of the vehicle. And as long as we require a person to maintain some level of control in the car, we need to design the system around them.

In the final chapter of this book, we share our thoughts about how we can do that, working towards a philosophy of human-centred design for automation. The roots of this go back to that early paper (Young & Stanton, 1997), which took inspiration from one of the foremost thinkers in automation human factors, the late Professor Raja Parasuraman:

> As Parasuraman (1987) asked, given the impact of automation on attention and the consequent effects on the human ability to monitor failures, when it comes to technology, it is very often not a case of whether we can, but whether we should. We are adapting this question to ask how we might, given that we probably will.
>
> (Young & Stanton, 1997, p. 335).

And coincidentally, this philosophy is echoed in another classic vintage sci-fi movie, Jurassic Park (1993 – based, of course on the 1990 bestseller by Michael Crichton), in which the mathematician character Dr Ian Malcolm comments in exasperation about the resurrection of the dinosaurs by saying, '…scientists were so preoccupied with whether or not they could that they didn't stop to think if they should'. We know much less about genetic engineering than we do about human factors engineering, but it comforts us to presume that the dinosaurs went the same way as the flying cars in Back to the Future Part II.

NOTE

1. I am grateful to Professor Nick Reed for introducing me to this story – and I highly recommend it. (MSY)

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Glossary

Term	Meaning	Definition
ABS	Anti-lock Braking System	A system designed to stop a car from skidding when braking sharply by automatically applying rapid cadence braking. See also Electronic Stability Control (ESC).
ACC	Adaptive Cruise Control	System that attempts to maintain the vehicle at a driver selected target speed following distance, using sensors and automation to regulate vehicle speed.*
ALKS	Automated Lane Keeping System	Hardware and software for low-speed application which is activated by the driver and which keeps the vehicle within its lane for travelling speed of 60 km/h or less by controlling the lateral and longitudinal movements of the vehicle for extended periods without the need for further driver input.*
AEB	Automatic Emergency Braking	Vehicle system that uses sensors and computer processing to detect when the ego vehicle could collide with an object in its path and applies the brakes automatically attempting to mitigate or avoid the collision, even if the driver takes no action.*
CWA	Cognitive Work Analysis	A structured framework for considering the driver's information requirements, taking account of the environment within which the task takes place and the effects of constraints imposed on the system's ability to perform its purpose.[a]
CRM	Crew Resource Management	Using all the available resources – information, equipment, and people – to achieve safe and efficient operations.[b]
EID	Ecological Interface Design	A theoretical framework for designing interfaces for complex sociotechnical systems, based on three principles: the capability for direct manipulation, the perceptual forms map uniquely onto work domain constraints, and the interface content represents all of the information identified by a model of the work domain.[c] See also Cognitive Work Analysis (CWA).

(Continued)

Term	*Meaning*	*Definition*
ESC	Electronic Stability Control	Vehicle system that continuously monitors steering and vehicle direction and compares intended direction to the vehicle's actual direction and intervenes by applying the brakes independently to each of the wheels to correct loss of control much faster than a typical human driver.* ESC incorporates anti-lock brakes (ABS).
LC	Lane Centring	Vehicle system that uses cameras or other inputs and automated controls to help the vehicle stay in the centre of the driven lane.*
MART	Malleable Attentional Resources Theory	Theoretical model in which the size of attentional resource pools varies according to the level of task demands imposed on the operator.[d]
MWL	Mental Workload	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.[e]
NASA-TLX	NASA Task Load index	A multidimensional rating scale designed to obtain subjective workload estimates from operators.[f]
TLX		See NASA-TLX

NB: Terms with an asterisk (*) are drawn from the British Standards Institution Connected and Autonomous Vehicles Vocabulary, version 4.0 (BSI Flex 1890 v4.0:2022-03). Available at: https://www.bsigroup.com/en-GB/CAV/cav-vocabulary/ (accessed 12 May 2022). Other sources are noted by superscript letters as follows:

[a] Stanton, Salmon, Walker & Jenkins (2017). See Chapter 9.
[b] Lauber (1984), cited in Flin et al. (2008). See Chapter 10.
[c] Vicente (2002). See Chapter 9.
[d] Young & Stanton (2002a).
[e] Young & Stanton (2001a). See Chapter 3.
[f] Hart & Staveland (1988).

Stage 1

Setting out

Chapter 1

Context

OVERVIEW

As we set out on our journey with this book, the first leg takes us through a potted history of automobile automation, establishes a number of definitions associated with such technology, and reviews a variety of classifications of automation from the human factors perspective. We consider where driving automation has been, where we currently stand (at the time of writing, at least), and where it might be going in the near- and long-term future. This gives us a basis to consider various contemporary definitions and classifications of automation, from classical approaches to more recent taxonomies. But more than anything, this chapter sets out our stall that the science of human factors is, and will be, critical in determining the success and safety of automated driving in the protracted transitional period as drivers start to let go of control. We stand on a tipping point with driving automation, whereby for the first time drivers will be able to legitimately 'switch off' from the driving task (albeit in limited circumstances). And until we reach full automation – which may be several decades away yet – we must put those drivers at the centre of our thinking around automated driving.

PRELUDE

Paris, France, in the year 1498. Louis XII has just succeeded his father, King Charles VII, to the French throne. Whilst this was literally a crowning moment for the new King, it also turned out to be career-defining for his loyal supporter, Archbishop Georges d'Amboise, who was made cardinal and prime minister on his friend's accession.

The success of Cardinal d'Amboise's administration is well-documented and, such was the confidence held in him by King Louis XII, there originated a satirical phrase in France around this time: 'laissez faire à George', or 'let George do it'.

Fast forward to mid-20th century northern England and the heyday of George Formby, the ukulele-playing star, writer and producer of more than

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20 films during the 1930s and 1940s, including the wartime classic 'Let George do it' in 1940. Formby's accidental war hero holds a mirror to the popular usage of the phrase at the time, as this was an attitude to be stamped out during the war years – you had to do 'it' yourself, or nobody else would do it.

Soon afterwards, though, when autopilots first became available in aircraft, the phrase was re-adopted in its original sense, since the autopilot was the only 'George' that you could legitimately delegate to. Using the autopilot therefore became 'letting George do it', and the autopilot itself came to be known as George.

This 'origin story' of automation may or may not be apocryphal, in whole or in part; theories abound on the internet about the source of the phrase 'let George do it' and why autopilots are colloquially known as 'George'. But what cannot be argued is the pervasiveness of automation in our modern, everyday lives. While George may have started out in aviation, automation is now commonplace in marine, rail, and space transportation. And, of course, automation is familiar on our roads. But up to now it has mostly relieved drivers of physical tasks, such as gear changing or rudimentary speed control. The latest generation of systems hitting the market takes this up a level by operating at a psychological level, taking over some decision-making elements of driving. We are on the cusp of a revolution in automotive technology as the balance of control is shifting towards the automation. In both literal and metaphorical terms, George has one hand on the steering wheel.

Such technology is heavily promulgated as the solution to a wide variety of transport problems including safety, congestion, and environmental impact. There is undoubtedly merit in this. But the focus on the technological push neglects the human impact, with potentially disastrous consequences. It may seem paradoxical to be concerned about the effects of automation on human performance – surely there is no human performance left to worry about, if we have automated the task? Is that not the point of automation (the engineers might say), to eradicate the unreliable 'human factor' from the equation?

But although we are gradually delegating more driving tasks to the vehicle, that level of full automation – where we can completely let go of human control or supervision, and completely trust in George – could still be several years away yet. Yes, there are several makes and models of vehicle available on today's market capable of controlling their own speed, keeping themselves in lane, and trying to avoid collisions. However, there is a fundamental difference between individual systems that, together, look like a fully automated car, and the technological sophistication needed to be truly driverless. Most of the current generation of so-called self-driving cars still require a human in the driving seat to watch over the automation and to deal with those scenarios that it is not yet capable of – or, more crucially, to take over should things go wrong.

In this protracted transitional period, then, we have to consider the role of the human, who faces fundamental changes in their familiar driving task. This is where the science of human factors comes in, for there is a wealth of knowledge in the discipline about the capabilities and limitations of people. In particular, we know that humans are particularly ill-suited to supervising automation in this way, for reasons we shall see in the chapters that follow. A key concern in this book is for mental workload, particularly the underload that occurs when playing such a passive role. But we also know that, when designed appropriately, machines can work very well with people, providing support in situations where human performance might need it. If the benefits of automation are to be realised without introducing a host of new problems, then it is essential that we put the human at the centre of these developments. It is less a case of finding a place for the human to fit in with this brave new world, but more about fitting the automation around the human. We will consider such notions further towards the end of this book.

Before we get there, though, it is worth spending some time establishing the context of what we are discussing. We have just hinted at the history and future of automotive automation, so we begin this chapter by tracing a more detailed technological timeline from the past, through present developments, to anticipate what we might expect (and when) in the future. Then we set out a consistent language for the book, by considering published definitions and terminologies associated with vehicle automation. Finally, we complete the foundation for the book by reviewing the considerable human factors literature aimed at describing and categorising levels of automation.

TIMELINE

Past

We could start by considering the 'auto-mobile' itself as a holistic example of automation. In 1896, England saw its first horseless carriage hit the roads, in the form of the Daimler Wagonette. During the course of the 20th century and into the 21st, the automobile has grown into one of the most technologically advanced mass market commodities available.

Of course, vehicle automation is far from being a new phenomenon (Young, 2013). Some readers may remember using a manual choke to start their car in the morning; the advent of automatic chokes has made this task all but invisible. More conspicuously, automatic gearboxes have been around since the 1940s, while conventional cruise control was invented in the 1950s. Towards the end of the millennium, cruise control evolved into adaptive cruise control (ACC). First introduced in consumer cars in 1995 (de Winter et al., 2014), ACC not only maintains a set speed (as with conventional cruise control) but also typically uses sensors (radar and/or lidar) to detect slower leading vehicles and adjust speed to maintain a consistent headway (see Richardson et al., 1997, for technical details). Whilst early versions of ACC had limited braking authority, being designed to work only at cruising speeds, in 2007 a 'stop-and-go' capability was introduced to ACC, which could bring your car to a standstill (thus enabling the use of ACC in traffic queues; see Stanton et al., 2011). These kinds of systems are often referred to as 'comfort and convenience' features for drivers (e.g., Richardson et al., 1997).

Meanwhile, other devices throughout history have been more explicitly aimed at improving safety. The early 1970s saw the introduction of anti-lock braking systems (ABS), which use rapid cadence braking to prevent the wheels locking up under extreme braking. By a similar token, electronic stability control (ESC), available since the mid-1990s, detects skids in cornering manoeuvres and applies braking (or power) individually to the four wheels in order to correct the skid and maintain control. Whilst ABS and ESC both apply a level of rapid corrective inputs that would be impossible for a human driver to achieve, systems soon began to influence vehicle control at a much more conscious level.

The first decade of the 21st century saw particular advancement in active safety systems – those which are designed to prevent, or mitigate the consequences of, collisions by taking automatic control of the vehicle in some way (as opposed to passive safety, such as seatbelts and airbags, which prevent or mitigate the consequences of injuries resulting from a collision). Such advanced safety features as emerged at that time include forward collision warning systems, blind spot monitoring, and lane departure warning systems (Jenkins et al., 2007).

Forward collision warning systems, introduced in 2006, take ACC a step further by using similar radar systems to detect an impending collision with a vehicle in front, and alerting the driver to it. Moving from warnings to actual vehicle control, the following year saw the extension of forward collision warnings to include automatic braking. By 2010, several manufacturers were offering what is now commonly known as automatic emergency braking (AEB), the system that detects a potential collision ahead and automatically brakes to mitigate or avoid the collision, even if the driver takes no action (Banks & Stanton, 2015). Although most of these systems had limited braking authority (as with ACC), some actually guaranteed that they would prevent a collision at low speeds. These systems would still brake at higher speeds, so mitigating the consequences of a crash, but they could not guarantee that the collision would be avoided.

Turning to lateral control, lane departure warning systems use on-board cameras and image processing technology to detect lane markings, and provide warnings to the driver if the vehicle is crossing one of these lines. The warnings vary between manufacturers, but are usually either auditory or haptic (e.g., vibrating the steering wheel or seat to provide a 'virtual rumble strip'). Typically, the warning will be cancelled if the driver is using the turn signals to indicate an intended lane change. Similarly, blind spot monitoring systems, introduced in 2005, use cameras to detect vehicles in the driver's blind spot when a turn has been indicated, and alert the driver usually with a visual warning in the relevant side mirror. The logical next step from lane departure warnings was to use the data gathered from the camera systems to control the vehicle instead of providing warnings; such lane-keeping assist systems have been available since around 2006. Many of these do not actually assume full steering control of the vehicle, but instead provide some haptic feedback on the steering wheel (e.g., increased resistance) to gently nudge the driver back into lane.

In the 1990s and 2000s, the trend was turning from systems that warned the driver, or at most took control of low-level driving tasks (i.e., preventing skids), towards those that actively intervened in more conspicuous elements of driving (Bishop, 2020). It is probably no coincidence that these decades also saw an increase in research activity directed at automotive human factors (Young et al., 2015), as automation started to impinge on those tasks that were once the preserve of the human driver (Banks et al., 2014; Stanton et al., 2001; Walker et al., 2001).

As far as driverless cars are concerned, the concept was first introduced by General Motors at the 1939 World's Fair (Bishop, 2020; Reed & Sellick, 2017). Further efforts in the 1950s and 1960s to develop automated road transport systems depended on electric cables embedded in the road infrastructure which, whilst successful, was a costly constraint that ultimately led to the demise of this particular approach and the move towards automated vehicles instead (Merat et al., 2012; Reed & Sellick, 2017).

Nevertheless, the research interest in automated driving did not wane, and indeed accelerated from the 1980s onwards (see e.g., Hancock et al., 2019; Noy et al., 2018). In both Europe and the US, major projects attracted significant funding to develop demonstrator systems, several of which proved successful. A prominent example of an EU-funded project was PROMETHEUS, which culminated in research trials of automated vehicles without human intervention on open roads. More recently, the HUMANIST[1] virtual centre of excellence established in 2007 addresses a number of human factors concerns with vehicle automation. Meanwhile, in the US the stimulus came from the Departments of Transportation and Defense, most notably with the Defense Advanced Research Projects Agency (DARPA) 'grand challenges' of the early 21st century (for more background on these, and other, developments, see Bishop, 2020; Reed & Sellick, 2017). The 2007 DARPA urban challenge saw driverless vehicles operating alongside human-driven vehicles on residential streets, handling various scenarios and manoeuvres (Bishop, 2020). Then, in 2010, Google entered the fray.

Present

Innovations in sensor technology and advances in computing power enabled Google to reveal its self-driving car project to the world in October 2010 (Reed & Sellick, 2017). Over the decade, this programme amassed millions of miles of on-road testing in four US states, and in 2016 it was spun out into the development company Waymo. In parallel, over the latter half of the decade Uber has conducted testing of its automated driving system in three US states[2] as well as in Toronto, Canada. Waymo and Uber are not the only companies eager to get in on the act either; as of March 2018, 52 companies possessed permits to test automated vehicles on the roads of California alone (Hancock et al., 2019). Similar trials were approved in China in late 2019, for self-driving taxis to carry passengers in Shanghai – albeit under limited circumstances and with a safety driver on board.

With these commercial projects perhaps acting as a catalyst, research and development into automated vehicles gathered a huge amount of momentum in the 2010s. Since 2014, the UK government has invested millions of pounds and has established a cross-governmental body, the Centre for Connected and Autonomous Vehicles (CCAV[3]), with the aim of coordinating this research and positioning the UK as a world leader in testing and development of automated vehicle technology (Jones & Holden, 2020; Reed & Sellick, 2017). Some of the more high-profile and large-scale projects funded under this initiative saw driverless prototype vehicles being tested on the streets of four UK cities and towns (Bristol, Coventry, Greenwich, and Milton Keynes; see Reed & Sellick, 2017, for more details).

One of the biggest achievements to date happened on 28 November 2019 under the HumanDrive[4] project, with the successful completion of the UK's longest and most complex autonomous road journey. A Nissan Leaf, fitted with GPS, lidar, radar, and camera technology, drove itself (with two engineers on board, one acting as a safety driver) 230 miles from Cranfield in Bedfordshire to Sunderland, Tyne and Wear, taking in a range of road environments from rural to highway.

Meanwhile, back in the consumer marketplace, vehicle technology was becoming more advanced and more widely available. In 2011, Ford Motor Company released its latest Focus model in the UK with a 'driver assistance pack' offered as an all-in-one package option. The pack included a range of assistance technologies seen largely on prestige models over the previous few years (such as parking assist, blind spot monitoring, and low-speed AEB) but now in a car targeted at the mass market.

Subsequent advances in camera technology allowed detection and recognition of hazards and obstacles to enhance the capability of collision warning and avoidance systems. Some cars now on the roads can actually recognise an object as a pedestrian, classify it as a hazard, and brake to avoid a collision. When taking into account the myriad ancillary controls that are now routinely automated (such as lights or windscreen wipers), it is true to say that most current vehicles have some level of automation (Banks et al., 2014; Hancock, 2019).

Moving towards the automation of everyday driving, it is now relatively commonplace to see features that relieve the driver of some fundamental aspects of the driving task. Recent years have seen extensions to the functionality of ACC, so that it can be used in a wider range of traffic and road scenarios, as well as lane centring (LC) or lane-keeping assist systems (which use cameras or other sensors to, respectively, keep the vehicle in the centre of its lane or away from the lane edges). Such is their market penetration, in fact, that in 2018 the European New Car Assessment Programme (Euro NCAP[5]) started including ACC, LC, and speed assist in its safety tests. Moreover, from 2022 in the EU, all new cars are mandated[6] to include a range of automated systems as standard in the interests of safety, including AEB, driver attention monitoring, intelligent speed adaptation, and lane-keeping assist systems.

Although the technologies are function-specific, more recent applications have combined the longitudinal and lateral control functions into a 'highly automated vehicle' (Banks & Stanton, 2016; de Winter et al., 2014; Eriksson & Stanton, 2017b). Perhaps the most prominent example at the moment is Tesla's Autopilot, introduced in 2016, although several other major manufacturers (such as BMW, General Motors, and Mercedes) also offer similarly branded packages.

As it stands, though, the 'highly automated' moniker is a misnomer (Eriksson & Stanton, 2017b). Although these cars may, on the face of it, appear to be driving themselves, the truly driverless car is not yet commercially available (cf. Teoh, 2020). All of the systems currently on the market are limited in some sense (typically by the type of road or environment), and all still rely on a human in the driving seat being ultimately responsible for monitoring the technology as well as the road, and taking action, if appropriate (Banks & Stanton, 2016; de Winter et al., 2014; Ulahannan et al., 2020).

Nevertheless, the very latest developments may see a step change in automation on the roads. In 2020, the UK government ran a consultation (CCAV, 2020, 2021) on the introduction of automated lane keeping systems (ALKS), anticipated to hit the market in the early 2020s. Innocuous though the system sounds, ALKS is a traffic jam chauffeur technology that controls lateral and longitudinal movement without driver input – and, crucially, without the need for human supervision or monitoring (albeit still under a fixed set of circumstances and at limited speeds up to 60 km/h). ALKS therefore presents, for the first time ever, the possibility for drivers to hand over full responsibility of driving to the vehicle. ALKS, then, paves the way for a fully automated future.

Future

Having discussed where we are in terms of vehicle automation, we move into the realms of uncertainty by trying to anticipate where we are going. It is worth prefacing this section with a heavy dose of caveats, as the market and the state of technological art changes so rapidly. The phrase 'at the time of writing' has never applied more.

We can illustrate this by going 'back to the future' and reviewing earlier predictions in this field. Around the turn of the 21st century, our colleague Guy Walker led a well-researched paper on the future of vehicle technology, based on a survey of seven motor industry professionals from five major manufacturers (Walker et al., 2001). Looking at the results in hindsight, many of the predictions were not far off reality, with collision avoidance and ACC amongst the automated systems that it was thought would be implemented by 2015. Nevertheless, the paper posited two hypothetical scenarios for a 2015 test drive, and even the pessimistic version presumed a level of autonomy that we have not yet reached.

More recently, Merat et al. (2014) wrote about three major manufacturers promising self-driving cars on sale by 2020. Now, whilst it could be argued that the so-called 'highly automated' offerings discussed earlier meet this promise, the limitations of those systems already noted mean that they are far from truly self-driving. Even the most highly automated vehicles in development at the moment (including Waymo's self-driving car) are constrained to specified roads (Reed & Sellick, 2017).

Indeed, the next milestone will only be another step towards that highly automated driving, in which the driver hands over responsibility to the vehicle, at least in certain defined circumstances (de Winter et al., 2014). We have just mentioned the prospect of ALKS in the very near future, and manufacturers are again lining up to offer this level of automation in the 2020s (Bishop, 2020). Given the imminence of these developments, it seems reasonable to assume that we will be handing over full control to the vehicle, albeit perhaps just on highways, within the decade (Kyriakidis et al., 2019; Stanton et al., 2021; Thatcham Research, 2019).

But what of full automation – the notion that a vehicle can negotiate any end-to-end journey, without any need for human supervision or intervention, in any road or traffic environment? Despite optimistic claims in the industry (Jones & Holden, 2020; Thatcham Research, 2019) – as well as public expectation (Kyriakidis et al., 2019) – that this 'autopia' (cf. Hancock et al., 1996; Young & Stanton, 2000) will soon be on our roads, the consensus seems to be that it will be many years, perhaps decades, before that is realised to any great extent (Brooks, 2017; Hancock, 2019). Researchers (Noy et al., 2018) and industry experts (Williams, 2019) alike believe we will not see full automation on the roads until the second half of the 21st century, while earlier predictions cited by de Winter et al. (2014) suggest it may even be perpetually out of reach. That said, the pessimism is predicated on the assumption that we are referring to private cars; there may well be earlier and wider deployment of fully automated vehicles for commercial applications such as public transport, taxis, goods deliveries, and agriculture (Brooks, 2017; House of Lords, 2017; Kyriakidis et al., 2019; Stanton et al., 2020; Veoneer, 2020).

Nevertheless, the more realistic medium-term future for private motorists will likely see a gradual evolution, rather than revolution (cf. Veoneer, 2020), of current technologies becoming more advanced and more widespread through the 2030s. It certainly seems that their penetration will peak in the latter half of that decade; moderate projections from the UK government (Transport Systems Catapult, 2017) identify a 25% global market share for automated vehicles by 2035, while their more optimistic case is for 84% (the UK government separately estimates[7] that the automated vehicle market will be worth £52bn by 2035). Similarly, Noy et al. (2018) anticipated a 75%

market share by 2040, although more pessimistic evidence presented by de Winter et al. (2014) suggests the figure will never reach 50%. For many years to come, then, we will have a mix of manually driven and (partially) automated cars on the roads (Brooks, 2017; Mueller et al., 2021), although the balance of numbers could tip in favour of the automated within the 2020s (Hancock, 2019).

And that is where the human factors problems will lie – apparently for some considerable time yet. Indeed, getting the technology right for user acceptance has been cited as a key reason for the delay in implementing it (Noy et al., 2018). While the technology has been developing apace, this has not been matched by the integration of human factors into these systems (Hancock, 2019). We are less worried about the endgame of full automation, because humans are cut out of the driving loop entirely by then. However, we are facing a prolonged interim period in which partial automation of driving gets gradually smarter, yet still relies on a human to be in some level of control of the vehicle. That is a situation which we know will cause problems (Banks, Eriksson et al., 2018; Banks, Plant et al., 2018; Brooks, 2017), and we will learn more about these in subsequent chapters of this book.

DEFINITIONS

Having alluded to various different types and levels of automation that have been, and will become, available, we should really define what we mean when we refer to 'automation'. Parasuraman & Riley (1997) defined *automation* as 'the execution by a machine agent (usually a computer) of a function that was previously carried out by a human' (p. 231). (Where Parasuraman said 'usually' a computer, we should probably rephrase that in this day and age to read 'almost always' a computer – since there will inevitably be a microprocessor or two at the heart of any such technological system that you can think of.)

But just because a computer is taking over a task from a person, this does not necessarily mean the computer is smart. Hancock (2017a, 2019) went further to distinguish automated from *autonomous*, where 'automated systems are those designed to accomplish a specific set of largely deterministic steps, most often in a repeating pattern, in order to achieve one of an envisaged and limited set of pre-defined outcomes', while 'autonomous systems are generative and learn, evolve and permanently change their functional capacities as a result of the input of operational and contextual information. Their actions necessarily become more indeterminate across time' (Hancock, 2019; p. 481). In other words, in an automated system, the same input will always lead to the same response, whereas in an autonomous system, that is not necessarily true. More specifically, the responses of an automated system are limited to those for which it has been pre-programmed; those of an autonomous system, on the other hand, are not so constrained, as it learns and changes independently over time – sometimes unpredictably (de Visser et al., 2018; Endsley, 2015).

As Hancock (2017a, 2019) notes, whilst there are many examples of automated vehicles available at the moment, by his definition we do not currently have autonomous vehicles on the roads (although we may not be far off, given developments from those such as Uber and Waymo). Indeed, in its standard on driving automation systems, the Society of Automotive Engineers (SAE, 2018) suggests that the terms 'autonomous' and 'self-driving' have been inconsistently and confusingly applied, and similarly recommend that we refer to automated *driving* rather than autonomous *vehicles*, since it is the task that is being automated (Stanton et al., 1997).

This confusion is not just a matter of semantic pedantry. Popular usage of terms such as 'autonomous vehicle' or 'self-driving car' and brand names such as 'autopilot' are usually laden with overpromise and have unrealistically raised consumers' expectations of what these vehicles are capable of. Names that suggest full automation, such as 'autopilot', are associated with the highest likelihood that drivers believe they can safely undertake non-driving tasks (even passing the Turing test; Stanton et al., 2020), whereas terms such as 'assist' or 'copilot' are less likely to be perceived as a high level of automation (Teoh, 2020). One industry survey found that 71% of motorists wrongly believed that autonomous vehicles were already available (Jones & Holden, 2020), while another revealed that many drivers misunderstand not just how to use automated driving systems but also the limits of their capabilities (FIA, 2020). In turn, these perceptions can lead to an inappropriate understanding of what behaviours are safe while using the system (Teoh, 2020); the same survey (Jones & Holden, 2020) found that 10% of drivers would consider taking a nap when a driver assistance system is activated. One need not look far on YouTube for plentiful evidence of these kinds of behaviours, despite all current systems requiring drivers to remain attentive and engaged with the driving task. In response, Euro NCAP now bases its safety tests[8] for driver assistance technologies on whether the support provided by the automation matches up to the perceptions that a driver might hold based on the system's name. Its 2020 tests[9] found that Tesla's Autopilot performed very well from a technical perspective, but quite poorly in terms of its interaction with the driver. According to Euro NCAP, this was partly due to the name 'autopilot' and its associated promotional material that implied full automation (even though the driver's handbook correctly set out the system's limitations).

From the human factors perspective, we are not just concerned with those systems that take over the entire driving task, whether or not that is limited to specific circumstances. Driving is a highly complex activity involving perceptual, cognitive, and motor skills at many levels (Chi et al., 2019). Basic vehicle control, such as steering and acceleration/braking, are considered as 'operational' tasks; hazard avoidance and car-following are examples of 'tactical' tasks, while 'strategic' tasks include route navigation (Carsten et al., 2012; Ranney, 1994). These levels also map onto skill development, as operational tasks are largely automatic (cognitively speaking, now), while more decision-making and conscious thought is needed when stepping up through tactical and strategic levels (Ranney, 1994; Stanton & Marsden, 1996). It is no coincidence that the evolution of driving automation systems has been steadily progressing up these levels (cf. Sheridan, 2017).

There are distinct echoes of this hierarchy in SAE's (2018) definition of the *dynamic driving task*, which includes all of the operational and tactical functions required to operate a vehicle in on-road traffic (such as longitudinal and lateral control, object and event detection and response, and manoeuvring). Any or all of these can be automated (for example, with ACC, LC, or AEB). Such systems have historically been collectively known as *advanced driver assistance systems* (ADAS), although some suggest that term is now out of favour and instead offer 'driver support features' as a substitute for ADAS (Fisher et al., 2020). Either of these terms would seem to suffice, though, since such systems purport to both assist and support the driver.

Victor et al. (2018) took a stronger view in suggesting that anything but full automation is merely driver assistance. Thatcham Research (2019) made a similar distinction between assisted and automated driving, whereby assisted is very much about supporting a driver who remains in charge if not in control (and hence cannot engage in non-driving tasks), while in automated driving the vehicle takes full control and responsibility. Automated driving therefore means the driver can engage in secondary tasks, although they may still need to remain available for the transition of control as necessary.

What this all comes down to, of course, is the fact that the limitations of present-day technologies mean they still rely on a human sitting in the driving seat, tasked with monitoring the system and picking up any loose ends that it cannot deal with. Thus, we should distinguish full automation (i.e., completely unsupervised) from a *highly automated vehicle*, in which the driver might still need to take over (de Winter et al., 2014) or otherwise monitor the system in some way (cf. Merat et al., 2012; Victor et al., 2018).

Many industry definitions of *automated driving systems* (ADS) echo that of the highly automated vehicle, explicitly acknowledging that the system specification may be limited to certain scenarios or conditions – what the industry calls its *operational design domain* (SAE, 2018). In the UK's Automated and Electric Vehicles Act 2018[10], automated vehicles are those which are '...designed or adapted to be capable, *in at least some circumstances or situations* [emphasis added], of safely driving themselves', where 'driving themselves' means they are not being controlled, and do not need to be monitored, by a person. Similarly, the SAE (2018) defines an ADS as one that is capable of performing the entire driving task on a sustained basis, regardless of whether it is limited to a specific operational design domain. This is distinct from a (confusingly named) *driving automation system*, which is the generic term for any system capable of performing part or all of the driving task (SAE, 2018). Clearly, these definitions overlap[11], so we can imagine them as subsets of each other (see Figure 1.1), where driving automation is the superset (automates part or all of the driving task

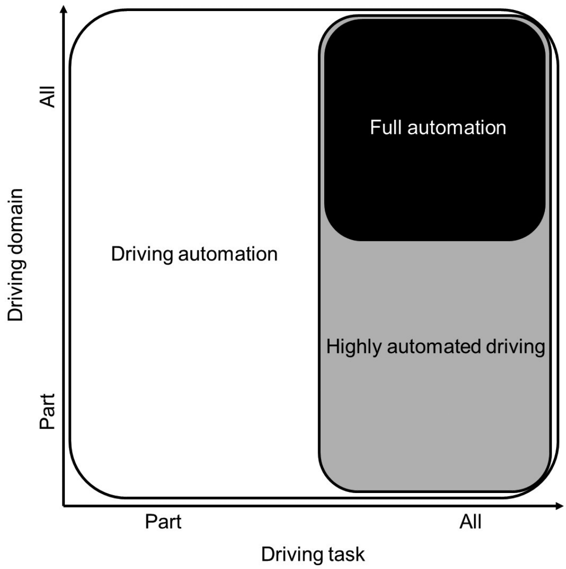

Figure 1.1 Conceptual representation of the different definitions of driving automation. 'Driving automation' can automate part or all of the driving task in part or all of the domain; '(highly) automated driving' automates all of the driving task in part or all of the domain; 'full automation' automates all of the driving task in all domains.

in limited or all situations), encompassing the subset of (highly) automated driving (automates all of the driving task in limited or all conditions), which itself encompasses full automation (automates all of the driving task all of the time).

But automation is automation, even if it is of only some aspects of the driving task, because they are occurring without driver input (cf. Noy et al., 2018). Since we have been thinking in terms of levels of the driving task, it makes sense to also think in terms of levels of automation.

TAXONOMIES

Classical taxonomies

Classical models of automation design in the human factors literature have focused on task-based divisions of labour. The original and well-known Fitts list, devised in 1951, was intended as a way of deciding how to allocate relevant functions between human and machine by specifying those activities for which human skills surpass those of machines, and vice-versa (Table 1.1).

Straightforward as it appears, this approach is rather coarse and has not been without criticism over the years. Schutte (2017) proposed that we should

Table 1.1 The original Fitts list (1951; based on that cited in Hancock, 2019)

Humans are better at	*Machines are better at*
Detecting small amount of visual or acoustic energy	Responding quickly to control signals, and applying great force smoothly and precisely
Perceiving patterns of light or sound	Performing repetitive, routine tasks
Improvising and using flexible procedures	Handling highly complex operations, i.e., doing many different things at once
Storing very large amounts of information for long periods and recalling relevant facts at the appropriate time	Storing information briefly and then erasing it completely
Reasoning inductively	Reasoning deductively, including computational ability
Exercising judgement	

think in terms of skills rather than indivisible task units, and share out aspects of tasks in a more collaborative manner. Similarly, Phillips (2018) argued that it oversimplifies the dichotomy between humans and machines (just because a task can be automated, does not necessarily mean that it should be), and questioned its modern relevance in a world which has seen monumental increases in computer processing power, and where machine learning is encroaching on those skills where humans were once dominant. In response, Phillips (2018) proposed a revised version of the Fitts list taking into account these advances (Table 1.2), although clearly this does not address the concern that it is still a dichotomous approach.

Later developments of this approach put forward more subtle taxonomies based on levels of authority. Seminal amongst these is the work of Sheridan & Verplank (1978), who classified the role of humans and computers according to the extent of their relative control of the task. For the human, they can either command (i.e., program the system), plan (consider alternatives), monitor, intervene, or trust (let the computer get on with it). Meanwhile, the computer can either extend the human's abilities (beyond what they can perform unaided), partially relieve the human of a task, backup the human in case of error, or replace the human entirely. Importantly, the first two of these (extending the human's abilities and relieving them of a task) are seen

Table 1.2 Modern-day revised Fitts list (after Phillips, 2018)

Humans are better at	*Machines are better at*
Abstractive reasoning	Deductive reasoning
Exercising judgement and sanity checking	Performing repetitive, routine tasks
Recalling relevant information in an ad-hoc manner	Detecting and responding quickly to small nuances in signals
Invoking morality in decision-making	Storing data and recalling accurately and immediately
Extracting meaning from qualitative information	Identifying trends in quantitative data
Transferring learned knowledge and skills to new tasks through adaptation and flexibility in working methods	Handling multiple operations simultaneously

as human and computer sharing control, while backup and replacement are instances of trading control between the two entities.

But the Sheridan & Verplank (1978) report is probably best known for its hierarchy of ten levels of automation which, as with the Fitts list, was offered as a tool for designers to decide how to allocate resources:

1. Human does the whole job up to the point of turning it over to the computer to implement
2. Computer helps by determining the options
3. Computer helps determine options and suggests one, which human need not follow
4. Computer selects action and human may or may not do it
5. Computer selects action and implements it if human approves
6. Computer selects action, informs human in plenty of time to stop it
7. Computer does whole job and necessarily tells human what it did
8. Computer does whole job and tells human what it did only if human explicitly asks
9. Computer does whole job and tells human what it did if it decides they should be told
10. Computer does whole job if it decides it should be done, and if so tells human, if it decides they should be told

In stepping through the levels, more and more of the task is gradually delegated to the computer (cf. Richards & Stedmon, 2016); the tipping point in terms of the balance between human and computer control is from level 6 upwards (Inagaki, 2003; Inagaki & Sheridan, 2019). Indeed, the landmark of Sheridan & Verplank's (1978) taxonomy was in the recognition that automation is not an all-or-none option, and that by exploiting different levels of automation it is possible to assist the operator rather than replacing them (Kaber & Endsley, 1997; Stanton et al., 2001).

Subsequent to the work of Sheridan & Verplank (1978), Endsley and Kaber (Endsley, 1987; Endsley & Kaber, 1999; Kaber & Endsley, 2004) further refined the levels of automation taxonomy to explicitly include consideration of supervisory control. Endsley & Kaber (1999) proposed another ten-level hierarchy, not dissimilar to Sheridan & Verplank's (1978) version but with a more nuanced division of control around the middle levels:

1. Manual control
2. Action support (system assistance)
3. Batch processing (human selects options and hands over to automation to execute)
4. Shared control (human and automation generate options, human selects, human and automation execute)
5. Decision support (automation generates options, human selects, automation executes)

6. Blended decision-making (automation generates options and executes if human consents, or human can generate alternatives for the automation to execute)
7. Rigid system (automation presents limited options, human selects, automation executes)
8. Automated decision-making (automation selects best options and executes from its list of alternatives)
9. Supervisory control (automation generates, selects and executes options, human intervenes if necessary)
10. Full automation (human out of the loop completely).

Several studies have shown the differing effects of these levels on factors such as mental workload, situation awareness and, ultimately, performance (cf. Endsley, 1987; Endsley & Kaber, 1999), factors that we will explore in more detail in Chapter 2. For now, the most relevant point is the consistent finding that whilst higher levels of automation are most beneficial under normal operating conditions, they can be detrimental if faced with an unanticipated situation requiring manual intervention (Endsley & Kaber, 1999; Sebok & Wickens, 2017). Such situations might involve a technical (software or hardware) failure of the automation, or it might simply be a situation for which the automation was not designed, or the automation could even be working perfectly well according to its design intent but just not as the user anticipated (Sebok & Wickens, 2017). In these circumstances, intermediate levels of automation facilitate a better recovery from the abnormal event, owing to the increased interaction with the task leading to improved situation awareness (Endsley & Kaber, 1999; Kaber & Endsley, 2004). Similarly, there is evidence that whilst automated assistance of physical tasks is beneficial, performance is actually hindered with assistance of higher cognitive functions – probably because there is additional workload involved (in monitoring the system and in making decisions from an increased range of options) which can be distracting (Endsley & Kaber, 1999). Thus, there is no such thing as a 'best' level of automation; the question is about overall system performance, of which human cognitive processing is a key part (Kaber & Endsley, 2004).

Contemporary taxonomies

Further developments of the levels of automation approach in more contemporary human factors research sought to take account of this role of cognition. In a number of related papers, Parasuraman and Wickens (Parasuraman & Wickens, 2008; Parasuraman et al., 2000; Wickens et al., 2010, 2015) introduced a new dimension to the taxonomy, by considering the four key stages of human information processing: sensory processing, perception and working memory, decision-making, and response selection. As first set out by Parasuraman et al. (2000), these input functions can be overlaid on the output functions of the earlier ten-level taxonomies to result in a model of

Table 1.3 Model of types and levels of automation, after Parasuraman et al. (2000) Darker shading reflects higher degrees of automation (see text for explanation). Levels 1 to 10 represent the ten-level taxonomy of Sheridan & Verplank (1978) described earlier.

	Information automation		*Decision automation*	
Level/Stage	*Information acquisition*	*Information analysis*	*Decision and action selection*	*Action implementation*
1				
2				
3				
4				
5				
6				
7				
8				
9				
10				

types of automation: information acquisition, information analysis, decision and action selection, and action implementation. Table 1.3 represents these orthogonal dimensions.

In a given system, then, automation can be applied at any of the ten levels within each of these four types, and can vary both within and between tasks. Another way of thinking about this is to view automation as offering anything from augmentation of driver performance (e.g., AEB), a prosthesis that replaces some aspect of driving (e.g., ACC), or an agent that acts on behalf of the driver (e.g., collision warning and avoidance; Lee & Seppelt, 2012). Automation is, therefore, far from binary: there can be a dynamic continuum of automation across all parts of a task. Increasing the level of automation within a stage, and/or implementing automation at later stages of information processing, is said to increase the 'degree of automation' (Wickens et al., 2010, 2015). Echoing the observations of Endsley and Kaber described above, Wickens et al. (2010) noted that higher degrees of automation improve performance in routine situations but adversely affect performance when dealing with automation failures.

As much as these performance issues are associated with mental workload and situation awareness (Endsley, 2017; Onnasch et al., 2014; Wickens et al., 2010), they may also be associated with the stage of information processing that is automated. A distinction can be drawn between the first two stages of processing, termed 'information automation', and the latter two stages or 'decision automation' (Parasuraman & Wickens, 2008; Sebok & Wickens, 2017). Information automation may be better for performance because the user is still engaged in generating courses of action based on what the automation has presented. If the automation is unreliable, the user may still evaluate it against the objective ground truth in the world. As such, high levels of information automation might be justified if reliability is extremely high (Parasuraman et al., 2000). Decision automation, on the other hand, causes performance problems if it is unreliable because the user has to effectively monitor and, if necessary, override it (Endsley, 2017). Furthermore, the available opportunities to recover a failure become increasingly limited as more information-processing stages are automated (Li & Burns, 2017). Consequently, high levels of decision automation may not be suitable if the human is ever expected to take over control – which, as we have seen, will be the case for a long time yet (Parasuraman et al., 2000). Parasuraman & Wickens (2008) recommended that decision automation should only be used at a low level of automation in high-risk settings, so as to avoid users unthinkingly following the automation.

As an interesting aside, Lee & Seppelt (2012) revisited the Fitts list with the information processing stages of automation in mind (see Table 1.4). Whilst they noted that the 'humans are better at' list is diminishing, people are still unmatched for their adaptability, flexibility, and 'seeing the big picture'.

One of the problems with implementing automation by degree, though, is that every step up in level of automation increases the risk of performance problems when returning to manual control (Onnasch et al., 2014). The implication of this is that humans should always be involved in decisions and actions if their performance is critical. Traditional levels-of-automation taxonomies

Table 1.4 Fitts list categorised against information processing stages (based on Lee & Seppelt, 2012)

Information processing stage	*Humans are better at*	*Automation is better at*
Information acquisition	Detecting small amounts of visual, auditory, or chemical signals Detecting a wide range of stimuli	Monitoring processes Detecting signals beyond human capability
Information analysis	Perceiving patterns and making generalisations Exercising judgement Recalling related information and developing innovative associations between items	Ignoring extraneous factors and making quantitative assessments Consistently applying precise criteria Storing information for long periods and recalling specific parts and exact reproduction
Action selection	Improvising and using flexible procedures Reasoning inductively and correcting errors	Repeating the same procedure in precisely the same manner many times Reasoning deductively
Action implementation	Switching between actions as demanded by the situation Adjusting dynamically to a wide range of conditions	Performing many complex operations at once Responding quickly and precisely

do not account for such involvement because, fundamentally, they are driven by technological capability rather than user requirements (Hoc et al., 2009), and assume that simple functional substitutions of humans by automation are zero-sum and do not otherwise affect human behaviour (Kaber, 2018).

Rather than think in terms of dividing tasks between humans and automation, then, an alternative is to consider human-machine *cooperation*, with each party pursuing its own goals while trying to facilitate a common task (in other words, teamwork; Annett & Stanton, 2000; Roberts et al., 2022). Hoc (2001) and Hoc et al. (2009) modelled this interaction from the perspective of human requirements, following the principle that automation should support, rather than replace, the human. The framework proposes three levels of cooperation, broadly relating to the operational-tactical-strategic levels of control described earlier: cooperation in action (i.e., task execution), cooperation in planning (aimed at maintaining a shared understanding and goals), and meta-cooperation (establish models of each other's operation and behaviour, in order to provide a platform for coordination).

Within each of the three cooperation levels are four cooperation modes, almost as a hybrid of Sheridan & Verplank's (1978) taxonomy and the information processing cycle in the model of Parasuraman et al. (2000). These modes cover perception, mutual control, function delegation, and full automation. Navarro et al. (2011) provides examples of these in the context of lateral vehicle control. The perception mode uses technology to augment the external world, such as vision enhancement of lane edges. Mutual control is about providing feedback on behaviour, so that could be represented by lane departure warning or lane-keeping assistance systems. Function delegation hands over part of the task to the automation, as with a LC system. Finally, full automation speaks for itself (although this does not necessarily rule out operating under driver supervision). Studies have demonstrated the advantages of this human-machine cooperation approach both in terms of factors such as situation awareness and trust (Hoc et al., 2009) as well as driver preferences (Navarro et al., 2018), suggesting that the quality of human-machine interaction is all-important (Eriksson & Stanton, 2017a; Stanton et al., 2021).

At the heart of Hoc's model is the notion of a common frame of reference (COFOR) at the planning level of cooperation. This COFOR is essentially a shared mental representation of system operation, but one which must be held by both human and machine about the other's behaviour. One of the key aspects of this is the mutual awareness of each other's context and intent and, as such, the COFOR depends critically on two-way communication between human and automation. Hoc et al. (2009) provide the example of a lane-keeping system in cars – which warns the driver when straying out of his/her lane. Clearly, sometimes this activity is legitimate – when overtaking, for example. The system has access to the vehicle's electronics, though, and so only provides a warning if the driver is moving across the lane markings without having used a turn signal. Whilst this is a crude rule, it illustrates the importance of intent and context in maintaining that common frame of reference and hence the smooth dynamics of the team. However, many of the human factors problems with automation are a result of less optimal communications between human and machine (Clark et al., 2019; Eriksson & Stanton, 2017a; Hoc et al., 2009). Hoc et al. (2009) commented that those automation systems which are commonly marketed as support devices are not really cooperative, as they remove parts of the driving task; the driver then has to manage the automation as well as their remaining driving task. 'True driver support should act as a human co-driver – providing advice when needed, assistance when necessary, but largely remaining in the background and invisible under normal conditions' (Hoc et al., 2009; p. 154).

Driving automation taxonomies

Invisible automation caught the interest of Young et al. (2007), who distinguished the automation of low-level, vehicle control tasks from higher-level cognitive driving tasks, and termed these 'vehicle automation' and 'driving automation', respectively. This distinction is, in fact, consistent with the subsequent definitions put forward by SAE (2018), who deprecated the term 'automated vehicle' in favour of 'automated driving' when we are talking about the driving task.

Traditional automatic systems usually only carry out operational elements of driving. The actions of automatic gearboxes, or even conventional cruise control, are largely mechanical in nature or take place at the highly skilled (and hence unconscious) end of the driving continuum. Going further, systems such as ABS or ESC augment driver responses beyond human capabilities and only reveal themselves to drivers in emergency situations. Navarro et al. (2011) viewed these kinds of systems as part of the vehicle dynamics from the driver's point of view, rather than human-machine cooperation in the true sense. Hence, these may be thought of as vehicle automation.

Driving automation, on the other hand, assumes more tactical and even strategic aspects of driving (cf. Ranney, 1994). For instance, ACC removes a cognitive task from the driver – perceiving speed of a lead vehicle, deciding whether to adjust speed in response, and taking appropriate action. Collision avoidance and collision warning systems take this a step further, by making a potentially stressful decision about whether to take emergency action. Even LC, which might appear to be an example of vehicle automation, relieves the driver of a significant cognitive workload (Young & Stanton, 2002b), owing to the fact that steering is a second-order tracking task (Wickens et al., 1998). As is evident from the evolution of technology we reviewed earlier, more and more driving automation systems have become a reality in recent years; it is no coincidence that they constitute the types of systems we are mostly concerned with in this book.

By relieving the driver of these more conscious cognitive tasks, driving automation has a much more conspicuous impact on human-machine cooperation. Drawing an analogy from marketing parlance, vehicle automation can be thought of as ‘below-the-line’, being in most cases subtle, unnoticeable, or even (as with systems such as ABS or ESC) opaque (cf. Hancock, 2019). Driving automation, though, is ‘above-the-line’ – visible, obvious, and prominent in the driver’s attention. As we shall see more in the next chapter, these are the characteristics that cause particular human factors problems, especially when – despite being visible – it is not transparent. Opacity when you are trying to hide is one thing (i.e., with vehicle automation); however, it is not desirable when someone else needs to see what you are doing.

Young et al. (2007) went on to describe another dichotomy in automation, depending on whether the human or the machine has ultimate authority over task decisions. In aviation, two different philosophies have emerged on this front: hard and soft automation (Hughes & Dornheim, 1995). Hard protection employs automation to prevent error, protecting against any inadvertent exceedance of safety limits, and hence it can intervene and override the human operator’s actions. For instance, some aircraft have hard speed envelope protection features that will prevent the pilot from stalling the aircraft and from pulling excessive forces, even in an emergency (Hughes & Dorheim, 1995). The rationale behind hard protection is largely to protect the airframe – if the pilot should inadvertently take the aircraft beyond its performance envelope, automatic interventions will prevent damage and maintain flight dynamics. Hard automation, then, has ultimate authority and can override the pilot’s inputs. In a sense, it relates to higher levels of automation in the taxonomies reviewed earlier.

Meanwhile, soft protection uses automation as a tool to aid pilots, giving them full authority to override the automated systems if they want (or need) to, without being overridden by the automated systems. There are still automated advisories in this soft protection scheme; if the pilot wishes to exceed set limits, they are required to apply more force than normal on the controls. As such, soft automation aligns with more moderate levels of automation.

Hard and soft automation therefore use similar sensors and control devices, but to different ends. Hard automation takes the pilot’s input, determines whether it is sensible, and if necessary takes its own action before passing the instructions on to the control surfaces. Soft automation makes a similar assessment of pilot inputs, but will only give feedback if the control requests appear to represent a safety risk. If the pilot persists, the soft automation will then pass the inputs directly to the control surfaces without intervention.

Both philosophies have advantages in certain situations. A good example is if the pilot has received a collision warning and, in a panic reaction, pulls hard back to gain altitude. Without an associated increase in thrust, the aircraft would soon stall. In that situation, the aircraft will itself apply the necessary amount of thrust to climb without stalling. However, there are certain situations in which the pilot may legitimately wish to take the airframe beyond its performance limits. An incident involving an engine failure on a China Airlines Boeing 747 in 1985 was only recovered after the aircraft had lost 30,000 feet in an uncontrollable dive (see NTSB, 1986; Norman, 1990). Needless to say, the airframe was significantly stressed during both the descent and the recovery, and substantial damage was caused (though only a few injuries were sustained on board). Interestingly, though, if that aircraft had been fitted with a hard protection system that prevented the pilots from stressing the airframe, it would likely have crashed (Borst et al., 2015).

With respect to vehicle and driving automation, automatic gearboxes can be categorised as hard automation – whilst the driver may usually make limited gear selections (e.g., the use of 'kickdown' or rudimentary gear lever settings), in the main the choice of gear is dictated by the automation. ABS and ESC systems are similar; their interventions are absolute and made purely on an assessment of the vehicle's braking dynamics. Conventional cruise control (which, remember, is also an example of vehicle automation) can instead be classified as soft automation – the driver decides how and when to set the system, and can override the system at any time. Similarly, ACC and LC (driving automation) represent examples of soft automation systems, in that they are fully selectable by the driver and any manual control inputs will override them. Similarly, collision warning systems offer information and advice to the driver without necessarily assuming control – similar to the soft protection systems in aircraft. Conversely, a collision avoidance system, set up to intervene automatically in an impending collision, is more akin to hard protection.

Both vehicle and driving automation systems, therefore, can be designed for hard or soft protection (see Table 1.5). It is probably too early in this book to speculate, but it is notable that the human factors concerns tend to be focused on driving automation rather than vehicle automation (by definition, since drivers interact more with driving automation than vehicle automation), and on hard automation rather than soft automation. We have already noted several researchers' concerns with the effects of higher levels of automation (comparable to hard automation) on human performance, particularly when having to deal with a failure of the automation (e.g., Onnasch et al., 2014). Similarly, Young et al. (2007) reviewed a number of aircraft accidents to

Table 1.5 Matrix of hard and soft automation categories against vehicle and driving automation types (after Young et al., 2007)

	Hard automation	*Soft automation*
Vehicle automation	Automatic gearbox ABS ESC AEB	Conventional cruise control
Driving automation	Collision avoidance Intelligent speed adaptation ALKS	ACC Lane departure warning LC / lane-keeping assist Parking assist Blind spot monitoring Collision warning

demonstrate the prevalence of hard automation aircraft in automation-related accidents. Nevertheless, there is compelling evidence that ESC (a hard-vehicle automation system) is effective in reducing road collisions (see Navarro et al., 2011), while ABS and AEB are similarly advocated by road safety organisations. So, clearly, not all hard automation is bad, and we might start thinking in terms of different philosophies for different types or levels of automation. That would certainly be in keeping with the human-machine cooperation model (Hoc, 2001; Hoc et al., 2009), which advocates supporting the driver rather than replacing them, by undertaking some components of the task or ensuring redundancy for certain functions, while leaving the driver in charge. We will be revisiting these ideas later in the book.

Notwithstanding all of these efforts in human factors to classify automation along more cognitive lines, the automotive industry's benchmark reverts to a more task-based levels-of-automation taxonomy of driving automation systems. The Society of Automotive Engineers standard J3016 (SAE, 2018) is positioned as a framework for discussion around aspects ranging from technical specifications to policy and legislation, and claims[12] to be 'the industry's most cited reference for automated-vehicle (AV) capabilities'. The SAE taxonomy has six mutually exclusive levels (including level 0 – no driving automation) based on the elements of the driving task carried out by the driver or by the automation, and the roles that they respectively play. These levels are detailed in Table 1.6, alongside analogous descriptions offered by Thatcham Research (2019) to reflect the level of driver involvement. The US National Highway Traffic Safety Administration (NHTSA) has a similar taxonomy but with five levels, where its level 3 broadly covers levels 3 and 4 of the SAE taxonomy (see Hancock, 2019; Norman, 2015; Richards & Stedmon, 2016).

At levels 1 and 2, the automation performs longitudinal and/or lateral control, while the driver carries out the rest of the driving task, supervises the automation, intervenes as necessary, decides whether and when to dis/engage the automation, and steps in to perform the entirety of the driving task whenever required or desired. This latter point is critically important, as it depends on drivers monitoring the automation and understanding its status at all times (Mueller et al., 2020). Whilst driving at these levels can become hands- and feet-free, then, it cannot be mind-free (Banks et al., 2014). At level 3, the driver becomes the 'fallback-ready user', receptive to the need to take over manual control from the automation, if necessary. 'Receptive', according to the SAE (2018), is the ability to reliably and appropriately focus their attention in response to a stimulus, whether that stimulus be an overt request from the automation or some cue that the automation is failing. Because the system cannot deal with all situations, it should be classified as assisted rather than automated driving (Thatcham Research, 2019). Levels 4 and 5 have no need for a fallback-ready user and the driver can effectively become a passenger (the distinction from level 4 to level 5 is the removal of any operational design limitation on the automation, such as environment or geography – at level 5, it is fully automated and can drive anywhere).

Table 1.6 Taxonomy of driving automation systems (adapted from SAE, 2018)

Level	*Description*	*Automation*	*Driver*	*Examples*[a]	*Analogy (Thatcham Research, 2019)*
Driver performs all or part of the dynamic driving task (driver support features)					
0	No driving automation	None	Entire dynamic driving task	AEB Blind spot monitoring Lane departure warning	'Feet off' (driver monitors driving environment)
1	Driver assistance	Either lateral or longitudinal control (but not both simultaneously) within specific operational design domain	Remainder of dynamic driving task	ACC *or* LC	
2	Partial driving automation	Both lateral and longitudinal control within specific operational design domain	Object and event detection and response; supervises the driving automation systems	ACC *and* LC	
Automation performs the entire dynamic driving task while engaged (automated driving features)					
3	Conditional driving automation	Entire dynamic driving task within specific operational design domain	Acts as fallback-ready user receptive to requests to intervene from automation, as well as to system failures, and responds appropriately	ALKS	'Hands off' (driver monitored)
4	High driving automation	Entire dynamic driving task within specific operational design domain	None (while the automation is active within its operational design domain)	Local driverless taxi (e.g., Waymo/ Uber)	'Eyes off' (system monitors driving environment)
5	Full driving automation	Unconditional and unlimited performance of the entire dynamic driving task	None	As level 4, but can drive anywhere in all conditions	'Brain off?'

Note: [a]Level 0 driving can be enhanced by active safety or driver assistance systems, but on their own these are not considered as driving automation systems in the SAE (2018) taxonomy because they do not perform the dynamic driving task on a sustained basis.

To reframe this in more human-centred terms, there are essentially two dimensions each with two levels (Noy et al., 2018): part-time vs. full-time, and partial vs. full automation (or supervised vs. unsupervised; Ljung Aust, 2020). Counterintuitively, the examples of level 0 automation (such as AEB) reflect full-time partial automation; levels 1 and 2 are largely part-time partial automation, while level 3 is the first step into full automation, albeit part-time. Only level 5 meets the criteria for full-time, full automation.

Relating the SAE levels of automation to the technology timeline we reviewed earlier, clearly level 1 automation has been around for many years (Inagaki & Sheridan, 2019), while we have recently seen more examples of level 2 automation on the roads, such as with Tesla's Autopilot, Volvo's Pilot Assist, or Audi's Traffic Jam Assist (Jones & Holden, 2020). Although there are currently no vehicles with level 3 automation available on the market (Teoh, 2020), that is the focus of much technological and policy effort at the moment (Inagaki & Sheridan, 2019; Jones & Holden, 2020). Indeed, we are about to embark on this ground-breaking (in technological and human factors ways) stage of driving, as represented by the imminent developments in ALKS described earlier in this chapter. There remains a technological barrier to implementing level 3 automation on open roads in mixed traffic, though, hence the leapfrog to level 4 automation in limited circumstances or in test trials (such as airport shuttles on enclosed courses or, of course, the noted Waymo and Uber trials; Jones & Holden, 2020; Reed & Sellick, 2017; SAE, 2018). Nevertheless, there are no signs of level 5 automation even on the horizon (Inagaki & Sheridan, 2019; Jones & Holden, 2020; Reed & Sellick, 2017), such is the technological leap required to achieve it in a naturalistic environment (Noy et al., 2018).

Despite the dominance of level-of-automation taxonomies in both literature and industry, they have attracted criticism from human factors researchers for neglecting the bigger picture of joint human-system performance (Kaber, 2018). Their arbitrary decomposition of functions is technology-centred and does not account for the cognitive work of deciding how and when to intervene (Dekker & Woods, 2002). There is a potential mismatch between drivers' perceptions of their respective roles when using driving automation systems against the industry's expectations of such as described in the SAE levels (cf. Ljung Aust, 2020): '…humans will not always do what engineers expect them to do' (Kaber, 2018; p. 15). Even drivers of level 2 cars are more likely to disengage from driving and engage in a secondary task that can draw their attention away from the road (Carsten et al., 2012; Mueller et al., 2021; Ulahannan et al., 2020), impairing their ability to resume control when required (Mueller et al., 2021).

As is evident from Table 1.6, the tipping point in the SAE (2018) taxonomy is level 3 upwards (Teoh, 2020), when the automation starts to perform the entire driving task on a sustained basis (SAE, 2018) – although the driver is still expected to be available to take over until we get to level 4 (Merat et al., 2014; Seppelt & Victor, 2016). Ljung Aust (2020) argued that this means the driver is still effectively driving. Level 3, therefore, presents a difficult transition because the driver no longer has control, may be free (and undoubtedly will want) to engage in non-driving tasks, yet must still monitor the system and the driving environment (Inagaki & Sheridan, 2019; Seppelt & Victor, 2016) and be ready to take over. For this reason, if for no other, the role of the human factor in automated driving has never been more critical.

THE HUMAN FACTOR

In this chapter, we have set out a potted history of automated driving systems in anticipation of where automation is going next (which will almost certainly have changed by the time you are reading this), described a number of definitions associated with such technology, and reviewed a variety of classifications of automation from the human factors perspective. From the technology timeline, it appears that we are just about to enter the difficult adolescent years for driving automation, as it grows out of playing a supporting role to the driver and starts to take on some responsibility, but has not yet matured enough to gain full independence. Or, in SAE (2018) terms, that transition from levels 1/2 at present, through level 3 very soon, to levels 4/5 at some point in the future. We are in the 'danger zone' for automation as it starts to wrest control from the driver but still needs looking after, underlining the importance of considering human factors (Emmenegger & Norman, 2019). Only at level 5 can we really cut the apron strings, but that autopia seems to be an increasingly distant ideal (cf. Brooks, 2017; Noy et al., 2018; Sheridan, 2017). Harking back to the Fitts list, humans still offer an adaptability and flexibility currently unmatched by machines (Phillips, 2018), but such is required to deal with all of the unforeseeable situations that a fully automated vehicle must cope with. Until such complete automation exists that can cope with all circumstances in all environments, the human driver will play a key role up to (and including) level 4 (Kyriakidis et al., 2019; Noy et al., 2018), even if that is in a supervisory capacity (Sheridan, 2017).

With the importance of the human, comes the importance of human factors if these systems are to be successful in bringing advantages for safety, performance, and satisfaction. It is certainly not the case that more automation will reduce the significance of human factors, despite all of the technological rhetoric around the push towards higher levels. The SAE (2018) taxonomy has come in for criticism from the human factors quarter for not being human-centred (Hancock, 2019; Noy et al., 2018), focusing as it does on the separation of tasks and roles rather than the interactions between driver and vehicle.

Fortunately, this is not representative of other standards and policy work in this area. Standardisation work at British[13] and International[14] level is considering the human performance implications of automated vehicles, while NHTSA's statement of policy[15] also has a research strand on human factors.

The issues are even recognised by the United Nations Economic Commission for Europe (UNECE) at its Global Forum for Road Traffic Safety, which adopted a resolution (ECE/TRANS/WP.1/2018/4/Rev.3[16]) that takes into consideration the role of the human in highly and fully automated vehicles (i.e., SAE levels 4 and 5). This reflects a systems view by focusing on requirements for the system to interact with the user, as well as requirements on the users themselves, and even implications for government policy.

The central thesis of this book is that, until the need for a driver is completely eliminated, driving automation has a wealth of implications for human factors. As such, human factors should be front and centre in any discussions about the design, implementation, and regulation of automated vehicles (Stanton et al., 2021). The trouble is, notwithstanding the considerable efforts of the human factors community to research these issues, the agenda has been very much driven by the technological imperative. In the next chapter, we will review the human factors concerns in detail and argue why it is a fallacy to think that automation will 'solve' human error.

KEY POINTS

- Historically, automobile automation has taken over lower-level, vehicle control tasks, but there is a fundamental difference between these and the more cognitive, driving tasks that are now being automated.
- We are now on the cusp of a revolution in driving automation, as the imminent arrival of level 3 systems will shift the balance of control away from the human driver and towards the technology.
- However, it will be many years before we will see full, level 5 automation, when humans can truly let go of driving in all situations; until that time, we must design automated systems around the people who will still play a crucial role.

NOTES

1. https://www.humanist-vce.eu/ (accessed 4 May 2022)
2. Uber infamously had to move to Arizona to test its vehicles after California refused the requisite permits; see Chapter 2 and Stanton et al. (2019).
3. https://www.gov.uk/government/organisations/centre-for-connected-and-autonomous-vehicles (accessed 4 May 2022)
4. https://humandrive.co.uk/ (accessed 4 May 2022)
5. https://www.euroncap.com/en/vehicle-safety/safety-campaigns/2018-automated-driving-tests/ (accessed 4 May 2022)
6. EU General Safety Regulation 2019/2144, available at: https://eur-lex.europa.eu/eli/reg/2019/2144/oj (accessed 9 June 2022).
7. https://www.gov.uk/government/news/government-moves-forward-on-advanced-trials-for-self-driving-vehicles (accessed 4 May 2022)

8. https://www.euroncap.com/en/vehicle-safety/safety-campaigns/2020-assisted-driving-tests/whats-new/ (accessed 4 May 2022)
9. https://www.euroncap.com/en/vehicle-safety/safety-campaigns/2020-assisted-driving-tests/ (accessed 4 May 2022)
10. https://www.legislation.gov.uk/ukpga/2018/18/pdfs/ukpga_20180018_en.pdf (accessed 4 May 2022)
11. In this book, we use the terms ‘automated driving’ and ‘driving automation’ to represent systems which still retain some role – however small – for the driver (as distinct from full automation).
12. https://www.sae.org/news/2019/01/sae-updates-j3016-automated-driving-graphic (accessed 4 May 2022)
13. https://www.bsigroup.com/en-GB/about-bsi/media-centre/press-releases/2019/july/bsi-launches-standards-programme-to-accelerate-british-leadership-in-automated-vehicles/ (accessed 4 May 2022)
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15. https://www.nhtsa.gov/staticfiles/rulemaking/pdf/Automated_Vehicles_Policy.pdf (accessed 4 May 2022)
16. https://unece.org/fileadmin/DAM/trans/doc/2018/wp1/ECE-TRANS-WP1-165e.pdf (accessed 4 May 2022)

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Chapter 2

Promises, promises...

OVERVIEW

With our journey underway, we now begin to examine the human factors of automated driving more closely, considering first the advantages and then, in more detail, the potential disadvantages of automation. Many of these lessons learned have stemmed from the aviation domain, and this chapter spends some time discussing research and case studies of accidents involving aviation automation. From there, we go on to review some of the higher-profile investigations into automated driving collisions. In drawing out human factors commonalities across these cases, this then forms a platform to review six of the most salient human factors problems with automated systems: vigilance, trust, complacency, behavioural adaptation, situation awareness, and mental workload (MWL). It is the latter concern that constitutes a theme across all of the other areas, and which forms a core thesis of this book. Automation can at once impose underload and overload on an operator, principally through a lack of feedback and the 'out of the loop' phenomenon. We note that performance problems with automation typically arise when the automation fails, and the operator struggles to intervene in a timely manner. But these are problems of automation design, and counter to the overriding technology-centred view that automation will eliminate human error.

INTRODUCTION

Let's start with the good news: automated driving unarguably has the potential to make our roads safer, more efficient, and even more enjoyable (Noy et al., 2018). Taking these in reverse order, there has long been a vision that relieving the driver of tasks which are inherently difficult or demanding can increase the enjoyment of driving (Biesterbos & Zijderhand, 1995). Many of the level 1 and level 2 automated driving systems in the current vehicle parc have been deliberately designed first and foremost as 'comfort and convenience' enhancements (cf. Richardson et al., 1997; Rudin-Brown & Parker, 2004). Meanwhile, in terms of efficiency, systems such as adaptive cruise

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control (ACC) smooth out driving by reducing harsh acceleration and braking events (Rudin-Brown & Parker, 2004; Seppelt & Victor, 2016), thus alleviating traffic congestion and increasing road capacity (Chira-Chavala & Yoo, 1994; DfT, 2016).

But the big one, of course, is safety. Motor vehicle crashes are one of the leading causes of deaths worldwide with 1.35 million fatalities per year (WHO, 2018), and the leading cause of death for those in the 15–29 age group (Noy et al., 2018). Take rear-end collisions, which are estimated to be the cause of anything from a quarter to over a half of all road crashes (Gilling, 1997; McKnight & Shinar, 1992; Zhang et al., 2021). These are, by definition, a matter of longitudinal control (accelerating and braking) and so, the argument goes, automating this element of driving should improve safety. In one study based on US data, automation of longitudinal control could save around 1,000 lives every year (Gilling, 1997; although some are more conservative about the potential safety benefits; Chira-Chavala & Yoo, 1994). There has consequently been a lot of research focused on such devices as ACC, automatic emergency braking (AEB), or forward collision warning. Forward collision warning with AEB has been shown to reduce those rear-end collisions by at least 50% (Mueller et al., 2021) and even up to 80% (FIA, 2020), while ACC can reduce tailgating and, consequently, the number and severity of such incidents (Rudin-Brown & Parker, 2004).

It is popularly quoted (typically in industry) that anything up to 90% of road collisions is due to 'human error' (e.g., CCAV, 2020; FIA, 2020; Foy & Chapman, 2018; NHTSA, 2003[1]; Victor et al., 2018), with such errors associated with recognition, decision or performance (Seppelt & Victor, 2016). If humans are so poor at driving, the justification goes, then we can virtually eliminate road collisions by substituting the weak link with something that is allegedly far more competent – automation[2] (cf. Williams, 2019).

But there is a fundamental fallacy with this argument (Read et al., 2021). The attribution of 'human error' is often really a proxy for 'not mechanical failure'; however, human error can equally creep in with the design or configuration of automation (Lee & Seppelt, 2012; Noy et al., 2018), which is potentially more insidious as it will affect all vehicles fitted with it, not just one errant driver (Banks, Plant et al., 2018). These problems are swept under the car mat, though, as automation cultivates an image of perfection by just opting out at the first sign of trouble (what is termed 'brittle automation; Endsley, 2015; 2017; Lee & Seppelt, 2012), leaving the human to pick up the pieces. The reason 'most' accidents are then (and will continue to be) classified as human error is because humans are the last line of defence in the system and, consequently, bear the greatest burden – present to catch anything that has made it through previous barriers, including automation (Schutte, 2016[3]). That some errors slip through the net to be blamed on the driver is therefore an inevitability (Banks, Eriksson et al., 2018) and an easy conclusion to jump to, referred to by Norman (1988) as 'taught helplessness'. Automation will not 'cure' human error, though, merely push it deeper into the sociotechnical system (Stanton et al., 2019). Moreover, despite the unacceptably high death toll, the collision rate of human-driven cars is actually very low, so the performance of automation will need to be exceptionally high in order to surpass that (Victor et al., 2018).

The purported benefits of automation therefore rest largely on the assumption of it being perfect, but some remain sceptical about its potential in that regard too (e.g., Chira-Chavala & Yoo, 1994; Hancock et al., 2019). As it stands, automation cannot be programmed for the complexity of all traffic situations (Noy et al., 2018), and it may struggle with ambiguities in the environment (Hancock et al., 2019) or less predictable contexts such as rural roads (Jones & Holden, 2020). Engineering estimates of the effectiveness of vehicle automation range from 100% (i.e., totally eliminating collisions) to 0% (no effect) and possibly even negative effectiveness (i.e., increasing collisions; Rudin-Brown & Parker, 2004). Official predictions also concede that the benefits of automation on traffic will be limited – possibly even negative – until some threshold of penetration in the fleet is reached (Brooks, 2017). One report (FIA, 2020) noted that if half of the vehicle parc was fitted with level 2 automation, this could reduce motorway collisions by just under 18%.

From this perspective, then, the idea that driving can be made safer, more efficient, and more enjoyable by simply relieving the driver of certain tasks is flawed. The rest of this chapter delves into the related human factors issues in detail, starting with lessons and illustrations from aviation and automobile accidents involving automation, before going on to review the fundamental human factors work in this field that now spans four decades (e.g., Bainbridge, 1983; Hancock, 2019; Hollnagel, 1993; Norman, 1990; Parasuraman & Wickens, 2008; Reason, 1990). To be clear, none of this is about being technophobic towards automation – we cannot, nor would we wish to, stop that particular tide. But if the promises of automated driving are to be realised, the system design has to take into account the human factor behind the wheel. Given that humans will continue to play a crucial role in automated vehicles for many years to come (Hancock, 2019), it is about ensuring that the benefits of the technology are maximised by considering how it fits around the driver (cf. Noy et al., 2018; Stanton et al., 2021) – a question we will return to in later chapters of this book.

LESSONS LEARNED FROM AVIATION

Suffice it to say that the road currently being explored by automobile automation has already been well trodden by another transport mode. Automation in aviation has been around for several decades and its complexity has reached the point where it is indispensable in some modern fighter jets, which are literally unflyable without the assistance of advanced avionics. In parallel, there is a considerable body of human factors knowledge about the ‘promises and problems’ (cf. Wiener & Curry, 1980) of aviation automation that can be – and, indeed, has been – transferred into the automotive domain. Stanton & Marsden (1996) did just that, extrapolating from experience in aviation to anticipate that whilst there would be advantages with the 'drive-by-wire' car (such as improvements in safety or reduced stress), these would be traded off against potential concerns with technical reliability, training and skills maintenance, equipment designs, and overdependence on the automated system.

In the 1970s and 1980s, the philosophy in aviation was to automate everything possible, with the overriding motivation being to reduce crew workload – and crew numbers from three to two (Billings, 1991; Dekker & Woods, 2002). Although this was achieved, it also brought a host of new problems with it. Any workload reduction that might have been offered by the automation was offset by the increase in workload on the remaining crew, because an automated system is not a pure substitute for a human crew member (Huey & Wickens, 1993). The nature of the automation also meant that workload was only reduced in cruise phases of flight when it was already low anyway; consequently, the majority of incidents involving vigilance failures and overreliance on the automation occurred during these phases when the pilot's primary role is monitoring and supervising (Molloy & Parasuraman, 1996). Conversely, in the high demand phases of take-off and descent, the addition of automation served to increase workload further (Billings, 1991). Under high workload, pilots tended to revert to manual control because they did not have time to deal with the extra demands of the automation (Wiener, 1989). So although pilots generally saw the automation in a favourable light, they had mixed feelings about its impact on workload, situation awareness, skill degradation and errors (Huey & Wickens, 1993; McClumpha et al., 1991; Wiener, 1989). Current wisdom accepts that modern flight decks have neither increased nor decreased MWL, but this could be a result of workload reductions in some aspects of the task while other aspects have increased, resulting in no overall change.

It remains debatable whether aviation automation has actually reduced human error; the reduction in the accident rate of fourth-generation automated aircraft has stagnated (Mohrmann et al., 2015). What we can be certain of, though, is that automation has introduced new types of error (Billings, 1991), and potentially more serious errors at that (Wiener, 1989). For instance, an error in programming a flight management system might not result in visible consequences until some time later, making failure detection difficult (Sarter & Woods, 1995). We have already discussed how errors at the design stage can be more insidious, and nowhere is this more apparent than in programming the computers that run the automation. It has been suggested that software programs can contain 20–30 errors for every 1,000 lines of code – to put that in context, an automated vehicle may contain many millions of lines of code – so automation could introduce new accident types associated with software failures (Noy et al., 2018).

Back on the automated flight deck, one of the most prevalent types of error is the mode error (Sarter & Woods, 1995; Stanton & Marsden, 1996). A mode error occurs when executing an intention in a way that is appropriate to one mode, when the system is actually in another (Norman, 1981; Sarter & Woods, 1995). One of the simplest examples of a mode error is attempting to set the time on a digital clock, when the clock is actually in alarm mode. The flexibility and functionality of automation technology results in a proliferation of modes, which can change automatically without input from (or feedback to) the operator, making it both more important and more difficult to maintain awareness of the system state (Sarter & Woods, 1995). Furthermore, the processing speed of automation technology means it can cycle through system states much faster than any human can keep pace, making its functioning even more opaque to the operator (Hancock, 2017a). Working with such 'strong and silent' automation can create new cognitive demands as the user tries to keep track of what the system is doing, why it is doing it, and what it will do next – which can increase workload just when operators need the support, a situation some have referred to as 'clumsy automation' (see Sarter & Woods, 1995).

Sarter & Woods (1995) described two major aviation accidents caused by mode errors, both involving Airbus A320 aircraft. On 14 February 1990 in Bangalore, India, the pilot of an Indian Airlines flight unwittingly engaged a descent mode in which the autopilot controlled the pitch of the aircraft, rather than its speed. The pilot did not realise this because it was an indirect effect of selecting a lower altitude when the autopilot was in a particular mode. However, a pitch-controlled descent meant that the aircraft could not maintain the glidepath and speed at the same time, so it sacrificed altitude in favour of speed. The crew only realised ten seconds before it crashed into the ground, when it was too late to recover.

A similar set of circumstances transpired on 20 January 1992 near Strasbourg, France. In this case, the descent mode was confused on the basis of extremely subtle information on the instrument display. Instead of entering a desired flight path angle of 3.3°, the crew did not notice the absence of a decimal point on the display, which was the only indicator on the display of which mode the flight management system was in, and instead entered a much steeper vertical speed of 3300 feet per minute. As the descent was then entrusted to the automatic system, the crew did not pay attention to other available clues about the abnormally high descent rate, and the aeroplane crashed into a mountain range.

The absence of feedback from automation can cause 'automation surprises' (Sarter & Woods, 1995), in which the system behaves exactly according to specifications, yet this is quite different to that which the operator expects. Indeed, automation rarely suffers genuine technical failures; instead, problems are caused by a mismatch in expectations and intentions (Dekker & Woods, 2002). As a further indictment of (lack of) feedback, these problems are often only resolved by noticing what the actual aircraft is doing, rather than the automation status displays (Palmer, 1995; Sarter & Woods, 1995). Automation surprises can catch out even experienced pilots (Hughes, 1995;

Hughes & Dornheim, 1995) and may result in accidents if the pilot does not respond appropriately, overcompensating for whatever they perceive the problem to be and getting themselves into all sorts of trouble in the process. Consequently, automation surprises are often determined to be the cause of aviation accidents involving highly automated aircraft (e.g., Learmount, 1994; Sedbon & Learmount, 1993).

A tangible and well-publicised example of this is described by Beaty (1995), in an account of an accident at an air show in Habsheim, France, on 26 June 1988. Another Airbus A320, which at the time was one of the new generation of automated aircraft, made a low pass over the runway with the undercarriage lowered. Under these conditions, the aircraft automatically assumed a landing mode, which meant throttling back the engines and, crucially, disabling many of the flight envelope protections. However, the pilot did not realise this was happening. Consequently, at the end of the pass, the pilot found that power was not available when he tried to pull up. The aircraft failed to gain height and crashed into trees at the end of the runway.

More recently, the crash of Air France flight 447 in the Atlantic Ocean on 1 June 2009 also resulted from an automation surprise (see Inagaki & Sheridan, 2019). At 35,000 feet, icing of an airspeed sensor called a pitot tube caused an automatic disconnection of the autopilot and autothrust systems. The autopilot effectively gave up and suddenly returned control of the aircraft to unprepared pilots. As if that was not enough, multiple alarms and alerts at the same time caused startle and confusion on the flight deck (Salmon et al., 2016). The pilots tried to take control but overcorrected, eventually resulting in the aircraft stalling. In a 2016 webcast covering this accident, Schutte[3] explained that icing of the pitot tubes was a design error that had previously been compensated for by pilots, but unfortunately not in this case; the pilots on board had more experience flying with the automation than flying manually. Schutte's point was that the pilots did not cause this accident, they just did not save it either: the aircraft would have definitely crashed if left to the automation.

Stanton & Marsden (1996) identified a range of psychological factors implicated in other automation-related aviation accidents, such as inattention under conditions of low workload, cognitive strain under conditions of high workload, and over-reliance on the technology. With echoes of the mode error accidents described above, Molloy & Parasuraman (1996) described two similar cases that demonstrate how overreliance can combine with distraction to cause an incident. The crash of Eastern Airlines flight 401, a Lockheed L-1011 TriStar, in the Florida Everglades on 29 December 1972 occurred when the crew did not detect the autopilot had disengaged, nor did they notice that they were losing altitude, because they were engrossed in diagnosing a possible fault with the landing gear. Meanwhile, the China Airlines Boeing 747 incident near San Francisco on 19 February 1985 (mentioned in Chapter 1) also resulted from the crew being preoccupied with an engine problem and not noticing that the autopilot was gradually losing control of the aircraft.

In many cases, problems arise due to a mismatch in expectations, understanding and awareness of what the automation is doing (and vice-versa). On 25 February 2009, Turkish Airlines flight 1951 crashed on landing at Schiphol airport, Amsterdam, due to the failure of a radar altimeter. The pilots were aware of the faulty sensor but did not appreciate that the autothrottle depended on it during the approach; consequently, the engines were commanded to idle while the aircraft was still at 2,000 feet, resulting in a stall (Borst et al., 2015). Similarly, Air Asia flight 214, a Boeing 777, crashed just short of San Francisco airport on 6 July 2013. The crew were focused on the glideslope and did not notice the speed falling dangerously low. The pilot thought the autothrottle was set to automatically intervene, but only realised it was not when it was too late to recover (Thompson, 2015).

Perhaps the most prominent examples in recent years, though, involve the Boeing 737 MAX aircraft. Two similar crashes within months of each other – Lion Air flight 610 on 29 October 2018 and Ethiopian Airlines flight 302 on 10 March 2019 – led to the aircraft being grounded (the details of this case study are drawn from NTSB, 2019a and Wilson, 2020). The 737 MAX incorporated new, larger engines, mounted higher and further forward on the wing than previous models. This caused a tendency for the nose to pitch up at high angles of attack, so to counter this Boeing introduced the Manoeuvring Characteristics Augmentation System (MCAS) which would automatically trim the nose down until the angle of attack fell below a threshold. Boeing assumed (incorrectly, as it turned out) that these automatic inputs would be readily apparent to pilots, and any necessary corrections would be within their extant skills and training. So no information about MCAS was provided in flight crew manuals or training. In the Lion Air crash, maintenance activity had resulted in an undetected bias on the angle of attack sensor of 21 degrees. In flight the next day, this sensor bias caused MCAS to initiate unintended nose down trim actions 24 times. These were countered by the crew, but MCAS just kept trying. The multiple alerts being generated imposed significant workload on the crew, while they lacked awareness and understanding both of how MCAS worked and of previous problems on the aircraft.

Whether or not there is a causal relationship between the level of aviation automation and accidents is moot. Wiener (1989) felt that there was not enough data at that time to determine whether high or low automation generate more errors; on the other hand, an analysis of automation incidents found that such errors were more frequent and severe in the more advanced aircraft (Kantowitz & Campbell, 1996). Using the dichotomy of hard and soft automation we introduced in Chapter 1, Young et al. (2007) analysed all of the major accidents involving aircraft of these types over the previous 20 years (including many of those discussed above). They classified the accidents according to whether they were deemed to be automation-related (that is, as having a direct cause attributable to some mismatch between human and automated activities) or non-automation-related (see Tables 2.1 and 2.2,

Table 2.1 Automation-related major aviation accidents (Young et al., 2007)

Date	*Automation*	*Fatalities*	*Location*	*Description*
26/6/88	Hard	3	Habsheim	Automated mode transition at air show
14/2/90	Hard	92	Bangalore	Engines in idle descent mode on approach; fell short of runway
20/1/92	Hard	87	Strasbourg	Confused descent mode resulting in controlled flight into terrain
14/9/93	Hard	2	Warsaw	Runway overrun as windshear on landing affected automatic braking systems
30/6/94	Hard	7	Toulouse	Ground impact following test flight take-off due to misunderstanding of autopilot mode and overconfidence in aircraft abilities
7/2/01	Hard	0	Bilbao	Heavy landing following turbulence on approach; crew attempted go-around but automatic protection envelope prevented it
20/12/95	Soft	160	Cali	Hit mountain after confusion over directional beacon in flight management system
6/2/96	Soft	189	Dominican Republic	Faulty airspeed indicator caused confusion with autopilot
15/4/02	Soft	129	S. Korea	Struck mountain on circling approach after captain had taken over from autopilot and lost situation awareness

Table 2.2 Non-automation-related major aviation accidents (Young et al., 2007)

Date	*Automation*	*Fatalities*	*Location*	*Description*
10/3/97	Hard	0	Abu Dhabi	Take-off difficulties led to runway overrun
22/3/98	Hard	0	Philippines	Thrust left forward on no. 1 on landing
23/8/00	Hard	143	Bahrain	Crashed during go-around; autopilot disconnected on visual approach
28/8/02	Hard	0	Phoenix	Poor reverse thrust control on landing
21/3/03	Hard	0	Taiwan	Landed on utility vehicle
2/8/05	Hard	0	Toronto	Runway overrun in poor weather
2/10/90	Soft	46	Guangzhou	Hit by crashing 737
26/5/91	Soft	223	Thailand	Reverse thrust isolator failed and deployed during flight
6/4/93	Soft	0	Guatemala	Runway overrun
4/11/93	Soft	0	Hong Kong	Runway overrun
5/8/98	Soft	0	Seoul	Runway overrun
2/10/96	Soft	70	nr Lima	Faulty instruments confused flight crew
14/9/99	Soft	0	Costa Brava	Stormy conditions and loss of visual references destabilised approach
31/10/00	Soft	83	Taiwan	Took off on wrong runway and hit construction vehicle
26/6/02	Soft	0	Japan	Tail strike during training touch & go
1/7/02	Soft	2	Überlingen	Mid-air collision after conflicting instructions from air traffic control and on-board collision avoidance system

respectively). These were contrasted against major accidents which are not automation related.

With twice as many major automation-related accidents being in hard automation aircraft, the data imply that this philosophy leads to more problems of human performance than the soft protection approach. Even the soft automation accidents in Table 2.1 are only tenuously related to automation, as they were primarily problems of situation awareness following some fault on the flight deck. Also clear is an almost reverse trend on non-automation-related accidents (soft automation: 10; hard automation: 6), and the fact that despite all of them being hull-loss accidents, many did not result in fatalities. Nevertheless, this was a coarse analysis and did not control for absolute numbers of aircraft of each type, nor their relative exposure (i.e., distance travelled, number of flights). As a rudimentary comparison, though, this analysis does suggest that the design of automation can have a significant impact on safety and performance in operation.

The lessons learned from aviation demonstrate, more than anything, that the people who once directly flew the aeroplanes are now relegated to the periphery, responsible more for hardware and software interfaces with a computer than control surfaces on the airframe (cf. Billings, 1991). This detachment under high levels of automation can cause mismatches in intent between human and machine, to the extent that flight crew end up fighting the aircraft for control. It has been said that instead, pilots should occasionally switch the computer off and look out of the window (Young, 2009).

Some might argue that these lessons are not transferable to the road domain, since aviation is such a complex environment and the autopilots more sophisticated. If anything, though, there is even more variability in the driving context (Hancock, 2019; Harris & Harris, 2004; Norman, 2015): time windows are much shorter as drivers have only seconds to react in emergencies; air traffic is tightly controlled compared to the relative free-for-all on the roads; aircraft design and maintenance follow strict standards; meanwhile, flight crews are much more highly trained than the average driver – and there are always at least two pilots ready to respond on the flight deck (Hancock et al., 2019). Indeed, it may be for these reasons that we are only just beginning to see such technological developments in automated driving! Let us turn now to consider recent accidents of automotive automation, to see just how prescient these lessons from aviation were.

AUTOMOTIVE ACCIDENTS OF AUTOMATION

Until recently, road traffic collisions were not investigated to the same depth and detail as aviation accidents. But that is not to say there were no such things as accidents of automation on the roads before. Even before we consider the higher levels of driving automation that are of most concern in this book, there is a notable history of collisions involving lower-level vehicle automation, in the phenomenon of unintended acceleration (Schmidt, 1993).

Typically associated with automatic gearboxes, the problem occurs when drivers unwittingly hold their foot on the accelerator pedal rather than the brake when selecting gear. Consequently, the car speeds off, and the driver – thinking their foot is already on the brake – gets into a state of cognitive lockup (Moray & Rotenberg, 1989), presses even harder, and the vicious circle only ends when the car crashes into an obstacle. Unintended acceleration has also been observed with cruise control for similar reasons, while Young (2004) postulated that ACC could cause problems of un*commanded* acceleration. As described in Chapter 1, ACC uses sensors to detect slower leading vehicles and reduce speed accordingly; if the ACC's sensors then lose sight of the lead vehicle (perhaps around a tight curve or if either vehicle is filtering off the road), the system would then accelerate to resume its original set speed. This could cause confusion and problems for the driver if they did not understand what the ACC system was doing.

It was inevitable that the first time a self-driving car caused a crash would create a stir and, on 14 February 2016, the Google autonomous car took that unwanted accolade. Only a few miles from Google's headquarters in Mountain View, California, it had been attempting to turn right but detected that the right-turn lane was blocked, so tried to merge back into the centre lane. It did so in front of a public bus, which did not give way (nor did it strictly have to), and the two vehicles collided at relatively slow speeds. The automation made an erroneous assumption about what the bus driver would do, the kind of assumption that is also fairly common among human drivers, since reading the behaviour of other road users is rather difficult for both human and machine (Brooks, 2017; Noy et al., 2018; Stanton et al., 2020). This was a minor crash in the grand scheme of things, but a significant milestone as it was the first time that at least some responsibility lay with the automated vehicle. There had been numerous occasions when the safety drivers disengaged the automation, and two other crashes when they were trying to reclaim manual control of the vehicle (Noy et al., 2018).

With the advent of level 2 automation becoming widely available to the public, there has been a corresponding rise in fatal collisions directly implicating these systems. These collisions have attracted the attention of the National Transportation Safety Board (NTSB) in the US, providing us with several examples of investigations that parallel the rigour of those carried out in other modes.

Collision between a Tesla Model S and a lorry, Williston, Florida, 7 May 2016 (NTSB, 2017)

A few months after the Google car collision, a Tesla was travelling eastbound on Highway 27A at 74 mph (119 km/h) when it crashed into an articulated lorry which was making a left turn across the carriageway ahead of it. The car's autopilot systems (ACC and autosteer) were engaged, but its forward collision warning and AEB did not recognise the white side of the lorry's trailer as an obstacle, because they are designed primarily for rear-end collisions. There was no indication that the driver attempted any evasive action either, or that he was aware of the impending collision. The investigation (NTSB, 2017) found that the probable cause was the lorry driver's failure to yield right-of-way to the car, coupled with the car driver's inattention due to overreliance on the vehicle automation.

This overreliance was due in no small part to the design of the automation, which allowed prolonged disengagement from the driving task (Banks, Plant, et al., 2018). The Tesla's handbook stated that drivers must keep their hands on the steering wheel at all times (which, it must be said, somewhat negates the benefit of an autosteer system), and the system measures driver engagement through detecting if their hands are on the wheel. If not, it presents a series of visual and auditory alerts, but several minutes can elapse before an alert is given. On the crash journey, the autopilot was active for 37 of 41 minutes (including the last six minutes before the crash), during which time it detected the driver's hands on the steering wheel on seven different occasions for a total of 25 seconds. The longest period between alerts with no hands detected on the wheel was nearly six minutes.

The NTSB (2017) report concluded that since driving is a primarily visual task, this hands-on-wheel detection is a poor surrogate for driver engagement, since it reveals nothing about where the driver's attention is focused. Other manufacturers have been developing driver state monitoring through eye-tracking. The NTSB investigation recommended that manufacturers develop more effective ways to sense driver engagement and alert the driver. Following the collision, Tesla released a firmware update for the autopilot that reduced the amount of time that a driver's hands can be off the wheel before an alert is given.

Tesla emphasised that responsibility lay with the driver, while also pointing out that its autopilot crash-fatality rate was lower than the US national average (Noy et al., 2018). Nevertheless, as the NTSB (2017) noted, there is evidence that the wider public misunderstands the limitations of partial automation. To address this, the NTSB recommended that manufacturers should incorporate system safeguards that limit automation use to those conditions for which they were designed.

Collision between Uber's developmental automated vehicle and a pedestrian, Tempe, Arizona, 18 March 2018 (NTSB, 2019b)

On the night of 18 March 2018, Uber, the ride-hailing company, was conducting a test of its developmental automated driving system (classified by the NTSB, 2019b, as level 4 automation), which was fitted to a Volvo XC90 with a test operator in the driving seat to monitor the system and take over if necessary. As it negotiated the second loop of an established test route around the streets of Tempe, Arizona, a pedestrian pushing a bicycle at her side crossed the road ahead of the car. Neither the car nor the driver responded to the pedestrian until it was too late; the car struck the pedestrian at a speed of 39 mph (63 km/h).

The automated driving system did actually detect the pedestrian 5.6 seconds before impact, but never accurately classified her as a pedestrian, apparently being confused by the presence of the bicycle. Because of the way the algorithms worked, this lack of classification meant that the system did not predict the pedestrian's trajectory, and only determined a collision was imminent 1.2 seconds before impact. By this point, the situation exceeded the system's braking limitations; it was deliberately designed not to activate emergency braking for collision mitigation, relying instead on the driver's intervention. In other words, the system behaved as designed. Ironically, the Volvo's native forward collision warning and AEB systems could have prevented the crash, but Uber had deactivated these over concerns they might conflict with the automated driving system.

For more than a third of the time during the test drive, the vehicle operator's visual attention had been directed towards her mobile phone in the centre console, on which she was streaming a TV show. In the last six seconds before the collision, the operator was looking towards the centre console, only returning her gaze to the road about one second before the car struck the pedestrian. She tried steering away from the pedestrian a fraction of a second before impact. The NTSB (2019b) report concluded that, had the operator been fully attentive, she probably would have been able to take action to avoid the collision. Uber expected its vehicle operators to monitor the driving environment as well as the automated driving system, and to keep their hands and feet hovering above the steering wheel and pedals ready to take over. But her prolonged distraction was, according to the NTSB (2019b), a consequence of automation-related complacency. The NTSB found that Uber did not recognise this risk or develop effective countermeasures to control it (Stanton et al., 2019). After the collision, Uber installed a driver monitoring system that alerts the vehicle operator if they gaze away from the road for more than a few seconds.

Collision between a Tesla Model X and a crash attenuator, Mountain View, California, 23 March 2018 (NTSB, 2020)

While travelling at 71 mph (114 km/h) on a highway with the autopilot engaged, the Tesla's autosteer vision system lost track of the lane markings that it used to maintain lane position. It drifted across a gore area separating the carriageway from the exit lanes, and struck a crash attenuator as well as two other cars.

The driver did not respond to what was happening because he was distracted by a mobile phone game, and because the autopilot system gave no warnings that it could no longer maintain autosteering. The NTSB (2020) report again cited the driver's overreliance on the automation and Tesla's ineffective monitoring of driver engagement, which facilitated the driver's complacency and inattentiveness. The investigation also highlighted an issue with the timing of alerts: most crash events develop in just a few seconds, while international standards require intermittent warnings over the course of about a minute before the system disengages.

The UK's Chartered Institute of Ergonomics and Human Factors published a paper (CIEHF, 2020b) critiquing the NTSB's findings relating to this collision, centring around the definition and use of the term 'distraction'. The paper argues that, because 'driver distraction' has historically been benchmarked against non-automated vehicles, its appropriateness to automated vehicles is questionable. The term 'distraction' implies some involuntary diversion from the primary task of driving (we will discuss some such distractions in Chapter 8), but partially automated driving facilitates a voluntary diversion of attention – even if the manufacturers' would, strictly speaking, see that as a violation. If automation is to relieve drivers of substantial portions of the driving task, it is to be expected that they will engage in other activities. Instead, the CIEHF (2020b) suggest that the driver in the Mountain View crash was inattentive, rather than distracted.

Lessons learned

Taken together, these collisions highlight consistent themes of driver inattention and overreliance on the automation, coupled with a lack of feedback from the system and ineffective monitoring of driver engagement by the automated systems. The manufacturers' argument invariably places responsibility on the driver to maintain control and supervision of the system, while promoting the safety benefits of automated vehicles; Tesla claims[4] that although its autopilot is not collision-proof, it has the potential to reduce road fatalities by a factor of 10. Research suggests that such claims are optimistic; crash rates for conventional cars are substantially lower than for automated vehicles, although frequency counts in the latter category are still small so the differences are not statistically significant (Noy et al., 2018).

Nevertheless, it may be true that there is excessive focus at the moment on crashes involving automated vehicles, and we need to balance that against the systems-level advantages not just for safety, but also efficiency, economy, and mobility (Hancock et al., 2019). To some extent, it matters less whether automation results in more errors and collisions; instead, we should direct our efforts towards understanding and controlling the types of errors that are associated with automation (cf. Wiener, 1989). We now turn to consider these human factors in more detail.

PROBLEMS AND IRONIES

As we learned in Chapter 1, achieving fully automated driving across the entire vehicle fleet and completely removing the requirement for human involvement is not going to happen in the foreseeable future (Endsley, 2017).

Progress may have seemed impressive so far, but we have only automated the easiest-to-automate elements of driving (which, ironically, are also the operational elements that human drivers are most proficient at and find easiest; Huey & Wickens, 1993); getting from here to level 5 will be more technically challenging (cf. Norman, 2015). Until that time, we will still need to have a human in the driving seat who is ostensibly on constant watch over the automation and, in principle at least, remains in supervisory control of the vehicle (Noy et al., 2018). Even completely automated systems almost always rely on a human be on hand to at least monitor it and deal with those situations that the automation could not anticipate (Dekker & Woods, 2002), because – as evidenced by the Tesla and Uber collisions – it is virtually impossible to design for every eventuality.

Not only does this defeat the object of automation in the first place (Hancock et al., 2019), but there is also plenty of evidence that people are better able to detect and respond to problems when they are manually controlling a system than when supervising an automated version of it (e.g., Desmond et al., 1998; Ephrath & Young, 1981; Huey & Wickens, 1993; Kaber & Endsley, 2004; Kessel & Wickens, 1982; Parasuraman, 1987; Seppelt & Victor, 2016; Wickens & Kessel, 1981; Young, 1969). What we have seen from the accidents of automation is that problems typically arise with reclaiming manual control, either due to automation failure or even simply because the situation has gone beyond its operational design domain. This has become known as the 'out-of-the-loop' performance problem (OOTL; e.g., Kaber & Endsley, 2004) and, in fact, this problem only reveals itself when things go wrong. Under normal circumstances, with the automation working within its design envelope, overall performance is usually improved. However, should the automation fail, or the human otherwise need to intervene, their ability to do so is diminished. These problems are further exacerbated by the level of automation, in that higher levels of automation result in a greater risk of performance impairment when it fails (Navarro et al., 2018; Onnasch et al., 2014; Wickens et al., 2015). This has been referred to using a 'lumberjack' analogy (cf. Kaber, 2018; Sebok & Wickens, 2017); in other words, the higher they go, the harder they fall.

Automation, therefore, qualitatively and fundamentally changes the nature of the driver's role from active controller to passive supervisor (Hancock 2019; Parasuraman et al., 2000), a role for which people are 'magnificently disqualified' (Hancock, 2019). The driving task, such as it is, becomes one of undertaking whatever sub-tasks remain unautomated, which may not form a coherent whole as automation increasingly takes over tactical and even strategic elements of driving (Hancock et al., 2019). Meanwhile, the 'driver' faces new tasks of configuring, engaging and monitoring the automation (Banks et al., 2014; Seppelt & Victor, 2016; Stanton et al., 2001).

These knock-on effects of automation introduce a plethora of new human factors concerns (Kantowitz & Campbell, 1996). Many authors have written about the problems of automation; readers familiar with this literature will recognise that some of the headings in this chapter have been borrowed (somewhat shamelessly) from a few of the classics (e.g., Bainbridge, 1983; Norman, 1990; Wiener & Curry, 1980).

In an article that still stands the test of time, Bainbridge (1983) described the 'ironies of automation'. The first irony lies in the designer's view of the human operator as being unreliable or inefficient. As we have already discussed near the top of this chapter, automation is popularly assumed to circumvent human error – by simply removing the human element in the system. What designers overlook, though, is that they are human too – and their errors in the system design can be a major source of new problems. Furthermore, Bainbridge argues, the operator is often left to do the tasks which the designer cannot automate; in other words, there is not even any considered allocation of function, the human is just there as a makeweight to fill in the gaps in the system requirements specification (cf. Inagaki, 2003). These tasks left over typically include monitoring, diagnosis, and takeover, each of which require a skilled response, but ironically which also suffer from the skill degradation of an operator-turned-supervisor who is now starved of rehearsal and feedback from not carrying out the task manually. There is a long-standing consensus that automation can lead to skill degradation over time, such that operators do not know how to reclaim control when necessary (e.g., Bainbridge, 1983; Parasuraman, 2000). In order to take over control, a human operator must be practised at the task – which is impossible when the automation has been controlling it. Automation can therefore hinder the acquisition of experiential knowledge (Böhle et al., 1994), meaning that such knowledge and experience is required before entering into an automated task (Gopher & Kimchi, 1989). Operator training is not the answer, though, since it is impossible to train for the unforeseeable or to simulate unknown faults, so only general strategies may be learned. The irony is then training the operator to follow procedures yet expecting them to provide intelligence in the system. Bainbridge (1983) suggests slowing computer operations to a rate whereby the human operator may track them, but this negates the benefit of having an automated system in the first place. Perhaps the final irony, Bainbridge (1983) notes, is that it is the most successful automated systems, with little need for human intervention, which require the greatest investment in operator training. We might even be so bold as to add one more, based on the observation that automation is sometimes used to support human performance of increasingly complex cognitive tasks – that is, those involving technology (Cuevas et al., 2007). Is it not ironic, then, that the greater use of technology gives rise to a greater need for automated support?

Reason (1987) expands on Bainbridge's point about skill degradation with his 'catch-22' of human supervisory control, in that humans are only present in an automated system to deal with emergencies. They do this by drawing on their knowledge and experience of the system. But with limited opportunity to practice procedural responses when the task is automated – coupled with the uniqueness of each emergency – they have little such knowledge or experience to draw upon. Reason (1990) states that supervisory control is a task specifically ill-suited to the limited cognitive capabilities of humans, a point echoed more recently by Hancock (2019). Reason (1988, 1990) concludes the catch-22 by stating that automation is most effective when it is least required, and vice-versa. That is to say, under normal operating conditions, automated systems can cope perfectly well. However, so do humans, thus begging the question of why automation has been implemented in the first place. In emergency situations, stressed humans can become overloaded and performance can deteriorate; it is under such circumstances when assistance would be most valuable. Ironically, it is in these situations when automation also surrenders, relying on the human to provide creativity and quell the emergency.

An alternative perspective maintains that it is not the presence of automation per se which is the problem, rather a case of inappropriate design (Norman, 1990, 1991). The problem with automation is in its intermediate level of intelligence, in many cases relieving the operator of perceptual-motor demands – which, ironically, are the tasks that people are typically most skilful at – while leaving them with more mentally demanding cognitive tasks. Moreover, automation often imposes even more cognitive demands by providing insufficient feedback about what it is doing, meaning that the user has to expend effort in actively gathering and keeping track of that information. Norman (1990, 1991) used the case study of the China Airlines Boeing 747 in 1985 (see Chapter 1) to illustrate the importance of feedback. In that incident, the autopilot attempted to compensate for an imbalance in the aircraft caused by a fuel leak. The autopilot waited until it could no longer cope before informing the crew, by which time the situation was much worse. Thus, the culprit is not necessarily the automation, rather a lack of continual feedback and interaction which keeps the operator uninformed and out of the loop. In the event of a failure scenario, operators are left without sufficient knowledge of the situation to be able to deal with it efficiently. All of this led Norman (1990) to a new irony of automation: that it is not powerful enough. Norman (1990) suggested either improving or removing automated systems by making them either more or less intelligent, but their present level is inappropriate under anything but normal conditions. If automation were perfect (i.e., never fails), feedback would be unnecessary. However, as we now know, technical (un)reliability precludes the possibility of a perfect automation system; for the foreseeable future, then, the unique skills and flexibility of human operators will continue to prove crucial in critical situations.

The treatises of Bainbridge, Reason, and Norman raise further concerns associated with human supervisors of automation who are mostly – but not quite totally – out of the loop. There is no doubt that monitoring performance is impaired if the task is executed by automation instead of a human (Molloy & Parasuraman, 1996; Parasuraman, 1987), and the problems are usually manifest in recovering control from automation failure (Endsley & Kiris, 1995; Kaber & Endsley, 1997; Stanton et al., 1997). We have already seen numerous telling examples of these in the aviation and automotive accidents reviewed earlier in this chapter, and what those case studies particularly highlight are the deeper cognitive processes at play in many of them. Such problems have variously been attributed to vigilance failures (Molloy & Parasuraman, 1996), trust in the automation (Kaber & Endsley, 1997; Molloy & Parasuraman, 1996; Parasuraman & Riley, 1997), complacency (de Waard et al., 1999), behavioural adaptation (Rudin-Brown & Parker, 2004), situation awareness (Endsley, 1995; 2015; 2017; Stanton, Salmon et al., 2017; Wickens et al., 2015), and/or MWL (Young & Stanton, 2002a). Whilst there is inevitable overlap between these areas (see e.g., Heikoop et al., 2016; Stanton & Young, 2000; Young & Weldon, 2013 for summaries), we now briefly summarise the key points of each.

Vigilance

Vigilance tasks involve monitoring for low frequency signals from a background of noise. The classic example is the wartime radar operator's task of spotting enemy submarines or aircraft, but vigilance principles are equally applicable to monitoring a highly reliable automated system for an infrequent failure. There is no doubt that monitoring performance is impaired if the task is executed by automation instead of a human (Molloy & Parasuraman, 1996).

It has been known for more than seven decades that it is virtually impossible to maintain high performance on vigilance tasks for any length of time (Mackworth, 1948). A performance decrement can be observed from as early as two minutes into the task (Makeig & Inlow, 1993); by 20–30 minutes a robust and substantial decrease in vigilance is consistently evident (Singleton, 1989; Warm et al., 1996). A plot of performance against time usually shows that this vigilance decrement follows an approximately exponential decay curve (Green, 1988). The vigilance decrement cannot be offset by feedback or motivation, although it is thought that cognitive automaticity (i.e., skilled performance) is immune to the detrimental effects of sustained monitoring (Fisk & Schneider, 1981; Tucker et al., 1997).

Contrary to popular opinion, the mental demands of sustained vigilance are quite substantial. Warm et al. (1996) advocated a resource depletion model of vigilance, whereby maintaining the effort required for vigilant monitoring eventually results in fewer resources than are necessary to carry out the task effectively (see also Sturman et al., 2020). Although others have suggested that the MWL of monitoring can still be considered to be low (Cain, 2007), it is generally accepted now that the workload of monitoring is considerable, while older arousal theories of the vigilance decrement (linked to underload or boredom) have been replaced by associations with trust or overreliance (Parasuraman et al., 1996b).

Failures of vigilance while monitoring an automated task are more common if the operator is engaged in concurrent activities (Molloy & Parasuraman, 1996). For example, a pilot supervising an automated flight deck is less likely to detect any problems if they are also concentrating on filing a flight plan, than if there are no distractions from the monitoring task. But, regardless of any secondary tasks, the very nature of the vigilance decrement shows that humans are just not designed for this kind of prolonged monitoring, and this is a relevant concern for automated vehicles: 'If you build vehicles where drivers are rarely required to respond, then they will rarely respond when required' (Hancock, 2019; p. 485).

Trust

Failures of vigilance with automation have been associated with excessive trust in the system (Molloy & Parasuraman, 1996; Parasuraman et al., 1996b), which can influence (over-)reliance on the automation (Lee & See, 2004; Parasuraman & Wickens, 2008). The level of trust that someone holds in an automated system – whether too low or too high – determines how they monitor and use (or misuse, or even disuse; Parasuraman & Riley, 1997) that system. As such, trust in automation is a topic that has attracted particular attention (e.g., Lee & Moray, 1994; Molloy & Parasuraman, 1996; Muir, 1994; Muir & Moray, 1996; Parasuraman & Riley, 1997; Parasuraman et al., 1992).

Muir (1994; see also Muir & Moray, 1996) developed a model of trust in machines, based on existing models of interpersonal trust. They proposed that trust is based on perceptions of competence and predictability, such that it can develop over time if there is little variability in system behaviour. Conversely, though, if trust has been broken (e.g., by a system failure), it will be slower to recover than it took to build it in the first place (Seong & Bisantz, 2008).

Trust is governed by self-confidence, confidence in the system, and the reliability of the system (Hancock & Parasuraman, 1992). Operators tend to choose automation when their trust in it exceeds their self-confidence in their own ability at the task (Lee & Moray, 1994; Parasuraman et al., 2008). Nevertheless, a general predisposition towards manual control was found in these studies, reflecting an underlying distrust in automation. For instance, one study found that operators are prepared to voluntarily incur increases in workload without increased satisfaction, purely for the sake of resuming manual control (Hockey & Maule, 1995).

Distrust and disuse can also be a consequence of high false alarm rates (Lees & Lee, 2007; Parasuraman & Riley, 1997), which are common with many automated warning systems (Parasuraman & Wickens, 2008; Sheridan & Parasuraman, 2000). However, such disuse (cf. Parasuraman & Riley, 1997) of automation negates any of its potential benefits. At the other extreme, misuse arising from overreliance could ultimately result in the kinds of serious accidents we reviewed earlier in this chapter (Mueller et al., 2021).

Banks, Eriksson et al. (2018) found that drivers using Tesla's Autopilot system exhibited behaviours indicative of overtrust and misuse in driving hands-free. As we already noted in Chapter 1, there is plentiful evidence in popular and social media of such behaviours, with several examples[5] of drivers asleep or otherwise inattentive while at the wheel. Although Tesla's defence is invariably that the drivers are always responsible for the vehicle, Banks, Eriksson et al., (2018) also found that drivers are not supported by the system in their newfound monitoring role.

The calibration of trust is therefore crucial for the consequent 'appropriate' use of automation (Lee & See, 2004; Parasuraman & Riley, 1997), and depends on the user's understanding of the capabilities of the system, its limitations, and its performance (Mallam et al., 2020; Mueller et al., 2021; Seong & Bisantz, 2008). In turn, this understanding depends on the design of the automated system as well as the feedback received from it (Lee & See, 2004; Parasuraman & Riley, 1997). If the system is designed to assume control with little input from or feedback to the driver, then the driver may have difficulty in developing an appropriate mental model of its operation in a given scenario. Without knowing exactly how it might behave, the driver could become distrustful of the system or develop misplaced trust (cf. Parasuraman & Riley, 1997). Parasuraman & Riley (1997) go further to suggest that abuse of automation in design – that is, a technology-centred approach which neglects the human operator – can promote both misuse and disuse of automation by human operators. Consistent with this assertion is the observation that higher degrees of automation may exacerbate the negative effects of overtrust (Parasuraman et al., 2000).

As with vigilance, multitasking interacts with trust to influence reliance on the system – if the automation is highly reliable and the user's attention is divided among multiple tasks, they can easily slip into overtrust and fail to detect automation failures. Conversely, when monitoring was the only task, operators detected almost all failures (Lee & See, 2004).

Equipment reliability is, therefore, a key determinant of trust, with associated problems having been observed in aviation and automotive automation (e.g., Kazi et al., 2005; Lee & See, 2004). Overreliance on a highly reliable automated system is closely associated with complacency (Parasuraman et al., 2008), a term which is loaded with accusation as it implies that the operator has neglected their task. But, as we shall see next, that view far from reflects the human factors concept of automation-related complacency.

Complacency

Vigilance, trust and complacency are closely related to each other. Where vigilance is about signal detection, overtrust in automation gives rise to overreliance and complacency in performance (Thornton et al., 1992), which can be particularly critical in the event of automation failure (e.g., de Waard et al., 1999).

Automation-related complacency is in part an attitudinal construct (Parasuraman et al., 1992), but is as much influenced by interactions between the operator, the task, and the automation itself. People may be particularly susceptible to complacency if they are inexperienced, fatigued, or facing high workload (Bailey et al., 2006; Parasuraman et al., 1992). Conversely, automation can reduce workload, but this also induces complacency as it detaches the operator from the task (Mohrmann et al., 2015). Higher degrees of automation can further disengage the operator as they learn to trust and rely on the system (Carsten et al., 2012; Wickens et al., 2015). Complacency therefore contributes to being 'out of the loop' (Sebok & Wickens, 2017).

As we just saw with trust, automation reliability is a key factor with complacency. Complacency can occur if the automation is highly – but not perfectly – reliable, as the operator might not monitor consistently or closely, and so fail to detect the very occasional failures (Onnasch et al., 2014; Parasuraman et al., 2000). The effect of complacency is amplified when operators have other tasks to perform (Parasuraman et al., 2000) and when automation reliability is imperfect but constant, as operators allocate attention away from the automation when they trust it (Parasuraman & Wickens, 2008; Parasuraman et al., 2008). It is a vicious circle: the more reliable the automation, the less the human has to do, so the less attention they pay to it (Endsley, 2017). Thus, more reliable systems inevitably make it difficult for operators to notice when something goes wrong (Ljung Aust, 2020).

Complacency might, therefore, seem to be a failure to pay enough attention to the automation. However, some argue that this should not be seen as complacency in the 'non-vigilant' sense at all (e.g., Moray & Inagaki, 2000), but instead might be a satisficing approach on the part of the operator to conserve effort (Kaber, 2018). In other words, what looks like complacency may actually be an optimal strategy to allocate limited attentional resources between highly reliable automation (that does not, in fact, need to be monitored very often), and other, more demanding, tasks (Wickens et al., 2015). Importantly, optimal sampling does not necessarily mean perfect – it is about detecting the maximum number of signals, not detecting all of them. That is what sets this argument apart from the traditional view of complacency, which expects the operator to detect all failures even in highly reliable systems, and any missed signals are somehow a failure on the part of the operator. The optimal level of sampling will depend on the rate of signals (i.e., faults or failures) as well as the need to monitor any other systems; it makes no sense to focus too much attention on the automation if it is highly reliable. Operators tend to allocate their attention to systems where they are expecting changes and which have higher value to their task; such expectations decrease as the reliability of automation decreases (Wickens et al., 2015). Continuous monitoring of the automation would not, therefore, be rational: paying too much attention to it (perhaps due to distrust) is counterproductive and wastes effort if the automation hardly ever goes wrong. Moreover, if your attention is on the automation, then it is not on anything else that might need it more.

Behavioural adaptation

Complacency can be seen as a form of behavioural adaptation, as operators become accustomed to the reliability of the automation and adapt their attention allocation strategies in response (Wickens et al., 2015). In the context of automation, behavioural adaptation occurs when it results in unintended or unanticipated behaviours, with negative consequences for the wider socio-technical system (Dekker & Woods, 2002; Parasuraman et al., 2000; Rudin-Brown, 2010).

To start with an anodyne example, lane departure warning and lane-keeping assist systems can be cancelled by use of the turn signals. But in some cases, it is not necessary to signal: in advanced driver training, signalling when there is no traffic around demonstrates a lack of situation awareness, since there is nobody to signal to. So drivers could end up being coerced into giving redundant signals so as to avoid interventions from the system. More insidiously, the presence of systems such as AEB or ESC in a car could potentially change the driver's style and thus negate some of the expected safety benefits. If drivers come to believe that the safety net will always catch them, it may influence their driving towards more risky behaviours (such as increased speed or shorter headways; Janssen & Nilsson, 1993; Lee & Seppelt, 2012), thereby 'pushing the envelope' to its limits (e.g., Cacciabue & Saad, 2008; Stanton & Pinto, 2000). As with aviation, what was the last line of defence ultimately becomes the first point of control (cf. Billings, 1997).

As a counterpoint, these vehicle automation systems (cf. Young et al., 2007), which mostly sit silently in the background until needed, may be less likely to elicit behavioural adaptation because there is no feedback from the system (Hedlund, 2000; Rudin-Brown, 2010). But as levels of automation increase, so too does the potential for unanticipated behavioural response. A classic case of behavioural adaptation is in drivers treating an ACC system as if it were a collision avoidance device, rather than as the 'comfort and convenience' system for which it was designed (cf. Richardson et al., 1997). Rudin-Brown & Parker (2004) found that drivers actively relied on the ACC system to keep a safe distance from the vehicle in front. However, the reduction in workload offered by ACC resulted in negative adaptation in the form of less attention to the driving task, more steering variability and worse reactions to a failure of the ACC system (Rudin-Brown & Parker, 2004). Behavioural adaptation is therefore an important variable in determining the effectiveness of vehicle automation; Rudin-Brown & Parker (2004) showed a 33% reduction in effectiveness of ACC as a result.

Ward et al. (1995) also explored the effects of ACC on driving behaviour, finding that steering and yielding behaviours were both adversely affected by the use of ACC, while drivers set higher speeds and shorter headways with ACC than they would normally drive. Similar studies of automated vehicle systems revealed problems with engaging and disengaging the automation (e.g., Rillings, 1997). In particular, when disengaging automation (such as when leaving a highway), the driver's choice of speed is influenced by the set speed of the automated vehicle (Bloomfield et al., 1995).

Speed choice does seem to be one of the principal mechanisms for behavioural adaptation in driving; as we have outlined above, people might speed up if they feel they are protected by an automated system. But the reverse is true too, and it does not have to be related to automation. Drivers tend to slow down when their capabilities are hampered, such as when using a mobile phone (Haigney et al., 2000; Strayer et al., 2003), eating and drinking while driving (Young et al., 2008), or even when their eyesight is getting worse (Higgins & Wood, 2005). We would not advocate such strategies as an excuse to drive when under such conditions, not least because the evidence suggests the level of speed compensation might not match the level of degradation (Higgins & Wood, 2005). Later in this book, in Stage 3, we will explore how automation may help to mitigate the effects of these impairments.

The reasons for behavioural adaptation with automation can be many and varied; Rudin-Brown (2010) proposed a qualitative model of behavioural adaptation which invoked factors such as locus of control, trust, and mental models. (Interestingly, this is a very similar set of factors as proposed by Stanton & Young (2000) in their psychological model of vehicle automation.) But perhaps the most prominent factor is the driver's mental model of the automation (Rudin-Brown & Parker, 2004), since our understanding of a system very much guides our interactions with it. Anyone who has ever experienced an ABS intervention knows that it makes a very conspicuous noise, which can be disconcerting for a driver unfamiliar with it; this could lead to them releasing the brake, believing that something is wrong with the car (Lee & Seppelt, 2012) – but that would be, of course, an inappropriate reaction in the circumstances.

Behavioural adaptation is in large part dependent on the person's belief about what the automation can do. There is evidence that drivers hold optimistic expectations about the capabilities of automated vehicles (e.g., Hancock et al., 2019; Kyriakidis et al., 2019), which potentially results in people relinquishing their supervision of the system at a lower level of automation than would be appropriate (i.e., at level 2 rather than level 3; cf. Banks, Eriksson et al., 2018; Mueller et al., 2021). In one study (Teoh, 2020), some 14% of drivers were unaware of what level 2 automation can and cannot do, and when they could legitimately engage in other, non-driving, activities; drivers were more likely to do so with level 2 automation as compared to level 1 or level 0 automation. Meanwhile, about half of all drivers assumed that the option to engage the automation would be locked out if it was not designed for use in a particular situation (Teoh, 2020).

Is it any wonder, then, that drivers appear to demonstrate 'risky' behavioural adaptation when using these systems? In other words, apparent misuse of an automated system beyond its design limits is actually more about the driver's (reasonable) expectations associated with the system's design and capabilities. These expectations are developed through experience of using the system, coupled with feedback and other information about how it works (Rudin-Brown & Parker, 2004), much of which is of course via the human-machine interface (Kyriakidis et al., 2019). To turn that around, behavioural adaptation could be mitigated by clear feedback from the system about its operating envelope, perhaps even locking out the system when outside its domain (as many drivers expect; Teoh, 2020), rather than relying on drivers to read the manual (Mueller et al., 2021). We could even go so far as to support positive behavioural adaptations through interface design (see Young & Carsten, 2013), reinforcing desired behaviours as much as minimising undesired ones (Stanton & Pinto, 2000). We will learn more about this in Chapter 9.

Thus, whilst it may be tempting to ascribe some blame to the human for their behavioural adaptations, as with all such human-machine interactions it is actually the design and implementation of the system that has 'encouraged' such use. By providing potentially misleading information about, or feedback from, a system, designers not only risk engendering inappropriate behavioural adaptations but also giving rise to problems with situation awareness.

Situation awareness

Out-of-the-loop performance problems, such as those involving vigilance or complacency (e.g., Molloy & Parasuraman, 1996), are arguably associated with reduced awareness of system states, caused by the lack of interaction with the system (Kaber & Endsley, 1997). Automated driving systems can induce drivers to engage in non-driving activities, causing distraction (or inattention; cf. CIEHF, 2020b) that can delay responses through reduced feedback, passive monitoring, and poor mental models (Lee & Seppelt, 2012). Being out of the loop degrades a driver's perception, understanding and prediction of the situation as it unfolds – the key components of situation awareness.

Situation awareness has been defined as '…the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future' (Endsley, 1995; p. 36). The concept has not met with universal approval, as some have highlighted the futility of trying to define in advance the most important elements of the situation that the operator is supposed to be aware of; such importance is dependent on context and only becomes obvious in hindsight (Moray & Inagaki, 2000; Sarter & Woods, 1995). To borrow a well-worn phrase, these are the 'unknown unknowns'.

Truism or not, individual situation awareness does seem to deteriorate with automation. Some of this may be due to people engaging in other tasks while the automation is active (cf. Teoh, 2020). But, more than anything, it is the passivity of the monitoring task that affects situation awareness; people are less aware of changes in the state of the system when those changes are under the control of another agent (Endsley & Kiris, 1995; Parasuraman et al., 2000).

It is these changes of state that are crucial in terms of situation awareness. Earlier in this chapter, we discussed the issue of 'automation surprises'; these unexpected state transitions are fundamentally a loss of situation awareness about the mode of the system (Endsley, 2017). Moreover, as with many of the factors we have already discussed above, problems with situation awareness tend to be manifest when dealing with an automation failure, even if there are no differences in MWL (Endsley & Kiris, 1995; Metzger & Parasuraman, 2001). This might be because automation just places different demands upon the operator (Endsley & Kiris, 1995), or because the operator's information requirements are different between normal and failure circumstances (Parasuraman et al., 2008). Nevertheless, for a given level of automation, situation awareness is the crucial factor determining performance during both routine operation and failure conditions (Wickens et al., 2010).

More recent work (e.g., Salmon et al., 2020) considers situation awareness not just in terms of the individual human, but from the perspective of the overall human-automation system. Under this distributed cognition approach, situation awareness is held not just by the people in the system, but also by the technological agents (i.e., the automation; Stanton et al., 2017), and is thus distributed around the whole system (cf. Artman & Garbis, 1998; Moon et al., 2020; Plant & Stanton, 2016). Other ways of thinking about this relate to the shared understanding of a situation across human and machine (cf. Salas et al., 1995), the degree to which each has the information they need to do their job (Endsley, 2015; Kaber et al., 2001), the understanding of each others' activities and intentions (Shu & Furuta, 2005), or the overlap in situation awareness between human and automation (Endsley & Jones, 1997). Failures associated with situation awareness are therefore more about communication between system elements and agents, to ensure that the right agent has the right awareness at the right time (Stanton et al., 2006; Stanton et al., 2017).

Distributed situation awareness is, and will be, an increasingly prominent concept in the future world of connected and autonomous vehicles (de Winter et al., 2014; Stanton, Salmon et al., 2011), where vehicles are communicating with each other, the road infrastructure, as well as with the people in the vehicles (be they drivers or otherwise). In a mixed parc consisting of highly sophisticated, automated vehicles travelling alongside dumb, manually driven cars (Stanton, 2015), there will be drivers, non-automated, semi-automated and fully automated vehicles each possessing different levels of understanding about the ambient traffic situation (Banks & Stanton, 2015; 2016). Cognitive functions are distributed between drivers and automation (Banks et al., 2014), but while automated systems can possess more accurate metrical information about the kinematics of driving (Stanton & Salmon, 2009; Young et al., 2007), human drivers understand much more about the motivations and potential actions of other drivers (Walker et al., 2015). No single agent will have anything more than partial awareness, yet the need to organise this real-time on-road flow of information is crucial to support safe and effective road travel (Salmon et al., 2012).

Sarter & Woods (1995) explain that such problems are often a consequence of technology-centred automation, as the design and capabilities of advanced automation make it both more important and more difficult to maintain awareness of the state and behaviour of the system. Interface design thus comes to the fore once again, then; the 'strong and silent' automation creates cognitive demand for a user trying to maintain situation awareness with little salient feedback on current or future system status, mode states or transitions (cf. Sarter & Woods, 1995; Stanton et al., 2011). This may seem counterintuitive; one might have expected situation awareness to be enhanced with automation as attentional resources have been released from carrying out the task manually. But it just serves to highlight another paradox (if not, strictly speaking, an irony) of automation: that it can both reduce and increase the MWL on operators.

Mental workload

For some time, MWL has become a predominant concern in the human factors literature, reflecting the increasing technologisation of our lives (Rumar, 1993; Singleton, 1989; Young et al., 2015). As modern technology in many working environments imposes more cognitive demands upon operators than physical demands, the understanding of how MWL impinges on performance is critical. We explore the effects of automation on MWL in more detail in the next few chapters of this book, so for the time being this section just provides an overview of some key points. The focus of Chapter 3 is on mental underload but, as we have already alluded to, automation also has the potential to cause overload.

Whilst automation is ostensibly designed to reduce workload, it also qualitatively changes the nature of the task, often in ways that were unanticipated or unintended by the designers (Metzger & Parasuraman, 2005). Such changes could, paradoxically, overload the operator, thus negating the intended benefits of automation in terms of comfort and convenience. Increases in MWL may arise from having to consider a whole new set of decision options generated by the automation (Endsley & Kaber, 1999; Hilburn, 1997), through having to integrate and interpret information (Lee & Seppelt, 2012), or through the increased demands of monitoring and managing the system (Endsley, 1987; Kantowitz & Campbell, 1996) and being ready to take over if necessary (Banks, Eriksson et al., 2018).

The design of the automation is a key factor in determining whether it has the potential to overload the operator (Onnasch et al., 2014; Verwey, 1993). Reinartz (1993) argued that operators and automation are members of the same team. Performance is therefore dependent upon how well that team works and communicates together. But, as we saw with some of the case studies earlier, automated systems are typically poor at communicating with the operator – that is, providing appropriate and timely feedback. The operator then faces an increase in MWL resulting from the additional task of actively seeking out and gathering information about the system state.

In the driving context, such an increase in cognitive workload can cause a 'tunnelling' of drivers' useful visual field, leading to narrowed or inefficient attention allocation (i.e., spending less time looking at areas in the peripheries, such as mirrors and instruments, and instead focus on looking centrally ahead; Harbluk et al., 2007; Liao & Moray, 1993; Summala et al., 1996), thus adversely affecting performance (Donmez et al., 2007; Horberry et al., 2006). This is particularly true if workload is already high (e.g., in urban driving; Liu & Lee, 2006) or if the driver has a lower capacity to respond (e.g., in the elderly; May et al., 2005; or simply by having less skill and experience; Summala et al., 1996). Conversely, automation has been shown to decrease drivers' visual attention to the road centre (Merat et al., 2014), almost implying the opposite of attentional narrowing – though perhaps equally detrimental for performance.

There is an argument that high MWL in driving is the exception (Stanton & Marsden, 1996), with suggestions that drivers may have up to 50% spare visual capacity during 'normal' driving (Hughes & Cole, 1986). Reducing MWL in cases where the level is already manageable is not necessarily desirable as it only serves to remove the driver from the control loop (Ephrath & Young, 1981). Furthermore, we also know that higher degrees of automation can reduce MWL (e.g., de Winter et al., 2014; Evans & Fendley, 2017; Onnasch et al., 2014; Young & Stanton, 2002b). It follows that most of the time, vehicle automation will relieve the driver of demands they can quite readily cope with. Ironically, then, automated systems have the potential for imposing mental underload. There is wide consensus that underload is at least as serious an issue as overload (Brookhuis, 1993; Hancock & Parasuraman, 1992; Leplat, 1978; Schlegel, 1993; Young et al., 2015), and can be detrimental to performance (Desmond & Hoyes, 1996), leading to performance decrements, attentional lapses, and errors (Wilson & Rajan, 1995). Indeed, underload is possibly of greater concern, as it is more difficult to detect than overload (Hancock & Verwey, 1997).

This apparent contradiction, that automation can both reduce and increase MWL, may be resolved by considering the suggestion that automation actually redistributes MWL across different stages of information processing as well as different aspects of a task (Lee et al., 2020; Tsang & Vidulich, 2006). Consequently, automation might only give the appearance of reducing MWL, whereas in fact it just imposes qualitatively different demands. Depending on the type of automation and the type of task, automation can variously increase or decrease workload associated with perceiving information, central cognitive processing, or response execution (see Wickens & Kessel, 1981; Wickens et al., 2015). In a similar way, part-task automation (remembering that truly full driving automation is still unrealistic) can ostensibly reduce MWL for those aspects of the task that have been automated, but if there is a patchwork quilt of tasks left over that do not form a coherent whole, this actually increases MWL[3] (see Stanton et al., 2021).

Meanwhile, it has been observed that autopilots in commercial aircraft can lead to mental underload during highly automated activities such as cruise flight, but mental overload during more critical operations such as take-off and landing (Endsley, 2015; Parasuraman et al., 1996b). This is the result of 'clumsy automation' as we described earlier in this chapter – making the easy tasks easier and the hard tasks harder (Lee & Seppelt, 2012). Similar issues are applicable in both aircraft and automobiles (Labiale, 1997; Lovesey, 1995;

Roscoe, 1992; Verwey, 1993). A human-centred approach would seek to do the opposite, optimising workload by providing automated support during high workload (flattening the peaks) but paring back that support when workload is low (filling in the troughs; cf. Parasuraman, 1987; Reichart, 1993; Rumar, 1993). We will revisit this notion of adaptive automation in Chapter 9.

The problem of lumpy workload peaks associated with clumsy automation is compounded by the willingness of operators to, ironically, delegate tasks to the automation more during low workload than with high workload (Lee & Seppelt, 2012), which has been observed with cockpit automation (Metzger & Parasuraman, 2005). The reduction in MWL offered by automation then enables the operator to exploit that and allocate attention to other concurrent tasks instead (Onnasch et al., 2014), which drivers are wont to do when using higher degrees of automation (Lee et al., 2020). Moreover, if such competing tasks present high MWL, then they will even draw the operator's attention away from the automated task (Endsley, 2017). However, now we are presented with one of the biggest problems of automation: the takeover scenario.

If attention has been drawn – voluntarily or otherwise – to secondary tasks in the vehicle, then reactions to a takeover request or automation failure will inevitably be affected (cf. Onnasch et al., 2014). Responses to unexpected takeover requests are slower when monitoring automation than when driving manually (Eriksson & Stanton, 2017b; Young & Stanton, 2007a), while takeover quality is impaired when the driver is distracted (Lee et al., 2020). Other studies showing adverse reactions to failures of vehicle automation have also observed reductions in MWL (e.g., de Waard et al., 1999; Stanton et al., 1997), although there are exceptions to this (e.g., Desmond et al., 1998; Nilsson, 1995). Thus the reduced MWL associated with automation can improve routine performance but present difficulties in coping with an emergency or system failure (Norman, 1990; Wickens et al., 2010), as operators face a sudden surge in demand. So whilst being relieved of the task may reduce MWL, this by no means offsets the value of being in active control (Kessel & Wickens, 1982).

CONCLUSIONS

As with Stanton & Young's (2000) psychological model of driving automation, the cognitive factors involved when interacting with automation that we reviewed here are all interdependent. For instance, mode confusions can both reduce situation awareness and increase MWL (Stanton et al., 2011), while increased vigilant monitoring demands can also overload the operator (Hancock & Verwey, 1997). Behavioural adaptation is linked to trust (Rudin-Brown & Parker, 2004), which in turn can reduce MWL by relieving the burden of monitoring the system (Kantowitz & Campbell, 1996). However, that raises the spectre of complacency, which has also been associated with reductions in MWL (de Waard et al., 1999).

The popular assumption set out at the start of this chapter, that automation will reduce or eliminate human error, is flawed, being rooted in technology-centred thinking without due consideration for the role of the human in these systems (Navarro et al., 2018; Read et al., 2020). Automated systems are not error-free and, when automation errors occur, they can be more insidious than manual errors (Banks, Plant et al., 2018). At best, automation errors go unnoticed; at worst, they are compounded by human errors. Since no system is perfect, the problems raised in this chapter will remain important for the foreseeable future (Parasuraman & Wickens, 2008).

It is fair to say that many of these problems of automation centre around the issue of taking over manual control (cf. Endsley & Kiris, 1995; Kaber & Endsley, 1997), whether by design, arising from an automation surprise, or due to automation failure. Such issues were evident in all of the accident case studies presented earlier, in both aviation and automotive domains. The response of vehicle manufacturers to these crashes has typically been that drivers should not rely on the automation as it is their responsibility to maintain control of the car. But in the light of the human factors research reviewed above, this response is disingenuous: 'Using the driver as a last line of defence is arguably a poor solution for addressing the shortcomings in the design and implementation of SAE Level 2 and 3 automation' (Banks, Eriksson et al., 2018; p. 144). Failures in driver monitoring, then, are really failures in automation design. As we move towards level 3 automation in the very near future (see Chapter 1), this so-called 'abuse' of automation (cf. Parasuraman & Riley, 1997) is likely to be amplified as drivers can now legitimately rely on the system – in some circumstances, at least. How will we manage the 'appropriate' use of automation within its operational design domain?

Questions of automation design will be addressed later in this book. Before we get there, though, we spend the next few chapters delving deeper into one of the key human factors concerns with automation from those reviewed above. Through all these 'problems of automation', we can see that MWL has been an underlying factor – sometimes too high due to lack of feedback or vigilance demands, sometimes too low because of complacency or overtrust. We have already noted that underload is just as bad for performance as overload, but we need to understand why having too little to do can be detrimental. That is where the journey of this book takes us next.

KEY POINTS

- There are undoubtedly benefits to be had from driving automation in terms of road safety, but the technology-centred assumption that automation will 'cure' human error is flawed; technology is not perfect either, and people are being expected to pick up the pieces – a role for which humans are 'magnificently disqualified' (Hancock, 2019).

- Because of this, lessons learned from aviation automation and investigations of accidents involving highly automated vehicles have demonstrated shortfalls in the anticipated benefits, as well as new problems arising from human interaction with the automated systems.
- There are multiple, interacting human factors concerns associated with automated systems but these all revolve around the central theme of MWL, which can be simultaneously too high and too low when faced with automation – and both overload and underload are detrimental to human performance.

NOTES

1. https://www.nhtsa.gov/sites/nhtsa.dot.gov/files/documents/13069a-ads2.0_090617_v9a_tag.pdf (accessed 28 April 2022)
2. In a 2016 interview at the Future Transport Solutions conference in Oslo, Elon Musk claimed that the probability of having an accident was 50% lower with Tesla's autopilot, making it 'almost twice as good as a person' (see https://www.youtube.com/watch?v=j-_R3OV0bVE&t=1345s, accessed 29 April 2022).
3. *How to Make the Most of Your Human: Design Considerations for Single Pilot Operations*. NASA Engineering & Safety Center Academy Webcast by Paul Schutte, NASA Langley Research Center, 17 March 2016. https://mediaex-server.larc.nasa.gov/Academy/Play/fdea070f17aa4ceaae5ab03dc8a6c2251d?catalog=6881410 (accessed 5 May 2022).
4. https://www.independent.co.uk/life-style/gadgets-and-tech/news/tesla-crash-police-autopilot-self-driving-car-a8376881.html (accessed 28 April 2022).
5. https://www.independent.co.uk/life-style/gadgets-and-tech/news/tesla-driver-sleeping-video-autonomous-car-model-x-autopilot-a8756261.html (accessed 28 April 2022).

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Chapter 3

Pay attention

OVERVIEW

Our journey through this book is nearing its first rest stop with the end of Stage 1, but before doing so we will examine the core human factors concepts that form the foundation of this book: attention, automaticity and, especially, mental workload. The reader is taken on the scenic route through the literature of the last 50 years as a lead-up to discussing the key problem of mental underload with automation. Mental underload is described as being a particular issue in an automation failure scenario, and several theories are considered as explanations for why that might be the case. Ultimately, we present our own hypothesis for this: malleable attentional resources theory (MART). Based on capacity theories of attention, MART posits that attentional resources actually shrink when faced with underload, as capacity adapts to meet the demands of the task. However, should demands suddenly increase – such as in an automation failure scenario – the operator no longer has the capacity to cope, and performance problems inevitably result. The chapter closes with an overview of the next section of the book, which presents a series of empirical studies to test MART.

INTRODUCTION

Towards the end of Chapter 2, we briefly reviewed the effects of automation on mental workload (MWL), seeing that it can result in overload and underload, both of which are detrimental to performance (Wilson & Rajan, 1995) and so should be considered at least as seriously as each other (cf. Hancock & Parasuraman, 1992). We also reviewed research throughout Chapter 2 showing that human operators of automated systems exhibit inferior performance than if they were controlling the system manually. Mental underload is a good candidate to explain some of these performance problems with automation, given the evidence that automation reduces MWL. What there has historically been less understanding of, though, is the mechanism of how and why underload leads to impaired performance. The present chapter (which

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is largely based on our earlier work in Young & Stanton, 2002a) puts forward our explanation for these effects. But in order to get there, we must first understand more about the nature of MWL itself.

MENTAL WORKLOAD REVISITED

In driving, MWL can be affected by a number of factors (Schlegel, 1993), which are either external to the individual (e.g., traffic, road type) or internal (e.g., age, experience). Dual carriageways, for example, impose lower workload than driving in a suburban environment (Foy & Chapman, 2018). In addition, different elements of the driving task (e.g., vehicle control and guidance, navigation) can impose varying levels of MWL. For instance, steering appears to be a significant source of workload in vehicle control (Young & Stanton, 2002b). These factors can interact, as different levels of traffic do not affect the skilled driver, but high traffic increases workload for the unskilled driver (Verwey, 1993). Harking back to the behavioural adaptation theories discussed in Chapter 2, there is also some evidence of MWL homeostasis in driving, as drivers have control over a key determinant of task demand: speed (Foy & Chapman, 2018). As such, drivers may seek to increase demands when the task is easy (i.e., by driving faster), and reduce demands (speed) if it is more difficult, thereby maintaining a constant level of MWL (Foy & Chapman, 2018; Zeitlin, 1995). Similarly, when faced with a choice of levels of automation, about one-third of the time people chose to carry out the task manually when demands were low, apparently to maintain MWL in a comfortable envelope (Navarro et al., 2018).

Clearly, then, MWL is a multidimensional construct (Evans & Fendley, 2017), determined by characteristics of the task (e.g., objective demands, performance), the operator (e.g., skill, attention; Leplat, 1978), and even the context within which the task takes place. Nevertheless, there is no universally accepted definition of MWL (see Young et al., 2015, for a discussion), although there are commonalities in the literature centred on the balance between task demands and the resources required to meet those demands (cf. Evans & Fendley, 2017; Schlegel, 1993). Collating this literature together enabled Young & Stanton (2001a, p. 507) to propose an operational definition of MWL:

> 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.

In this definition, the 'level of attentional resources' is assumed to have a finite capacity,[1] which may be allocated to one or more tasks, but if the limit is reached then any further increases in demand are manifest in performance degradation. 'Performance criteria' can be imposed by external requirements, or may represent the internal goals of the individual. Examples of 'task demands' are time pressure or complexity. 'External support' may be in the form of peer assistance or technological aids. Finally, 'past experience' can influence MWL via changes in skill or knowledge. Essentially, then, MWL represents the proportion of resources required to meet the task demands (Welford, 1978). If demands begin to exceed capacity, the skilled operator either adjusts their strategy to compensate (Singleton, 1989), or performance degrades.

The concept of MWL is, therefore, inextricably linked with theories of attentional resources, so let us turn to learn more about such theories in our continuing quest to understand the mechanism of mental underload.

ATTENTION

The classic and oft-cited early work in attentional resources is that of Kahneman (1973), who proposed a capacity model of attention as an alternative to bottleneck or filter theories (e.g., Broadbent, 1958; Deutsch & Deutsch, 1963; Treisman, 1964). Essentially, the capacity model proposes a single resource view of attention – that is, attention is viewed as one unitary pool of resources. This pool has a finite limit; therefore, the ability to perform two separate concurrent activities depends upon the effective allocation of attention to each. Interference between tasks depends upon the demands which each separately impose – when task demands drain the pool, performance will suffer.

Others have echoed the notion of a common resource pool. Norman & Bobrow (1975) described how performance may be constrained by the quality of input (data-limited) or by processing resources (resource-limited). Again, this view holds that if the demands of two tasks exceed the upper limit of resources, interference will occur and performance will deteriorate.

Later research found some flaws with the single resource approach. For instance, Wickens (1984, 1992) described experiments whereby two tasks were perfectly time-shared (i.e., performed concurrently) even when the difficulty of either was manipulated (this latter point is important, since two tasks may impose different levels of MWL yet exhibit little variation in overt performance if both are still within the total capacity of the operator). This was seen as a limitation of single resource theory, which predicted that the difficulty manipulations should eventually lead to some change in performance on one or both tasks. Thus emerged multiple resources theory (Wickens, 1984; 1992; 2002; Wickens & Liu, 1988). Multiple resources theory posits that there are separate pools of resources along three dichotomous dimensions. The first dimension is processing stages – early vs. late. Perception and central processing (i.e., cognitive activity) are said to demand separate resources from response selection and execution. The second dimension is input modalities – auditory vs. visual. Performance of two simultaneous tasks will be better if

	Perceptual/Cognitive				
	Perceiving		*Central processing*	*Response*
	Visual	*Auditory*		
Verbal	Print	Speech	Problem solving Mental arithmetic	Voice
Spatial	Flow field (e.g., driving) Spatial patterns		Mental rotation Imagery	Manual response

Figure 3.1 Relation between the dimensions of multiple resources. Examples of tasks are defined by processing codes (verbal vs. spatial) and processing stages (perceptual/cognitive vs. response). Input modalities (auditory vs. visual) are relevant at the perception end of this diagram, and both modalities may receive verbal or spatial information. (Adapted from Wickens et al., 1998.)

one is presented visually and the other presented auditorily, rather than using the same modality for both. Finally, the theory states that there are separate resources for whether a task is processed verbally or spatially. This dichotomy also holds for response execution, whereby less dual-task interference occurs if one task is responded to vocally and the other demands a manual response (see Figure 3.1 for an elaboration on the relationship between these dimensions). Wickens (2002) later added a fourth dimension to the model, subdividing the visual modality into focal and ambient channels. According to multiple resources theory, there will only be a trade-off between task difficulty and performance to the extent that two concurrent tasks share resources on any of these dimensions (Wickens, 1992) – interference is a joint function of difficulty (resource demand) and shared processing mechanisms (resource competition).

Attentional resource models provide a rational framework for defining MWL as per the definition cited above (Young & Stanton, 2001a), reflecting as it does the relationship between demands and resources. There has been some debate as to whether single resource models are more appropriate than multiple resource theory for understanding MWL. Firstly, multiple resource explanations of MWL are context dependent, having been derived in dual-task laboratory settings, making it difficult to draw quantitative predictions for real-world applied contexts (Hancock & Caird, 1993; Liao & Moray, 1993). In addition, multiple resource models do not consider non-attentional factors, such as experience (Selcon et al., 1991). As an alternative, Liao & Moray (1993) posited that a single channel MWL model is of more use in real world situations, which generally have more than two tasks. However, they also stated that the multiple resource approach remains a superior model in purely dual task scenarios.

In practice, the reality probably sits somewhere between the two. The notion of a general reservoir of attentional resources underlying the separate resource pools has some merit (cf. Brown, 1997; Matthews et al., 1996; Young & Stanton, 2007b); alternatively, there could be some dedicated cognitive resource responsible for allocating attention between tasks (Tsang &

Velazquez, 1996), which would then have a blanket impact on their performance. In his computational model of multiple resources, Wickens (2002) essentially acknowledged that there is unlikely to be any such thing as perfect time-sharing between two tasks since there will always be some baseline conflict between concurrent tasks, 'or general capacity for which all tasks compete in a time sharing situation' (Wickens, 2002; p. 170). The implications of this are that it will generally be better to divide attention between tasks drawing on different resource pools than common ones, but there will still be a performance impact purely due to the fact that there is competition for attention.

An alternative perspective takes into account the level of operator skill, and the extent to which cognitive processing is automatic. Gopher & Kimchi (1989) reviewed evidence that MWL in real world tasks is determined by the balance of automatic and controlled processing involved. This is consistent with the attentional resources approach, as automaticity releases attentional resources for other tasks, with a resulting decrease in MWL. The natural analogue with automation leads us to consider the role of human automaticity and how it may interact with machine automation.

AUTOMATICITY

Automatic processing is defined as being fast, attention-free, unconscious, and unavoidable. By definition, automaticity is the converse of controlled processing, which is slow, attention-demanding, under conscious control, and adaptable (see e.g., Anderson, 1995; Underwood & Everatt, 1996, for reviews of the groundwork in automaticity). As such, automaticity is associated with highly skilled performance.

Skill acquisition has often been described along three stages (Anderson, 1995; Fitts & Posner, 1967; Norman & Shallice, 1980; Rasmussen, 1986). The first is associated with novice performance, whereby operators act in a declarative or knowledge-based manner. With no experience of working with a device, the operator is forced to calculate algorithms for the task at hand, perhaps referring to operating manuals, and relying heavily on feedback to check that the correct action has been taken. This reflects controlled processing. As operators learn about their task, the need for cognitive control gradually diminishes and performance becomes proceduralised. This is the second stage, using rules-of-thumb to guide performance. Progression through these two stages eases feedback requirements, as operators come to depend less on instruction, and more on task-intrinsic feedback. Finally, a great deal of experience on an invariant task completely removes the dependence on conscious processing and the need for feedback, and automaticity is achieved. At this point, and with reference back to attentional resource models (cf. Norman & Bobrow, 1975), skilled performance has become data-limited, rather than resource-limited (Brown, 1978). The stages of skill acquisition are only meant as descriptive and there is no discrete boundary between them; the development of automaticity is a continuous process (although see Hockey, 1997, for a more dichotomous view of automatic and controlled processing).

An alternative (but compatible) perspective views automaticity as knowledge (Bainbridge, 1978; 1991; 1992). Skill acquisition is considered as a change in knowledge and decisions, such that the expert performs by implicit anticipation (i.e., 'open-loop' behaviour) rather than feedback. Learning increases the knowledge base, which allows such anticipative behaviour. Novices, on the other hand, make more control actions and task-unrelated decisions, thus increasing their workload. Where experts use their knowledge to describe the task and guide future actions, novices need their capacity simply to understand the task, leaving less available to actually do it. Automaticity, then, is a situation of low uncertainty and high predictability, thus drawing little from attentional resources. If demand increases, the situation is no longer familiar; predictability then breaks down and the operator is forced to resort to a feedback (i.e., novice) strategy.

Along with the different stages of skill acquisition, there is also a hierarchy involved with skill itself (Underwood & Everatt, 1996). Low-level processing, typically associated with the execution of motor tasks, tends to be the most consistent and is therefore automatised easily. Higher cognitive functions and strategic tasks, however, are more variable and so more difficult (though not impossible; Logan, 1988) to process automatically. This leads to the idea of part-task automaticity, in that some lower-level elements of the task may be automatised, whilst higher functions remain to be processed in a controlled manner. In terms of driving, this broadly relates to the hierarchy of vehicle control covered in Chapter 1 (cf. Ranney, 1994). For instance, a learner driver may use automatic processing for operational elements of vehicle control functions (e.g., steering, changing gear), yet still need cognitive control for the higher strategic demands of driving (e.g., navigation, hazard perception; cf. Ranney, 1994). Indeed, all drivers lie at some point on the automaticity continuum, and individual differences in experience and perceptual-motor skills determine where cognitive control begins to be released.

Driving involves disparate skills from information acquisition, through perceptual-motor coordination, to situation assessment and risk estimation (Chi et al., 2019) and, at some levels at least, offers a classic example of automaticity (Stanton & Marsden, 1996). Whilst some feel that the driving task is too variable to promote the development of automaticity (Groeger & Clegg, 1997), the role of experience and skill in driving has led many to the conclusion that at least some elements of the task represent automatic behaviour (e.g., Stanton & Marsden, 1996). These are perhaps most evident in the low-level operational control elements of driving, such as vehicle control (Blaauw, 1982) and brake reaction time (Liebermann et al., 1995; Nilsson, 1995; Young & Stanton, 2007a). Consistent with this is the observation that such physical skills can be acquired relatively quickly, whereas higher strategic elements can take years to develop (Helander, 1978), while some may never reach automaticity (Rumar, 1990).

On the face of it, there seems to be a lot in favour of automatic processing. Indeed, many place value on such tacit or experiential knowledge over technological support, as these skilled workers can cope with unplannable situations (Böhle et al., 1994; Hockey & Maule, 1995). Expertise is commonly associated with efficiency, and is consequently seen as a positive indicator of performance. Differences in performance between novice and experienced operators increase as difficulty of the task increases (Anderson, 1995). Moreover, automatic processing has been demonstrated to bypass the vigilance decrement of sustained attention tasks, tasks that apparently only suffer if controlled processing is used (Fisk & Schneider, 1981). Automaticity is also useful in multiple task situations, as the automatised process hardly interferes with concurrent tasks (Liu & Wickens, 1994). Finally, automaticity has been cited as a prerequisite for situation awareness (MacLeod, 1997; Svensson et al., 1997). The advantages of automaticity in driving are realised in areas such as vehicle control (Blaauw, 1982) and brake reaction time (Nilsson, 1995). In a study by Nilsson (1995), drivers avoided a collision when a car pulled out in front of them because braking was considered to be an overlearned and automatic response.

Automaticity and expertise, then, have definite advantages. Consistent performance of an invariant task leads to constraints on actions, which can increase speed and improve performance. These constraints, though, will upset performance if the task changes and they no longer apply, as the acquired expertise is no longer relevant. Therefore, the drawbacks of expert performance are associated with the fact that automatic processes are unconscious and unavoidable, and there can be adverse consequences when the overlearned and unconscious response takes precedence in an inappropriate situation. The classic example is the Stroop effect, whereby one highly practiced task interferes with the performance of another, controlled task. Errors occur due to strong, inflexible expectations influencing selective attention (Rumar, 1990; Van Elslande & Faucher-Alberton, 1997). Any change in the overlearned conditions will result in massive proactive interference and a disruption of skill-based performance as cognitive resources are reallocated (Ranney, 1994). Performance decrements are especially apparent in such situations if the task has been learned by rote rather than understanding, as the operator cannot adapt to new circumstances (Norman, 1988). Another example is the challenge-response verbal checklist, typically used by aircraft crew to check the status of the aircraft systems. After numerous repetitions, the procedure can become automatic and very fast, but as a consequence, positive responses (i.e., system status is acceptable) may be erroneously made. Barshi & Healy (1993) see a paradox in the checklist procedure – automatic performance is equated with expert performance; however, routine tasks are complex and susceptible to error, thus the operator must execute controlled processing in order to avoid errors. Yet, by definition, it is impossible to perform at once both in an automatic *and* a controlled manner.

Similar paradoxes exist in driving, for instance, when drivers have a strong expectation that a familiar junction will be clear and fail to see oncoming traffic (Hale et al., 1988), in what has come to be known as the 'looked-but-failed-to-see' error (see e.g., Hole, 2007). Consider also advanced driving techniques taught by bodies such as the Institute of Advanced Motorists in the UK. By definition, these drivers are highly skilled. However, their training constantly reminds them to keep all elements of the driving task (from vehicle control to hazard perception) in conscious awareness at all times. On the advanced driving test, the examiner often asks for a concurrent verbal commentary on the drive to assess the extent to which drivers perceive the environment and their task. The paradox is thus in expecting drivers to process their task and respond with the speed and accuracy of an expert, yet still asking them to maintain conscious awareness and an active control over all of their decisions.

There is, then, an irony involved with automaticity, in that expert performance needs to be monitored in a controlled fashion if errors are to be detected and corrected, but controlled processing does not by definition equate with expert performance. Naturally, if the task is consistent and there are no problems, automatic processing should guarantee virtually error-free performance. However, if task demands change, a controlled monitoring process is necessary to ensure flexibility in response. These two processes would inevitably be in competition. This point is highly relevant to technological automation too.

It will eventually become the case that any driver may step into a highly automated vehicle, regardless of their experience. Initially, novel technologies are fitted to prestige models only, implying that the drivers who have access to them are generally more experienced. However, just as with power assisted steering, anti-lock brakes, and even automatic transmission, these new devices will eventually filter down to become widely available. It is conceivable that, in the not-too-distant future, a newly qualified driver with basic training could immediately use a vehicle equipped with, for instance, an automated lane keeping system (ALKS).

The interaction of skill and automation is important for a number of reasons. We suggest that all operators – novices and experts alike – essentially satisfy the criteria for automaticity when faced with automation. Whilst inexperienced users almost certainly use different cognitive processes, many of the criteria for automaticity (e.g., fast, attention-free, unconscious) are essentially satisfied. This is just an analogy, though, and we should perhaps restrict it to observable performance, rather than underlying cognitive processes. But consider Bainbridge's (1978) point in discussing the theory of automaticity as knowledge, that increased demand essentially transforms an expert into a novice. It is surely plausible to assume that the reverse would be true in a situation of unusually low demand (i.e., driving with automation). However, whereas the expert has an enhanced knowledge base and can anticipate events, the novice does not have this ability. Thus they will not react as experts in critical situations, such as the overlearned braking response (e.g., Nilsson, 1995). This is where the underload problem reveals itself.

THE 'PROBLEM' OF UNDERLOAD

So that brings us back to the question posed at the end of Chapter 2: why is underload detrimental to performance? Actually, even this has an air of nuance about it because, in fact, there are no such problems as long as everything is working as it should be. There may even be benefits for performance; Ma & Kaber (2005) found that a reduction in workload when using ACC actually improved steering performance under normal (i.e., non-critical) driving situations. However, the underload problem manifests itself in an operator who has been subjected to excessively low mental demands (such as with automation), and then struggles to cope when workload suddenly increases (such as when the automation fails or the situation goes beyond its operational design domain). As a counterpoint to the Ma & Kaber (2005) study, Rudin-Brown & Parker (2004) also found that ACC reduced workload, but this was associated with slower reaction times and fewer safe braking interventions in response to a hazard. In the automated vehicle, these kinds of takeover situations may occur in a matter of seconds, placing great demand on the driver with the rapid transition from low to high workload (Hancock et al., 2021).

To be clear, underload is not about being completely relieved of all relevant demands – it is not merely another word for boredom. Underload is about doing very little (such as ensuring safe progress of an automated vehicle), but it is not about doing nothing – there is, by necessity, some level of task engagement, even if that engagement is not very stimulating (Young, 2021). Current automated driving systems exemplify this kind of task – indeed, it is seen as a selling point, on the basis that it releases drivers' attentional capacity to perform other activities (Hancock et al., 2021). But, as we now know, this is disingenuous if drivers are still expected to be responsible for control of the vehicle, since that capacity is not (or, at least, should not) be truly released.

That gives us some idea of what underload is, but it still does not tell us why having too little to do is detrimental. An intuitive answer would be to appeal to vigilance degradation, but it is uncertain whether this occurs with dynamic signals (Parasuraman, 1987), and driving is a dynamic task. Moreover, as we saw in Chapter 2, maintaining vigilant monitoring is a considerably demanding task (cf. Warm et al., 1996) and, as such, depletes attentional resources, so quite the opposite of one that can induce underload. Along with vigilance, Chapter 2 reviewed a variety of other factors affecting performance with automation (trust, situation awareness etc.), but the reason we are particularly interested in mental underload is that, in theory, it may also affect performance in the absence of automation.

In several studies of simulated driving performance, stress and fatigue were demonstrated to have a more detrimental effect on easier driving than when the driving demands were higher (Desmond et al., 1998; Matthews & Desmond, 1997; Matthews et al., 1996). Stressed or fatigued drivers show poorer vehicle control (lateral and longitudinal) on straight road sections than on curves (Matthews & Desmond, 1997), in single-task than in dual-task conditions (Matthews et al., 1996) and, yes, in automated than in manual driving (Desmond et al., 1998).

These studies led to another explanation for the effects of underload, concerning the amount of effort the operator is investing in the task. Investing resources in a task is a voluntary and effortful process to meet demands, so performance can be maintained at the cost of individual strain or vice-versa (Hockey, 1997). Desmond & Hoyes (1996) concluded that a decrease in performance at low levels of demand might be due to a failure to mobilise effort appropriately to match the task, which may be particularly susceptible if the operator is also stressed or fatigued (Desmond et al., 1998; Matthews & Desmond, 1997). Others have offered similar theories. The 'par hypothesis' (Buck et al., 1994) states that, as demands fluctuate, operators increase or decrease the amount of effort invested in a task to maintain performance at their personal par. Similarly, 'equifinality of effort' (Hancock & Chignell, 1988) is an adaptive strategy whereby effort is adjusted to attain a goal. In later research, Wickens et al. (2001) suggested effort conservation as the explanation as to why pilots in a simulated aviation task actually devoted more visual attention to an instrument panel when the task was easier. At the other end of the workload spectrum, Liao & Moray (1993) found that participants invest more effort with higher time pressure, which may increase capacity. Elsewhere, underload has also been associated with passivity, with optimal MWL reflecting a need to exercise a level of control or engagement with the task (Endsley, 2017; Hancock, 2017b; Hockey et al., 1989). In semi-automated driving, there is a concern that this could lead drivers to seek out and engage in more stimulating activities (Biondi, 2017).

The notion of optimal workload is a natural corollary to the twin demons of overload and underload (Wilson & Rajan, 1995). Taken together, these predict the classic theoretical inverted-U shaped relationship between performance and MWL (Figure 3.2), whereby performance decrements occur at both ends of the curve (e.g., Desmond & Hoyes, 1996; Foy & Chapman, 2018; Huey & Wickens, 1993; Longo, 2015), while optimal MWL results in optimal performance (Hancock & Caird, 1993; Wilson & Rajan, 1995; Young et al., 2015). Such optimisation involves a balancing act between demands and resources (Byrne & Parasuraman, 1996; Gopher & Kimchi, 1989), based on attentional resource theory. As we have already explained, overload occurs if the demands of a task are beyond the limited attentional capacity of the operator, while low MWL leads to difficulties in maintaining attention (Foy & Chapman, 2018; Longo, 2015).

One of the implications of this curve is that there will be some break point – or 'redline' – at each end where performance starts to significantly degrade, and one can notionally be said to have transitioned into underload (perhaps

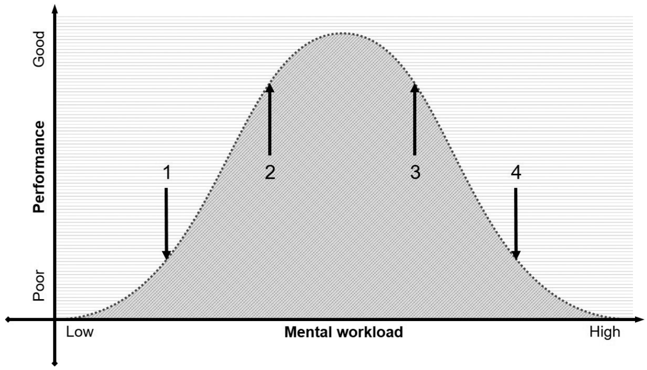

Figure 3.2 Theoretical relationship between mental workload (or arousal) and performance. See text for explanation of numbered arrows.

at arrow 1) or overload (arrow 4), respectively. Identifying these redlines is an important practical challenge (Hancock, 2017b), some might say the 'holy grail' of MWL research, but it has long vexed human factors researchers (Young et al., 2015). The overload redline represents the point at which demands approach the maximum available resources (Stokes et al., 1990); in pure time occupancy terms, some observations suggest that errors begin to occur around 80% capacity, so the redline is not necessarily at the exact point where demands exceed resources (see Young et al., 2015, for a review). Similarly, the underload redline reflects an under-supply of resources relative to demands (Young et al., 2015).

Although we are of course concerned here with detrimental effects of underload, we can deduce from the curve that there are circumstances when a reduction in MWL can improve performance, if demands are otherwise high and the reduction moves the operator out of the overload zone (from arrow 4 to arrow 3 on Figure 3.2). Sure enough, there is evidence that this is the case (although, notably, only with reliable automation; Metzger & Parasuraman, 2005). Conversely, gradual increases in MWL (up to a point) might not necessarily degrade performance and may even appear to be beneficial. If the operator is working on the 'low' side of the curve (i.e., underloaded; arrow 1 on Figure 3.2), then an increase in MWL (towards arrow 2) would move them up towards the optimal level (e.g., Taylor et al., 2013). There is some evidence consistent with this too. Using a low-fidelity flight simulator, Thornton et al. (1992) found that pilots' solutions to difficult problems were better in manual conditions (with subjectively higher workload) than when using the autopilot. In addition, Moss & Triggs (1997) found that attention-switching during a simulated drive was faster under dual-task conditions. That is, the additional MWL actually facilitated performance. In a similar way, but somewhat controversially now, there is evidence that using a mobile phone when driving can improve performance if workload is otherwise low or manageable (Liu, 2003) – though we would urge the reader to balance that against the mass of research indicating how detrimental mobile phone use can be for driving performance (e.g., Haigney et al., 2000).

In reality, the peak of the curve is probably more of a plateau, as individuals can absorb a certain amount of MWL (Hancock, 2017b) either by investing more effort (Huey & Wickens, 1993) or adapting their strategy by load-shedding in order to manage their performance (Huey & Wickens, 1993; Parasuraman et al., 2008). As such, we might imagine two tasks of objectively different workload, but resulting in similar performance (arrows 2 and 3 on Figure 3.2). If there is a sustained increase in demand, though, it is difficult to maintain this as performance starts to become resource-limited (Huey & Wickens, 1993), leaving little capacity to respond to any further sudden increases in demand (Parasuraman et al., 2008). The problem is that we cannot tell, based on the current state of the science, where the purported 'redlines' for overload and underload lie (cf. Young et al., 2015) – there are just so many variables associated with the individual and the task, that it is a constantly moving target.

There has been some discussion of defining redlines according to some of the subjective MWL rating scales available in the literature (more on which in the next chapter). Whilst a handful of scales refer explicitly or implicitly to redlines, the relative nature of subjective ratings makes it difficult to define thresholds in absolute terms (Hancock et al., 2021; Hart, 2006). In relation to one of the most widely used subjective metrics, the NASA Task Load Index (TLX; Hart & Staveland, 1988), Hart (2006) called for a large-scale meta-analysis to help towards this cause. That wish was granted in 2021 with a review of 556 studies resulting in reference values for the TLX across domains and applications (Hertzum, 2021). If we take 10th and 90th percentile values as arbitrary 'redlines' for now, overall workload at these points was 26 and 57, respectively. We could potentially think of these values as the thresholds of underload and overload.

It may also be possible to define these redlines according to physiological arousal, seeing as the inverted-U curve mirrors the well-established one between arousal and performance (Yerkes & Dodson, 1908). Arousal fuels attentional resource supply (Kahneman, 1973) and thereby affects performance (Huey & Wickens, 1993; Lee et al., 2020), albeit with some lag (Young et al., 2015). Given a linear increase in demand, there will initially be a shortage of resources until arousal catches up; the underload redline is therefore at the crossover point when resources match demands. As demands continue to increase, they will eventually exceed the maximum capacity (as per the traditional overload model), thus defining the overload redline. Nevertheless, these remain theoretical explanations, and are difficult to quantify (Young et al., 2015).

On the face of it, then, it would seem that there is a relationship between MWL and physiological arousal. Indeed, many physiological measures of MWL depend on this relationship (Jorna, 1992; Roscoe, 1992). But we also know that such metrics are influenced by physiological noise and only account for part of the variance in MWL and performance (Jorna, 1992; Taylor et al., 2013). So, there must be a more direct connection between MWL and performance without going via arousal. If arousal affects attentional resources, then perhaps MWL could have a similar effect. That is, attentional resources could fluctuate as a direct consequence of MWL. The influence of MWL (and underload in particular) on performance could then be explained as a relative insufficiency of resources to cope with demands. That led us to develop the hypothesis of malleable attentional resources (Young & Stanton, 2002a).

Malleable attentional resources theory (MART)

MART is grounded in the established theories of attentional resources we reviewed earlier in this chapter (Kahneman, 1973; Wickens, 1984; 1992; 2002). But most applied research in this field implicitly assumes that the size of resource pools is fixed. Capacity may change with fluctuations in arousal (according to the inverted-U curve), mood state (low mood leads to a loss of efficiency), or age (during the development of the young and the degradation of the elderly; Hasher & Zacks, 1979; Humphreys & Revelle, 1984; Kahneman, 1973). With the possible exception of arousal, though, these effects would seem to be relatively long-term. In most research involving short-term tasks, these factors would be stable within participants, hence the assumption of fixed capacity. Performance therefore simply depends on demand not exceeding an upper limit.

Fixed capacity models assume that performance remains at ceiling, and is data-limited, as long as demands remain within the attentional capacity of the operator (Norman & Bobrow, 1975; Stokes et al., 1990). Figure 3.3

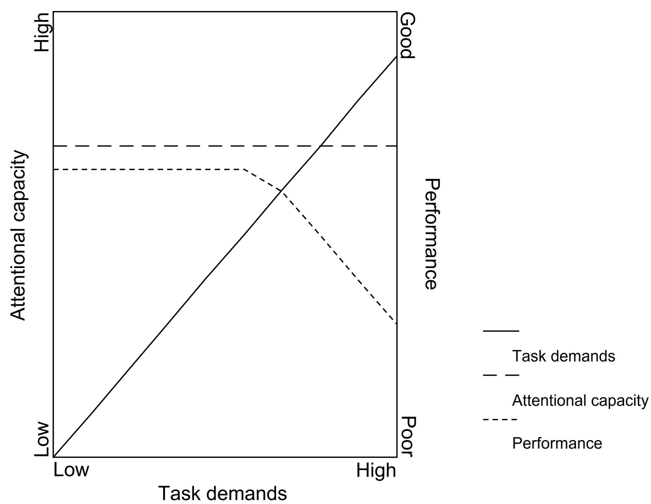

Figure 3.3 Relation between task demands and performance under a fixed capacity model (adapted from Stokes et al., 1990). Upper limit of attentional capacity is fixed (dashed line), and as task demands (solid line) approach that limit, performance (dotted line) degrades.

represents the textbook approach, in which performance remains constant until task demands begin to exceed capacity, when it starts to drop away. But this model still does not explain why an excess of capacity at low levels of MWL should result in impaired performance.

Under MART, capacity is still finite, so the mechanism of overload at the upper end of MWL remains the same. However, the theory posits that the size of attentional resource pools may change with short-term variations in demand, 'calibrating' to periods of acute underload (cf. Hancock, 2017b) and shrinking when MWL reduces in response to the demands of the task. In the same way that sports players sometimes seem to raise or lower their game according to the ability of the opposition, so too attentional capacity fluctuates to match the demands of the task. However, where the sports player can voluntarily adjust their level of play if the game turns against them, the operator faced with mental underload is unable to exceed their reduced capacity limit. They simply cannot invest resources which are not there. This is where MART differs from other explanations of mental underload. A maladaptive mobilisation of effort theory (e.g., Desmond et al., 1998; Desmond & Hoyes, 1996; Matthews et al., 1996) implies that there is some level of voluntary authority over investment of effort in performance. MART has no such mechanism – reduced capacity is an involuntary and inevitable consequence of reduced demands, so operators cannot instantly increase their attentional capacity on demand, even if they wanted to. Nevertheless, MART is not entirely incompatible with this theory, since effort is related to the supply of attentional resources (Young et al., 2015). Furthermore, since MART is an attempt to explain performance in underload scenarios, it extends beyond previous explanations of human interaction with automation (such as inappropriate feedback or out-of-the-loop performance problems). If MWL is low, then performance will suffer – irrespective of whether or not the source of underload is automation (e.g., Desmond et al., 1998; Matthews & Desmond, 1997; Matthews et al., 1996).

As can be seen in Figure 3.4, these ideas neatly predict the inverted-U relation between task demands and performance. In effect, the cause of underload is the same as that for overload – MART predicts that performance is essentially resource-limited for the full range of task demands (cf. Norman & Bobrow, 1975). Others have noted that both high and low MWL can lead to low levels of attention (Foy & Chapman, 2018), in tacit support of MART.

MART therefore helps to explain the underload problem when there is a sudden increase in demand, such as an automation failure or abrupt transition to manual control. Imagine someone driving a highly automated vehicle. This is a situation which considerably reduces MWL. Under an attentional demand model of MWL as described earlier, this translates to low demand on resources. In the absence of any other task-related demands, MART predicts that the size of the relevant attentional resource pool will temporarily

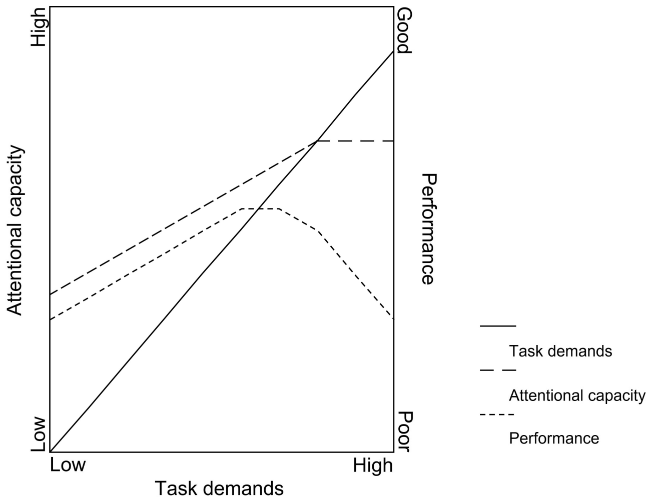

Figure 3.4 Relation between task demands and performance under the MART model (cf. Stokes et al., 1990). Note the 'inverted-U' shape of the dotted performance curve.

diminish, as it is not required. But that does not matter just yet, because the reduced demand is within the reduced capacity of the driver. Now imagine that the driving situation has gone outside the design limitations of the automation, and it needs to hand back control to the driver. The shrinkage of attentional resources has momentarily limited the performance ceiling of the driver and, as per the standard model, if task demands exceed that ceiling, then performance degrades (e.g., through attentional narrowing; Hancock, 2021). So when the demand on resources suddenly increases (i.e., to takeover manual control from automation), the driver is unable to devote the necessary attention to the task, because the resources are simply not available (cf. Lee et al., 2020). Had the driver already been under higher MWL and faced with a similarly demanding situation, it is likely that they would have coped with it more effectively. Thus it is the increase in workload on resuming manual control that can result in the kinds of performance problems observed in previous studies, whether the transition is planned (Scallen et al., 1995) or unexpected due to automation failure (Desmond et al., 1998; Nilsson, 1995; Stanton et al., 1997). Figure 3.5 illustrates this situation, with the bars representing the level of MWL and, by the logic of MART, the respective attentional resource level of the operator. The heavy line indicates the level of attentional resources a critical event (such as resuming manual control from automation) would demand. Crucially, this is within the ordinary capacity of the high MWL operator, but beyond that at low MWL. It is for this reason that performance in responding to critical situations is predicted to be worse in conditions of mental underload.

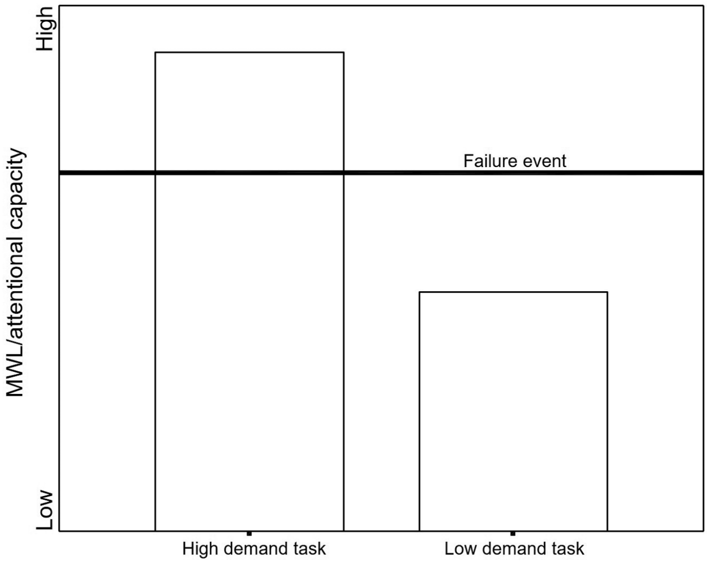

Figure 3.5 Hypothetical correlation of attentional capacity and MWL under MART.

Of course, there may be other possible reasons for performance problems in the face of sudden increases in demand (Matthews et al., 2015). An alternative explanation in this scenario is that resources have been reallocated to other tasks, rather than reduced. With highly reliable automation, operators reduce their monitoring of it and then take advantage of the reduced demand by redirecting attention to other tasks (Seppelt & Victor, 2016). But, again, this implies some voluntary change of strategy for allocating attention (cf. CIEHF, 2020b), whereas MART presumes that there is literally less attention available when the operator is underloaded.

Another interesting counterview to MART is the notion of a hysteresis effect in performance against demand, whereby performance levels during an increase in demand outshine those during the parallel decrease in demand (Farrell, 1999). In other words, in a situation when demands first increase and then symmetrically decrease, performance at a given demand level will be better on the way up than on the way back down. Farrell (1999) draws on evidence from air traffic control to support the idea, where more near misses were observed after a sustained period of high workload. Consequently, it is argued, this is not about capacity limits, but instead may be partly due to the operator's expectancy or their sampling strategy.

Nevertheless, other studies have since given credence to MART in the context of human supervision of reliable automation (Bailey & Scerbo, 2007) and as a possible consequence of monotonous air traffic control tasks (Straussberger et al., 2005). Some have even offered physiological data ostensibly supporting MART, relating the supply of attentional resources to cerebral blood flow

(Matthews et al., 2010) or autonomic nervous system activity (Ruscio et al., 2017). In the next section of this book, we put MART to the test in a series of empirical studies involving a range of automated driving scenarios. We start out by looking for a relationship between MWL and attentional capacity. Given we have said that the underload problem occurs with sudden increases in workload, this implies there is some temporal factor in the shrinkage and recovery of attentional capacity, so we explore that too. The parallels between automaticity and automation are investigated by introducing driver skill as an independent variable. We then focus in on a particular wrinkle associated with the effect of ACC on MWL. Finally, the big question: whether any of this actually explains 'the underload problem' when automation fails.

KEY POINTS

- Driver mental workload can be affected by numerous factors associated with the person, the road or the environment, not least of which is the presence of automation.
- Mental workload itself is a multidimensional construct inextricably linked with theories of attentional resources.
- Driver skill can interact with both mental workload and automation – but automaticity in cognitive processing is not the same as automating a task with technology.
- Mental underload associated with automation is known to be detrimental to performance; malleable attentional resources theory (MART) explains this effect through a shrinkage of attentional capacity.

NOTE

1. We tend to use 'resources' and 'capacity' interchangeably in this book.

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Stage 2

Taking the load off

Chapter 4

How low is too low?

OVERVIEW

On stage 1 of our journey, we reviewed research that shows driving automation significantly reduces mental workload, and that this consequent underload can be detrimental to performance. We also hypothesised a link between attentional capacity and underload as a mechanism for this effect, which we termed malleable attentional resources theory (MART). Now we move on to the next major stage which takes us through a series of empirical studies to test MART. In the first experiment, presented in this chapter, 30 participants drove four automation conditions (manual, adaptive cruise control, lane centring, and adaptive cruise control plus lane centring) in a medium-fidelity driving simulator. Measures of driving performance and mental workload (using secondary task and subjective techniques) were recorded, along with direction of attentional gaze to infer attentional capacity. The results provided support for MART in that, as mental workload decreased with automation, so too did the inferred metric of attentional capacity. Further analysis demonstrated that such shrinkage occurred relatively quickly, within the first minute of being underloaded. The results are discussed with reference to potential 'redlines' of underload and directions for future research, which form the topic of subsequent chapters.

INTRODUCTION

In Chapter 1, we argued that the latest generation of automation in vehicles has the potential to relieve drivers of psychological as well as physical elements of the driving task. Chapters 2 and 3 reviewed the various impacts of such automation, focusing in on mental workload (MWL) and, in particular, the effect of underload on performance. We presented MART as an explanation for the underload effect, by positing a shrinkage of attentional capacity in response to excessively low MWL.

In this chapter, we revisit one of our first empirical studies (Young & Stanton, 2002b) to investigate the predictions of MART by examining the effects of different automation conditions on MWL, attention and performance.

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In particular, we were interested in testing adaptive cruise control (ACC) and lane centring (LC) systems (see Chapter 1 for more on these systems). At the time we conducted these studies, ACC had been available for a few years, and most of the extant research on automated vehicles had focused on ACC (e.g., Nilsson, 1995; Stanton et al., 1997; Ward et al., 1995). We extended that to also consider a rudimentary LC system, which was relatively new (and was then referred to as active steering). Part of the reason for researching these systems is that with both engaged, the vehicle control elements of driving are essentially fully automated, albeit with no object or event detection other than that provided from the ACC system. By today's standards, using the SAE (2018) terminology, engaging ACC or LC alone would constitute Level 1 automation, while the combined ACC+LC condition represents Level 2 automation (according to Mueller et al., 2021). To complete the picture, we also included manual (Level 0) driving. We expected MWL would decrease as more levels of automation were introduced, and that such reductions might be associated with decrements in attentional capacity.

As well as attempting to find evidence for attentional shrinkage per se, we were also interested in establishing the precise nature of any resource degradation over time, so that we might be able to predict exactly when performance may begin to suffer. If we can continuously plot attentional resources against time, we can analyse just how quickly capacity shrinks. In the present chapter, then, we also summarise the work we later published (Young & Stanton, 2006b) to derive a time-decay curve across the duration of the experimental trial.

GENERAL METHODOLOGY

The series of experiments presented in this and the following three chapters all used the same underlying methodology. So, while the specifics of the design for each study will still be explained in each chapter, here we present the generic aspects of the method so as to avoid repetition.

Each experiment was designed to investigate aspects of MART in driving, looking at the potential effects of automation on driver mental workload and consequent performance. For the most part, the main independent variable was the automation condition as a within-subjects factor with four levels: the three combinations of system described above (ACC, LC, and ACC+LC), as well as a manual driving condition. In general, the manual condition was used as the reference category because it served as a conceptual baseline, as advocated by Young & Stanton (2002b). Since this programme of research was primarily concerned with performance differences when using automation, it was more sensible to compare (say) longitudinal control in the manual condition with that in the LC condition. This allowed comparison of human performance under fully manual and partially automated conditions.

We carried out the research in a driving simulator in our laboratory at the University of Southampton: the Southampton Driving Simulator (SDS; see Box 4.1). A simulated environment was chosen for several reasons. Firstly,

BOX 4.1 THE SOUTHAMPTON DRIVING SIMULATOR (SDS)

By the standards of the time, the SDS was a medium-fidelity, fixed-base driving simulator consisting of the front half of a Ford Orion (see Figure 4.1). The steering wheel, accelerator, and brake pedal produced analogue voltages. Appropriate hardware read these voltages and converted them into digital signals to be fed into the simulation computer. An Acorn Archimedes computer fitted with an analogue I/O card read the controls, ran the simulation, and generated the display image. A medium-resolution colour monitor displayed a view of the road and a simulated instrument panel on a forward projection screen. The area of the screen occupied by the road view was approximately 2 metres wide by 1.1 metres tall, and approximately 2.9 metres from the participant's eyes, providing a visual angle at the driver's eyepoint of approximately 40 degrees horizontal by 20 degrees vertical. The refresh rate was 25 frames per second.

The display showed: a single-carriageway road, in solid colour with a central broken white line; other traffic in both directions; and simple roadside objects such as speed limit signs. Collisions with other vehicles or the edge of the road were detected and led to simulated crashes. Other vehicles followed a fixed path with scripted speed changes.

The automated systems in the simulator were simplified versions of those which are now commonplace on the roads. The ACC system was operated via a button on the instrument panel, and was designed to engage at the current driving speed (i.e., if the participant was driving at 70 mph (113 km/h) when the button was pressed, the system maintained 70 mph). It was not possible to adjust the set speed without disengaging the system. Furthermore, headway control was set by the system at approximately 2 seconds time headway, and was not adjustable by the user. For lateral control, LC was simply designed to maintain the position of the user's vehicle in the exact centre of the left-hand driving lane (bearing in mind this study was conducted in the UK, where the road rules are to drive on the left), and was also engaged via a pushbutton on the dashboard. Both

Figure 4.1 The Southampton driving simulator (SDS).

systems could be disengaged either by a repeat press of the relevant button, or by some manual control input (i.e., pressing a pedal would disengage ACC, turning the steering wheel would disengage LC). There was no physical movement of pedals or steering wheel by the automated systems when they were engaged. The simulator was set up to run with automatic transmission at all times.

there are the classic advantages of laboratory research (Sanders, 1991), in that carefully controlled experimental studies can be conducted. In a real road environment, there is a wealth of uncontrollable factors (weather, traffic density, road conditions) which can affect performance, so any significant results may not be attributable to the experimental manipulations. Simulator trials, on the other hand, can be repeated time and time again safe in the knowledge that there are no changes in task conditions. Furthermore, participants can encounter risky situations in the simulator which would be ethically unsound to create in the real world (e.g., the participants can crash without any danger to their health or safety). Finally, one compelling practical argument favoured the use of a driving simulator. At the time these studies began, the automation devices had not been fully developed, and were not available for road trials.

Driving performance data

The simulator software recorded data at a rate of 2 Hz on the following variables: speed, lateral position on the road, distance from the vehicle in front, distance from oncoming vehicle, steering wheel and pedal positions, and collisions. The simulator software recorded collisions if a participant hit another vehicle, or if the subject vehicle drifted more than 2 metres from the edge of the road.

For the purposes of this research the dependent variables considered to be most relevant to driving performance were speed, lateral position, and distance headway. Various derivatives of these measures have been previously used in studies of driving performance (e.g., Bloomfield & Carroll, 1996; Fairclough, 1997; Verwey & Veltman, 1996; Wierwille & Gutmann, 1978), which can be divided into measures of longitudinal and lateral control.

Longitudinal control measures involve speed and headway. However, simple measures of location (i.e., mean, median) do not necessarily provide evaluative information about how well participants are performing. Given the instructions to participants (maintain constant speed and headway), it would be logical to adopt a measure of consistency (or rather, inconsistency) for these variables. Bloomfield & Carroll (1996) described such a measure, in their derivation of *instability*, being the standard error of the regression line for a series of data points on the relevant variable, which represents the driver's ability to maintain stability in the measure. This is a better measure of driving performance than standard deviation, as it reflects the drivers' (in)consistency in their own performance, rather than deviation from an absolute measure. The sampling rate of the SDS allowed such equations to be calculated for the 1200 data points (across a 10-minute trial) on each of the speed and headway variables.

For lateral control, we considered that instability measures would not be an appropriate reflection of driving performance on a road which involved both curved and straight sections. Popular measures of lateral control (such as standard deviation of lane position or time-to-line-crossing) assume that 'good' driving performance is characterised by the vehicle remaining consistently in the centre of the lane. These measures would be confounded if participants used modern driving techniques to negotiate the curves on the road, which advise drivers to approach a bend as far to the outside of the curve as is safe to do so, in order to obtain maximum vision around the curve. The driver should then cut across the apex, and exit on the inside of the curve. Good driving is therefore not necessarily characterised by maintaining a constant lane position, and the instability score described above would be inflated by an advanced driving style. Instead, then, simple measures of lane excursions were used to evaluate lateral control, with the assumption then being that good driving performance is rewarded with fewer lane excursions. Total number of lane excursions, and time spent out of lane, were the dependent variables for lateral control. All of the driving performance measures were filtered for outliers and extreme values (i.e., any values outside two standard deviations from the mean), and these data points were removed prior to analysis.

Average lane position, speed, and headway across the trials were also recorded and analysed as a matter of course, to determine any differences in the location of these variables. The simulator recorded lane position in terms of deflection from the centre of the road, measured at the centre of the vehicle. Therefore, with the full road width set at 10 metres (i.e., two lanes of 5 metres each), a value of 0.0 means the participant is driving on the central white line, in the middle of the road. A value of -5.0 puts the participant over the left kerb, and consequently a lane position of -2.5 means the participant is driving in the middle of the left-hand lane.

Mental workload data

Given our discussion in the previous chapter of mental workload as a multidimensional construct, there is an equally diverse range of techniques available to measure MWL (for concise summaries, see Hancock et al., 2021; Young et al., 2015). In keeping with advice in applied research to use a battery of measures to assess different aspects of workload (Foy & Chapman, 2018; Gopher & Kimchi, 1989; Hancock & Matthews, 2019; Hockey et al., 1989; Matthews et al., 2015), we used three of the main categories of metric in our studies: primary task performance, secondary task performance, and subjective ratings.

Performance measures on primary and secondary tasks are widely used in workload assessment and it makes sense to use them in conjunction with each other. The basic premise is that a task with higher workload will be more difficult, resulting in degraded performance on that task compared to a low workload task. Of course, though, based on a capacity model of MWL (cf. Young & Stanton, 2001a), an increase in difficulty (workload) may not affect performance if the increase is still within the capacity of the operator. Thus an additional, secondary task, designed to compete for the same resources as the primary task, can be used as a measure of spare attentional capacity. According to our definition of MWL proposed in Chapter 3, the level of MWL in a task can be directly inferred from measures of attentional capacity. The level of secondary task performance represents the capacity remaining from the driving demands – thus increases in secondary task performance (i.e., more spare capacity) imply decreases in primary task demands (Pew, 1979), and vice-versa. In other words, differences in workload between primary tasks are reflected in performance on the secondary task. In the secondary task technique, then, participants are instructed to maintain consistent performance on the primary task, and to attempt the secondary task only when the primary task demands allow them to, so as to maintain that measure of spare capacity.

The secondary task is entirely appropriate for this kind of study, since it is useful for quantifying short periods of workload (Verwey & Veltman, 1996), spare attentional capacity (Wierwille & Gutmann, 1978), and even automaticity (Liu & Wickens, 1994) and individual differences (Brown, 1978). Secondary task measures have also been used to discriminate MWL levels across varying driving demands (Harms, 1991; Verwey & Veltman, 1996). Notwithstanding these benefits, we need to be aware that the secondary task can also be intrusive, particularly at low levels of primary task workload, affecting both primary task performance and subjective ratings of MWL (Wierwille & Gutmann, 1978; Young & Stanton, 2007b).

We have already described above the primary (driving) task performance measures used in these studies. As for the secondary task, this was a self-paced mental rotation task (as used by Baber, 1991, and proved by Stanton et al., 1997, in the SDS), presented in the lower left corner of the screen (see Figure 4.2). Each stimulus was a pair of stick figures (one upright; the other rotated through 0°, 90°, 180°, or 270°) holding one or two flags. The flags were simple geometric shapes, either squares or diamonds. The task was to make a judgement as to whether the figures were the same or different, based on the flags they were holding. Each stimulus was discrete and remained on screen until the participant made a response. Responses were made via buttons attached to the steering column stalks, and brief visual feedback was provided before presentation of the next stimulus. As per the underpinning premise of the secondary task technique as described above, participants were instructed to maintain their performance on the driving task and attend to the secondary task only when they had time

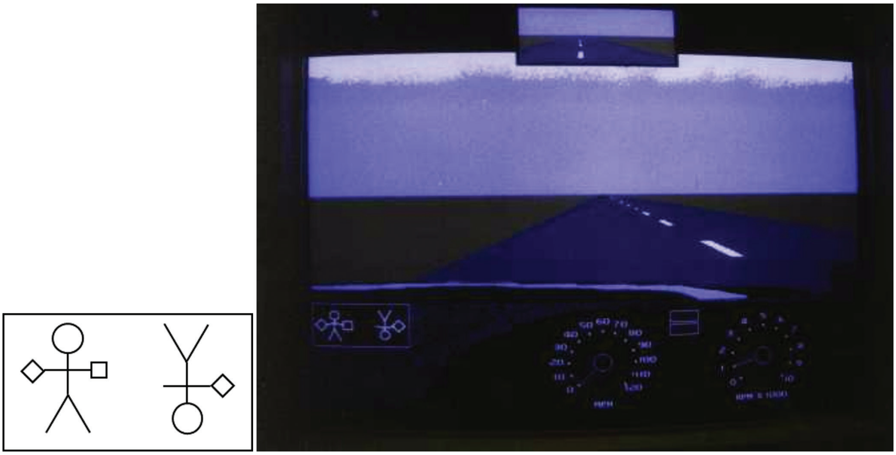


Figure 4.2 Screenshot of the simulator display showing the secondary task in the lower-left corner of the screen, alongside a schematic close-up of the secondary task stimulus (in this case, the figures are different).

to do so. The dependent variable associated with the secondary task was number of correct responses. Since the secondary task was self-paced and participants only attended to it when the driving task allowed, response time was not used as a dependent variable since it did not provide meaningful information.

The secondary task was visuospatial, requiring a manual response, and, as such, was intended to draw on the same attentional resource pools as driving (cf. Brown, 1978; Wickens, 1992). This ensured that the task was indeed a measure of spare mental capacity (based on multiple resources theory), and not some alternative cognitive resource. Driving is a primarily visuospatial task (e.g., Kramer & Rohr, 1982; Wickens et al., 1998), while the rotated figures task is assumed to be a spatial secondary task (Baber, 1991). Furthermore, research has shown that drivers will prioritise driving over a visuospatial secondary task (Robbins et al., 2021). Therefore, the use of the rotated figures task as a secondary task to measure spare attentional capacity in the driving domain appears to be justified.

Alongside the primary and secondary task performance measures, we also used subjective ratings of MWL. Many authors claim that these may well be the only index of 'true' MWL (e.g., Hart & Staveland, 1988). In particular, subjective MWL scores are sensitive to the presence of automation where other measures of MWL may not be (Evans & Fendley, 2017; Liu & Wickens, 1994). Criticisms of subjective techniques are primarily concerned with the metacognitive abilities of the operator (Petrusic & Cloutier, 1992; Praetorius & Duncan, 1988). That is, given the fact that the measures are necessarily administered post-task, one might question their reliability, particularly for long task durations.

There is a wide selection of subjective rating scales available in the literature (e.g., the Cooper-Harper Scale, Cooper & Harper, 1969; Subjective Workload Assessment Technique – SWAT, Reid & Nygren, 1988); we used the NASA-Task Load Index (TLX; Hart & Staveland, 1988) in our studies. The TLX is one of the most widely used and widely respected subjective MWL techniques (Hart, 2006), and was selected over other measures for a number of reasons (Young et al., 2015). Firstly, a multidimensional technique was preferred over unidimensional measures to provide some diagnosticity for the components of MWL which characterised the experimental task. For instance, Warm et al. (1996) discovered a MWL signature for vigilance tasks using the subscales of the TLX. This kind of discovery would not be possible with a simple measure of overall workload (OWL). Of the multidimensional measures, TLX and SWAT were the most widely used (e.g., Hendy et al., 1993). We settled on the TLX because it was more acceptable to participants, thus increasing the likelihood of genuine responses (Hill et al., 1992), as well as being more sensitive to MWL differences than SWAT, particularly at low workload levels (Nygren, 1991). Hart & Staveland (1988) claimed their procedure is practically and statistically superior to SWAT; the independent components of TLX provide additional diagnostic information unavailable in SWAT. Finally, and most importantly, the TLX is far easier to administer than other multidimensional scales. This is particularly true in the light of research suggesting that the weighting procedure of TLX is superfluous and may be omitted without compromising the measure (Hendy et al., 1993; Hill et al., 1992; Nygren, 1991). Thus, the modified 'raw TLX', as described by Hendy et al. (1993), was used in these studies.

The subscales of the TLX are: Mental Demand (MD), Physical Demand (PD), Temporal Demand (TD), Own Performance (PE), Effort (EF), and Frustration (FR). Each dimension was rated on a visual analogue scale, with five-point steps between 0 and 100. Participants were given definitions of the rating scales to assist them in making their assessments. As the purpose of the subjective ratings was to determine differences in perceived MWL between the automation conditions, participants were instructed to only rate the primary driving task, not the combined primary and secondary task demands. The dependent variables were simply the raw scores from each of the six subscales, and the arithmetic mean of these scores, which constitutes OWL. The OWL scores were of most interest in these studies; however, the subscales were also analysed to diagnose the nature of subjective MWL under these task conditions.

Finally, and for completeness as part of the present review, physiological measures (such as heart rate/heart rate variability, EEG, or brain oxygenation; see Young et al., 2015, for more detail) offer advantages such as continuous monitoring of data, greater sensitivity, and that they do not interfere with primary task performance (Brookhuis, 1993; Fairclough, 1993). Whilst many physiological measures have been reliably associated with mental effort (e.g., Foy & Chapman, 2018; Helander, 1978; Matthews et al., 2015), there are also a number of disadvantages involved with these methods. First, these measures are confounded easily, as they tend to be hypersensitive to extraneous noise from sources such as muscle movements, and the rhythmic nature of circadian activity in the central and autonomic nervous systems. Also, there is a certain amount of physical obtrusiveness involved in using such bulky equipment (Sanders & McCormick, 1993). Therefore, it is generally recommended that physiological measures are only applied if they are unobtrusive and reliable (Fairclough, 1993), and in conjunction with other measures of workload (e.g., Backs & Walrath, 1992). Considering these downsides, in particular the practical difficulties of collecting and analysing such data, for the most part we did not use physiological measures of MWL in this research. The exception, with its own justification, was one study presented in Chapter 7, and the details of the measurement used can be found in that chapter.

Attention data

To test the predictions of MART, a quantifiable measure of attentional capacity was needed, but this had proved (and remains) difficult to achieve (Huey & Wickens, 1993; Wickens et al., 2015). Typical methods used static recall (e.g., Engle, 2002; Weber, 1988), which essentially measures working memory capacity, whereas we needed a continuous measure of total attentional capacity to determine whether resources shrink as a result of mental underload.

We derived a measure of 'attention ratio' as a proxy for attentional capacity (Young & Stanton, 2002a; 2002b). The attention ratio exploited the fact that we were using a secondary task to measure MWL, and is based on the premise that the primary and secondary tasks together occupy the participant's total pool of resources. That is, if it is possible to combine primary and secondary task performance in an additive manner, they should always equal some unitary constant under a fixed resources model. The attention ratio attempts to tap that constant by recording two aspects of spare capacity: number of correct responses and time on task (cf. Grimes, 1991; Pew, 1979). We simply combined these measures into a ratio (Figure 4.3) reflecting the number of correct responses on the secondary task against the total duration of glances towards the secondary task (a measure which can vary independently from secondary task responses themselves). This analysis does assume that attention and eye movements are related, but other research suggests

$$AR = \frac{ST_{cr}}{ST_t}$$

Where AR = Attention Ratio
ST = Secondary Task
cr = correct responses
t = time

Figure 4.3 Derivation of attention ratio used to infer attentional resource capacity: number of correct responses on the secondary task is divided by total duration of glances directed at that task.

that this is not an unreasonable assumption (Kahneman, 1973; Underwood & Everatt, 1996). To collect the data for glance duration, direction of visual gaze was recorded using an on-board low-light miniature camera, and time spent looking at the secondary task was later coded by video analysis.

The null hypothesis, then, expects no differences in attention ratio between workload (automation) conditions. In other words, under a fixed capacity model of attention the proportion of attention devoted the secondary task should correlate directly and positively with the number of correct responses. If, however, resources fluctuate with MWL (as predicted by MART), then any increase in attention on the secondary task will not be proportionate to the increase in correct responses on it, and the pattern of attention ratio scores should reflect the pattern of MWL results. Consistent with this prediction, some studies have found longer visual fixation durations in lower MWL conditions, and vice-versa (Evans & Fendley, 2017; Foy & Chapman, 2018).

To illustrate the point, if participants direct twice as much attention to the secondary task in one condition compared to another (i.e., when objective demand is lower, and spare capacity is higher), under a fixed capacity model they should also be able to make twice as many correct responses. Any less, and it could indicate that their capacity had shrunk, providing evidence in favour of MART.

It is important to remember that the attention ratio is not being used as a measure of MWL, but of overall capacity. The rationale is based on the assumption that participants allocate the sum total of their attentional resources between the primary (driving) and secondary tasks. This total will be invariant under a fixed capacity model, regardless of primary task workload. Figure 4.4 presents this hypothetically, showing how a low MWL

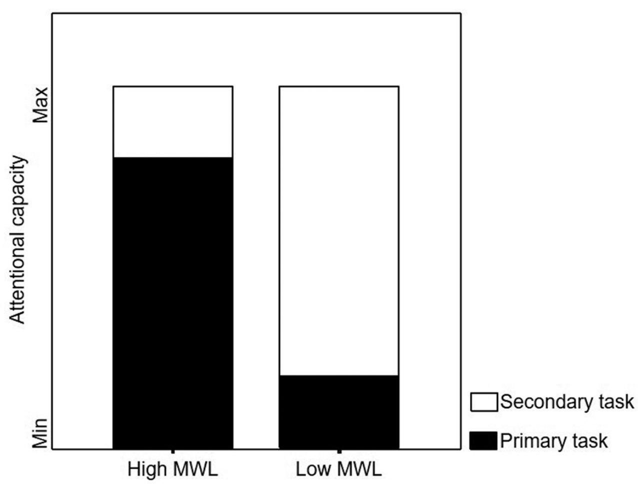


Figure 4.4 Hypothetical representation showing relative attentional demands of primary and secondary tasks under a fixed capacity model.

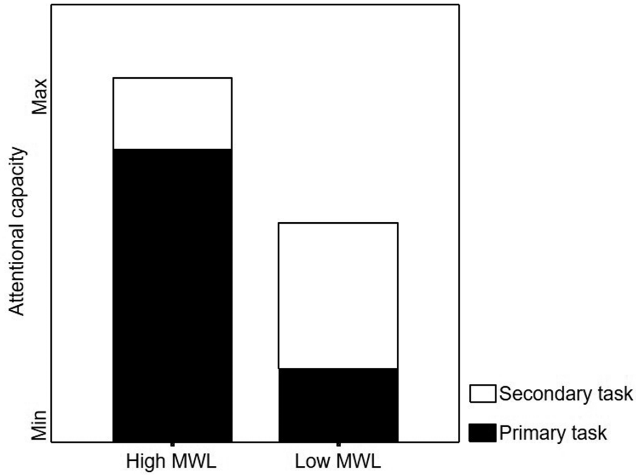


Figure 4.5 Hypothetical representation showing relative attentional demands of primary and secondary tasks under MART.

primary task that demands less attention releases more spare capacity (and, by association, more time) to devote to the secondary task (cf. Schlegel, 1993). In this case, the low MWL primary task draws on approximately a quarter of the resources of the high MWL task. Crucially, though, the height of the two stacked bars remains constant, so the total resources has not changed.

If the attention ratio decreases, either due to fewer correct responses or increased time on task, this is seen as evidence of resource shrinkage. Under MART, the pattern of attention ratio scores should reflect the pattern of MWL results, indicating a reduction in total attentional capacity associated with reductions in MWL. Thus, whilst secondary task responses can still increase (indicating lower primary task workload), the *proportional* increase in spare capacity may not equate to 'full' capacity. Figure 4.5 illustrates how spare capacity (i.e., secondary task performance) increases when primary task demands are low, but the total capacity (represented by the height of the stacked bar) has shrunk overall.

METHOD – THE PRESENT STUDY

Design

For this study in particular, then, a within-subjects design was used, with 30 participants, all of whom held full UK driving licences. The independent variable was automation condition, with four levels: manual (the participant controls speed, headway, and steering), ACC (longitudinal control is automated), LC (lateral control is automated), and ACC+LC (both longitudinal and lateral control are automated). Order of presentation of these conditions was randomised to counterbalance practice effects. Dependent variables included the primary task performance measures of longitudinal and lateral control, secondary task and subjective (NASA-TLX) measures of MWL, and the attention ratio metric to evaluate MART, as described earlier. In order to plot the attention ratio curve over time, the data were divided into 10 one-minute blocks.

The design of this experiment served – to a certain extent – to rule out competing explanations for any underload effect observed. By monitoring performance on both primary and secondary tasks, it will be possible to determine whether boredom or motivation have influenced the results. If so, there should be a general decline in performance across both tasks. On the other hand, MART would predict a specific shrinkage in capacity (as inferred from the secondary task) while primary task performance is maintained at a constant level. The counterbalanced presentation of conditions also helps to reduce the influence of fatigue across the duration of the study. Finally, given the low levels of physical interaction with the simulator in all conditions, it was assumed that physiological arousal would be roughly constant throughout.

Procedure

After entering the SDS, participants were first given a minimum 15-minute practice run to acclimatise to the conditions of driving a simulated vehicle. Following this, experimental instructions were given, including advice on how to operate the automated devices and how to respond to the secondary task. To check that the participants had understood the nature of the secondary task, three example stimuli were presented prior to the experimental trials beginning. Once participants were sufficiently familiar with the operation of the simulator, the experimental trials would begin, each of which lasted 10 minutes.

In all of the experimental conditions, participants were faced with a single-carriageway road which was a mixture of curved and straight sections. The track was quite simple, with no hills or wind gusts to disturb longitudinal or lateral control. The experimental task used a ‘follow-that-car’ paradigm to standardise non-manipulated demand across the independent variables. Participants were instructed to first catch up and then follow a leading vehicle, which was travelling at a constant 70 mph (113 km/h) (cf. Stanton et al., 1997), for the duration of the trial. There were no other vehicles in the participants’ lane (so no overtaking was necessary), although oncoming traffic was encountered infrequently, encouraging participants to remain in their own lane. In the automation conditions, participants engaged the equipment themselves by means of a button on the instrument panel when they had achieved a constant speed (this was not necessarily when they had caught up with the lead vehicle). Participants were required to maintain a constant distance from the lead vehicle, although the choice of that distance was left to the individual. There were a number of advantages to this approach. Firstly, it meant that participants did not have to disengage the automatic devices (for instance, in order to overtake), thus avoiding contamination of conditions. Secondly, following a car motivated participants to drive at a relatively constant speed, thereby controlling objective demand across conditions. Otherwise, participants may have compensated for increased workload by reducing speed, which again would contaminate results. Finally, a constant speed implied that participants all drove approximately equal distances, again controlling for workload and attention differences which may otherwise have been incurred. While driving, participants were expected to attend to the secondary task only when they felt able to do so (this instruction was emphasised to participants in order to minimise secondary task interference). At the end of each 10-minute trial, participants completed the NASA-TLX. The whole procedure lasted approximately 75 minutes.

RESULTS

Driving performance data

To avoid confusion, in this section we focus mainly on the results where significant differences were observed; descriptive statistics for these variables are presented in Table 4.1. Predictably, using LC improved lateral control, with a significant reduction in both number of lane excursions as well as time spent out of lane in both the LC and ACC+LC conditions. Leaving aside the fact that automation controls steering more accurately than a human driver, the more interesting comparison for lateral control is between the manual and ACC conditions – because steering is controlled manually in both, while another element of the driving task (i.e., longitudinal control) has been relieved from the driver. However, there were no significant differences in either of the lateral control measures between these two conditions.

For longitudinal control, when compared to manual driving speed instability significantly reduced (i.e., performance was better) in the ACC+LC condition, with a non-significant tendency towards lower instability in the LC condition as well.

Mental workload data

As a reminder, an increase in the number of correct responses on the secondary task implies more spare attentional capacity, or lower MWL. Analysis of these data showed a significant increase in mean number of correct responses in the

Table 4.1 Descriptive statistics for driving performance variables

	Manual	*ACC*	*LC*	*ACC+LC*
Number of lane excursions	42.0	39.7	1.04	1.61
Time spent out of lane (s)	111.1	101.7	2.68	4.69
Speed instability (mph)	10.2	9.17	8.92	7.13

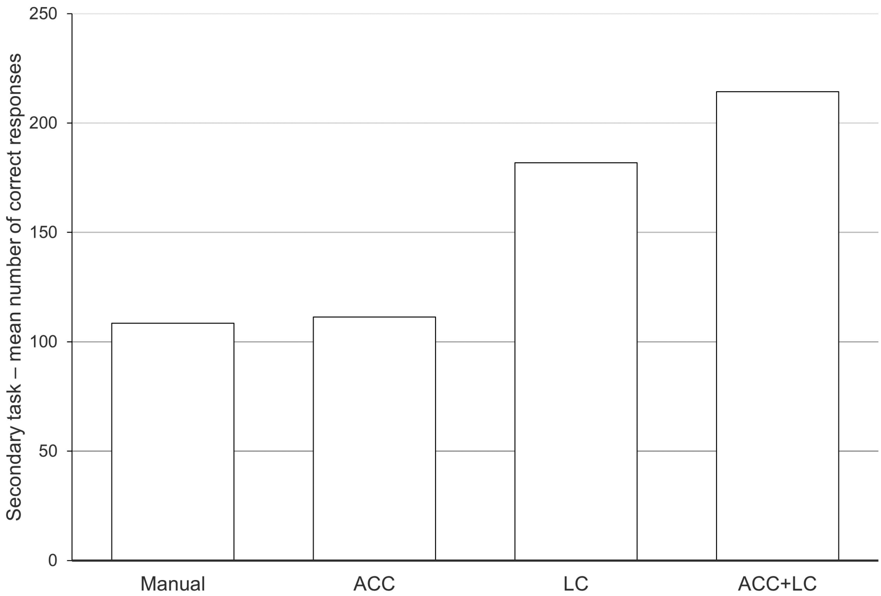


Figure 4.6 Secondary task scores in each condition. Higher score implies more spare attentional capacity, and thus lower MWL.

LC condition, and a further significant increase in the ACC+LC condition; there was no difference between manual and ACC conditions (see Figure 4.6).

Subjective workload, as measured by the OWL score on the NASA-TLX, presented a very similar picture to the secondary task data. Again, whilst there was no difference between manual and ACC conditions, workload significantly reduced with LC, and reduced even further with ACC+LC (Figure 4.7).

Attention ratio data

The attention ratio is derived from the secondary task score and the amount of visual attention directed at the secondary task. The latter is gathered from the video data, which could not be analysed for all participants as in some cases the video recording was not clear enough to reliably code the eye movements (e.g., due to the participant wearing glasses). Therefore, the attention ratio analysis was performed on a subset of 20 participants. Suffice it to say, the pattern of secondary task responses in this subset mirrored that of the main sample, as presented above.

The effect of automation on the attention ratio reflected the secondary task, with no difference between the manual and ACC conditions, but significant reductions in attention ratio in the LC condition and again in the ACC+LC condition (see Figure 4.8).

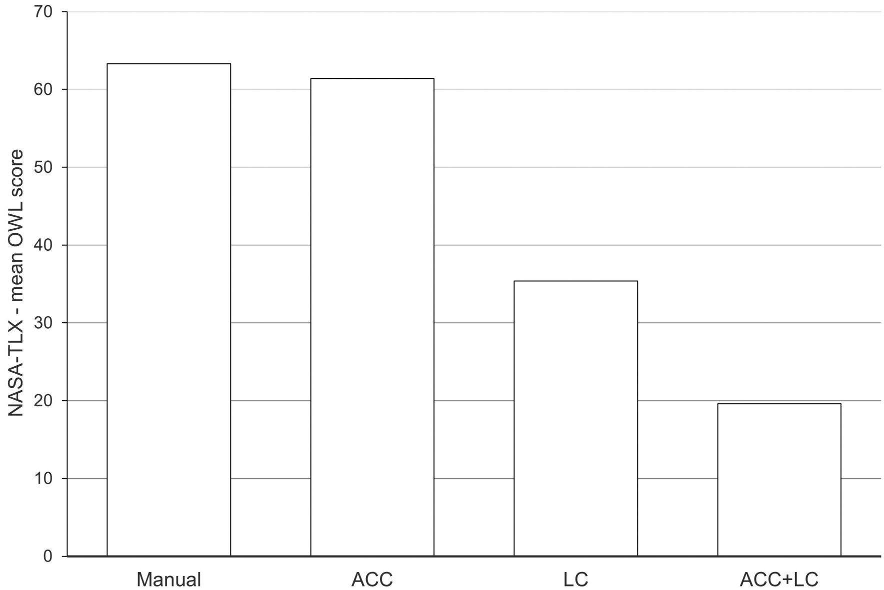


Figure 4.7 Mean overall workload (OWL) score on NASA-TLX across automation conditions (high score indicates high workload).

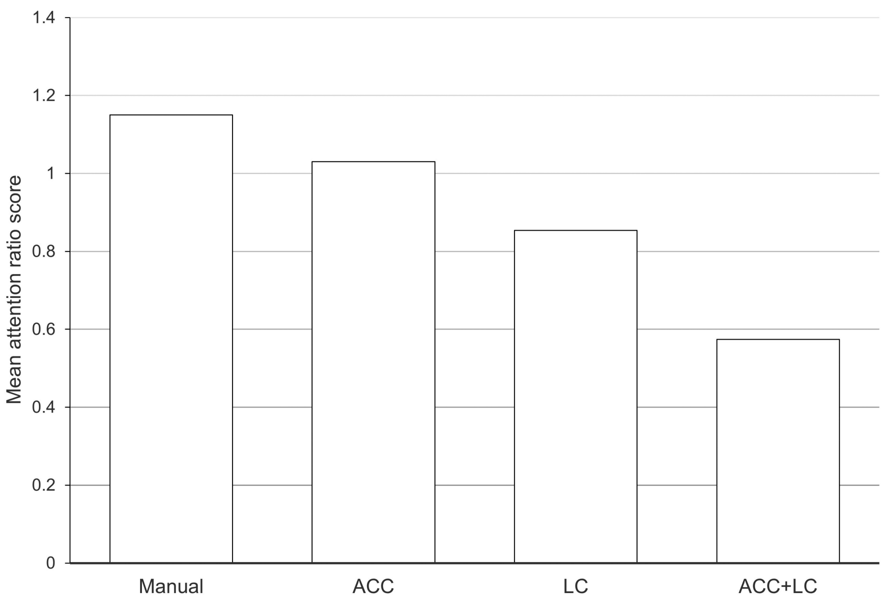
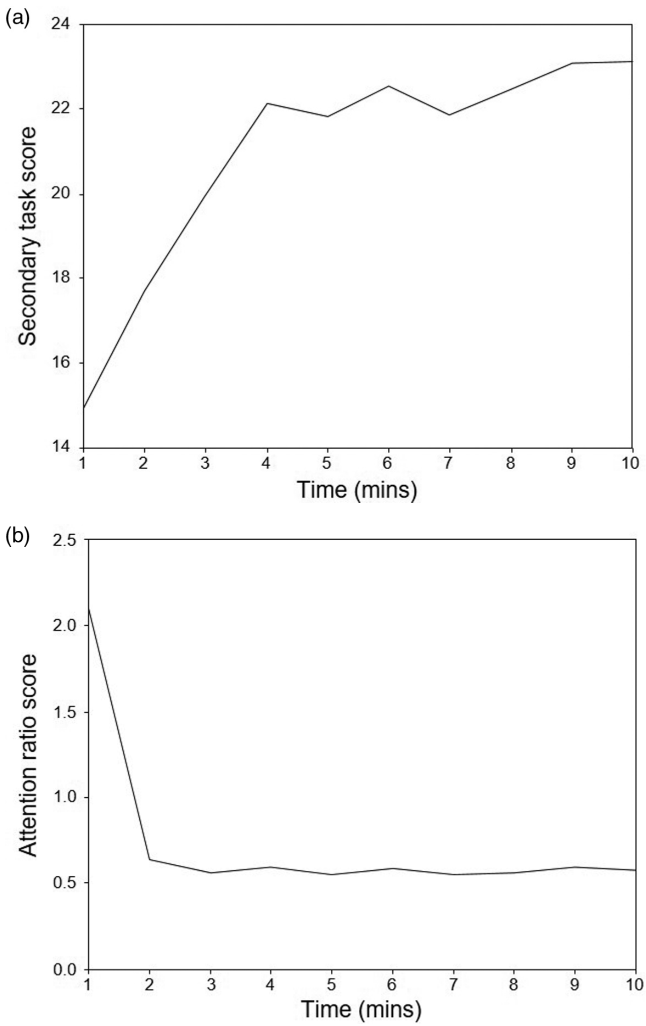


Figure 4.8 Attention ratio score in each condition. Lower score implies smaller attentional resource capacity.

Now, to determine the temporal decay of resources, we first needed to establish the pattern of MWL over time. For the present purposes, we have restricted the timeline analysis to the ACC+AS level of automation, as this condition represented the lowest level of workload, and hence the greatest amount of resource decay. Figure 4.9a shows the pattern of secondary task responses across the duration of the trial (remember that the secondary task score is a measure of spare capacity, and thus a higher score implies a lower level of workload on the primary task). A visual inspection of the curve suggests that mental workload gradually decreases until around the fourth minute



Figures 4.9a and 4.9b Timeline plots of secondary task responses and attention ratio scores for the underload condition.

of the trial, when it stabilises for the rest of the drive. Statistically speaking, though, when compared to the first minute of the trial as a baseline, workload actually reduces significantly straight away in the second minute of the trial.

Turning to the timeline plot of the attention ratio data (Figure 4.9b), again we see that resource capacity mirrored mental workload in this condition. Indeed, the effects on capacity appear even more dramatic than those for workload, with the graph displaying an immediate drop in capacity after the first minute before stabilising for the duration of the trial, which was again statistically significant. The attention ratio scores when underloaded appear to be around one-quarter of that in the baseline section. In other words, participants are spending four times as long per response as they would do when under normal conditions.

DISCUSSION

Implications: mental workload and performance

The results of this study (Young & Stanton, 2002b) indicated that automation does indeed have a significant effect on driver MWL (both subjective and objective), although the specifics of this effect depend on the level of automation. Apparently, LC has a far greater influence on workload than ACC, despite both ostensibly being Level 1 automation systems, while MWL is lowest when both systems are engaged together (i.e., Level 2 automation). Whilst not all research had observed such reductions in MWL (e.g., Desmond et al., 1998, found that the combination of lateral and longitudinal automation did not affect subjective MWL), our results are consistent with other studies that found similar systems did reduce both subjective (de Waard et al., 1999; de Winter et al., 2014) and objective (Carsten et al., 2012; de Winter et al., 2014) metrics of workload. In particular, Carsten et al. (2012) used a similar set of automation conditions as Young & Stanton (2002b), but drivers were free to either pay attention to the roadway or engage with a range of in-vehicle non-driving tasks. Unsurprisingly, with increasing support from the automation, drivers diverted more attention to these secondary tasks. Just as in the present study, automated lateral control had a bigger effect on drivers' allocation of attention and their effort (as measured by heart rate) than automating longitudinal control.

It should not be surprising that automated steering has a greater effect on MWL than automated longitudinal control. Controlling speed and headway is a first-order tracking task governed by feedback, whereas lateral control is a feed-forward, second-order tracking task (that is, involving accelerations rather than velocities; Carsten et al., 2012; Wickens et al., 1998). Since tracking difficulty increases with control order, it makes sense that LC should relieve MWL to a greater extent than ACC.

In general, the results of this experiment suggested that there are no adverse consequences of reductions in MWL for performance. Whilst automated lateral control reduced MWL as measured by the secondary task, this did not have any significant effect on speed and headway maintenance (the remaining manual subtask in the LC condition). On the face of it, this might seem to mitigate against any concerns of underload, as we may have expected a decline in performance particularly in the LC condition. However, comparable studies of that era addressing similar questions (e.g., Desmond et al., 1998; de Waard et al., 1999; Nilsson, 1995; Stanton et al., 1997) observed performance problems in critical driving scenarios (e.g., automation failure) rather than 'normal' driving as in the present study. The fact that reduced MWL did not affect performance may have been due to the fact attentional resources were shrinking to *match* task demands, as MART predicts.

Implications: malleable attentional resources theory

The attention ratio results are striking, being directly correlated with the secondary task data across the four automation conditions. It appears that, when MWL decreases, the allocation of attention to the secondary task becomes less efficient. This could either represent shrinkage of attentional resources (as predicted by MART), or simply a change in strategy by the participants – perhaps reflecting a speed-accuracy trade-off. However, an analysis of secondary task error rates found that the percentage of correct responses remained stable in all four conditions, so it is unlikely that such a strategic change in allocation of attention was occurring. Therefore, MART seems to be the most likely explanation for these data. This finding was possibly the single most important result to emerge from the experiment, providing the first piece of evidence in favour of MART. The fact that participants' responses on the secondary task did not vary consistently with the amount of attention they were directing to the task suggested that the size of the resource pool can change. On the basis of MART, it was expected that the attention ratio score would decrease in line with the MWL data from the secondary task. This prediction was directly upheld by the observed data, providing strong evidence for an association between task demands and attentional resource capacity.

These are very encouraging results for MART. Further support is provided by the primary task performance data, as these reductions in demand are not accompanied by changes in driving performance. It could be argued that these results are due to different attention allocation strategies, or a qualitative change in the driving task (from active operator to passive monitor), allowing more time to be devoted to the secondary task in the light of a perceived reduction in driving demands. If participants' allocation policies were inappropriate to the relative task demands though, either a decrement in driving performance or an improvement in secondary task performance should be observed. This was not the case: driving performance remained constant regardless of attention ratio score, and no improvement in secondary task error rate was observed. Therefore, all attention devoted to the secondary task really did represent *spare* capacity. Furthermore, the fact that driving performance did not improve with reductions in task demands implies that *all* spare capacity was allocated to the secondary task. It is reasonably safe to assume, then, that the sum of primary and secondary task demands reflected the total attentional capacity of the driver. Given this assumption, and the fact that increases in secondary task scores were not proportional to increases in visual attention, it is logical to conclude that attentional capacity had shrunk.

The study also gave us an insight into how attentional capacity responds to underload, by delineating the temporal nature of MART-related resource decay. By analysing the attention ratio score within a proven underload condition, we demonstrated that presumed resource capacity appears to shrink directly in line with reductions in mental workload. Moreover, to all intents and purposes, this shrinkage appears to be virtually instantaneous, occurring within the first minute of the trial.

That resource decay occurs so quickly was surprising, to say the least, as it was anticipated that there may be some lag as attentional capacity adapts to the task demands (cf. Young et al., 2015). Nonetheless, the results provided further clarification of the mechanism by which MART explains the relationship between underload and performance.

The obvious next step would be to look at the recovery curve for attentional resources following a post-underload return to 'normal' MWL. That was the aim of a separate study by Young & Clynick (2005), which followed the model of Young & Stanton (2002b) but also broke new ground for MART by taking it outside the driving domain as well as looking to test it in a non-automation scenario. Using a medium-fidelity fixed-base flight simulator at the University of New South Wales, a small sample of student pilots faced a flying task with two conditions: one at a high level of demand (induced by continually adjusting altitude to a changing target), the other at low demand (flying at constant altitude). These conditions aimed to represent normal MWL and underload, but in this case with no automation involved. After 10 minutes, a critical event was instigated by the introduction of a stiff cross-wind, which gradually pushed the aircraft off track and required the pilot to make correctional inputs in order to maintain their heading. Following the critical event, participants flew for another 10 minutes, but this time at normal workload in both conditions. The same secondary task was used to measure MWL, while participants' direction of attentional gaze was recorded using a video camera to calculate attention ratio as before, with the analysis divided into one-minute segments across the full 20 minutes of each trial.

Disappointingly, however, the MWL manipulation appeared to be unsuccessful for Young & Clynick (2005), as there were no substantive differences in responses to the critical event, MWL or attentional capacity (as inferred by the attention ratio) across the conditions. There was something of an increase in MWL around the midpoint in both conditions, associated with the critical event, while the attention ratio also appeared to peak at the same time, potentially indicating that capacity can recover as quickly as it decays. However, this peak in attention ratio turned out to be statistically non-significant. Otherwise, the attention ratio was fairly flat throughout both conditions, negating the effort to track decay and recovery of resources. Young & Clynick (2005) wrote these results off to the experimental design, concluding that the two conditions were not sufficiently far apart (or just in the wrong places) on the inverted-U performance curve (refer back to the numbered points on Figure 3.2 in Chapter 3, which illustrate how tasks can differ in MWL without venturing into the underload region). However, they also considered whether the lack of an effect might also have been due either to differences in the nature of the flying task compared to driving (given that pilots are trained to continuously visually scan the instruments and the outside world, which could have served to maintain their attention and, hence, their workload) or, even, the possibility that MART might not be applicable in a non-automated scenario.

A related study by Merat et al. (2012) raised an alternative possibility. They compared responses to a critical scenario in manual and highly automated driving with explicit reference to MART, in terms of the transition from relatively low to unexpectedly high workload. However, in their study, the presence or absence of a secondary task (in this case, a twenty questions game designed to be analogous to a telephone conversation) was manipulated as an independent variable, to determine its effect on performance. Interestingly, the worst performance in response to the critical event was in the automated condition with the secondary task – after a period of underload with the automation, drivers' attentional resources had been distracted from the driving task. Without the secondary task, drivers were equally capable of dealing with the critical scenario whether in manual or automated conditions. The implication is that the secondary task draws attention away from driving. In support of this conclusion, there is other evidence that detrimental effects of automation are only evident when there are concurrent tasks competing for attention (Endsley & Kaber, 1999). For the experiment presented in this chapter (Young & Stanton, 2002b), then, the secondary task may be serving to draw attention away from the driving task. Whilst that did not result in performance decrements in the benign circumstances used here, it could be a factor if investigating critical scenarios. We will bear this in mind in Chapter 7 when we explore how drivers deal with an automation failure.

Another perspective might appeal to the classic vigilance decrement (e.g., Mackworth, 1948; Singleton, 1989) as an explanation for the results obtained here. However, the present experimental design does not qualify it as a vigilance task. Observations elsewhere (Singleton, 1989; Warm et al., 1996) typically find that a vigilance decrement sets in after 20–30 minutes. Given the 10-minute trials in the current study, it is unlikely that vigilance would have caused a problem. Furthermore, Parasuraman (1987) argued that continuous, dynamic tasks do not lend themselves to vigilance problems, and it is easily arguable that the task of driving fits these criteria. Therefore, MART seems to be a more likely explanation for these data.

Finally, other competing explanations relate to the nature of the task, and centre around issues of motivation and arousal. One might suggest that participants were simply bored or less motivated to maintain performance on the secondary task in the underload conditions. If this were the case, it would be expected that a lack of motivation would have a general effect on performance. Since manual performance on the remaining primary (driving) task was not affected (that is, when using ACC or LC individually), the balance of evidence favours MART. Similarly, although physiological arousal was not measured in the present study, all of the experimental conditions posed fairly equal levels of physical demand, so it is unlikely that physiological arousal influenced the results. Meanwhile, the counterbalanced conditions should have mitigated any confounding effects of motivation or arousal. However, it is acknowledged that mental demands might only have influenced attentional capacity via an effect on arousal. Again, we present a further study to address this question in Chapter 7.

CONCLUSIONS

In the last couple of chapters, we have argued that the introduction of automation into the automobile can significantly reduce driver MWL, and that this is a potential factor in explaining the problems that many drivers have with reclaiming control in critical situations. A possible mechanism for this is MART, whereby underload affects the attentional capacity of drivers. Under MART, the reason for such performance decrements would be a reduced ability to devote appropriate levels of attention to the situation. This potentially offers a definitive and parsimonious explanation of mental underload, as well as the opportunity to make practical predictions for performance with automation.

The study presented in this chapter (Young & Stanton, 2002b) supported the predictions of MART by showing that the (inferred) size of attentional resources shrank directly in line with reductions in mental workload. In other words, as drivers of automated vehicles – even at level 2 automation – become faced with underload, it is feasible that they would have less attentional capacity available to deal with any unanticipated events. Perhaps surprisingly, the data also showed that this decay occurs relatively quickly, within the first minute of being underloaded. Unfortunately, a subsequent study was unsuccessful in trying to establish how quickly (or otherwise) attentional capacity recovers after workload returns to normal.

Eventually, we would hope to identify a threshold of resource decay beyond which true underload (i.e., in terms of degradation of performance) can be predicted. If we accept the absolute figures on the attention ratio curve in the present study, we can venture to suggest that a shrinkage factor of 75% was necessary to produce underload. Now, we do not necessarily believe it is that straightforward and intermediate levels of workload would need to be analysed to establish other relative shrinkage factors. But if we can plot similar curves under a number of other conditions, it may well be possible to isolate a cut-off point for underload. Levels of workload and attentional resources could then be used in an *a priori* manner to predict performance given a level of task demands – and thus putting us in a strong position to establish the elusive 'redline' of mental workload research.

From an applied perspective, though, there is a curiosity in the results of this study, in that ACC alone did not reduce MWL, but when combined with LC there was a significant reduction in workload. Why, then, should the same system produce differential effects on MWL depending on whether or not the driver is also steering? The next study in this series attempts to answer that question.

KEY POINTS

- A driving simulator study showed that although adaptive cruise control on its own did not affect mental workload, lane centring did significantly reduce workload and there was a further reduction when using both systems together (level 2 automation).
- When only part of the driving task is automated, performance on the remaining manual task was largely unaffected, even when workload was reduced.
- A proxy measure for attentional capacity demonstrated that these reductions in mental workload were mirrored by a shrinkage in attentional resources, in support of malleable attentional resources theory (MART); moreover, this shrinkage occurred within the first minute of driving.

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Chapter 5

When is ACC not ACC?

OVERVIEW

Since the introduction of adaptive cruise control (ACC), the current generation of automated driving systems has offered the potential to relieve drivers of mental as well as physical workload. Previous research, though, has raised some puzzling conflicts about the effects of ACC on driver mental workload (MWL). Some studies have reported reduced MWL with ACC compared to manual driving, whereas others have found no effect. Two hypotheses are proposed in an effort to explain these discrepancies: a) that any potential MWL reductions due to ACC could be masked by the overriding influence of steering demand; or b) that the tasks designed in some experiments does not exploit the adaptive functionality of the ACC system. Two related experiments were conducted to test these hypotheses. In experiment 1, a constant-speed task was combined with a straight road to minimise the steering demands, in an effort to make the dependent variables more sensitive to any effect of ACC. Experiment 2 reverted to a mixed (straight and curved) road design, but introducing a variable-speed task to test the adaptiveness of ACC. Taken together, the results favoured the latter explanation: constant-speed tasks do not realise the MWL benefits of ACC.

INTRODUCTION

In the last chapter we established a pattern of mental workload (MWL) over four automation conditions, ostensibly representing levels 0 through 2 on the SAE (2018) taxonomy: manual, adaptive cruise control (ACC), lane centring (LC), and ACC+LC. Whilst using ACC alone did not really affect MWL compared to manual driving, switching on LC did significantly reduce MWL. We explained this in terms of the greater demand of the steering task, being a second-order tracking task (cf. Carsten et al., 2012; Wickens et al., 1998). Interestingly, though, using ACC with LC (level 2 automation) resulted in a further significant reduction in MWL over LC alone. So ACC must have had some impact on the driving task, even though that was not apparent when drivers were still steering manually. In this chapter (which is based on Young & Stanton, 2004), we focus in on whether and how ACC might affect MWL.

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To recap, ACC was one of the first driving automation technologies to become available on the mainstream market. The introduction of ACC offered the capability not just to maintain a set speed, similar to conventional cruise control, but also to detect other vehicles in front and adjust speed to maintain a set headway. So, whereas standard cruise control simply relieves the driver of physical workload (keeping the foot on the accelerator pedal), ACC removes some of the decision-making elements from driving (perception of closing speed, time-to-contact; Stanton et al., 1997; Stanton & Young, 1998). Consequently, it has the capability to relieve the driver of some MWL.

The results of previous research, however, are equivocal regarding the specific effects of ACC on driver MWL, with some studies reporting reduced MWL compared to manual driving, while others found no effect. Two of the earliest published studies on this question (Nilsson, 1995; Ward et al., 1995) found no differences in subjective MWL (using the NASA-TLX) between manual and ACC conditions. Later research did demonstrate reductions in MWL with ACC, both in a driving simulator (Ma & Kaber, 2005) and on a test track (Rudin-Brown & Parker, 2004).

More recently, a meta-analysis of 32 studies (de Winter et al., 2014) found workload was slightly lower with ACC compared to manual driving, but much lower with highly automated driving. The majority of the studies in the review were conducted in fixed-base simulators and variously used subjective or secondary task measures of MWL. To some extent the effects depended on the trial duration. In one of the reviewed studies, there were no differences in MWL after 10 minutes, but after 50 minutes there was significantly lower MWL in the highly automated drive, largely due to the fact that MWL in the manual condition had increased over that time.

Meanwhile, a study by Stanton et al. (1997), also in the Southampton Driving Simulator (SDS), found that ACC did cause a significant reduction in MWL on the secondary task measure. However, the Stanton et al. (1997) study used short trials (two minutes) and, because the experiment was also about testing responses to ACC failure, the conditions were not counterbalanced. Participants always drove the manual condition first, followed by ACC, then ACC with a failure, so the improvement in secondary task performance is more likely due to a practice effect rather than differences in mental demands between the conditions.

Nevertheless, there is further evidence that ACC can reduce driver MWL in certain situations. Bar-Gera & Shinar (2005) suggested that car-following and headway monitoring is a demanding task, and that devices such as ACC can relieve these demands. Likewise, Ma & Kaber (2005) argued that ACC relieves MWL and hence improves situation awareness, which in turn enhances performance. They used a medium-fidelity driving simulator to show that ACC reduced workload and improved driving performance in terms of speed, headway, and lateral variability.

One explanation for the conflicting findings could relate to the experimental design. Our work in the SDS (Young & Stanton, 2002b) used a task which involved following a constant-speed lead vehicle along a course which was a mixture of curved and straight sections. The lack of a MWL effect when using ACC alone could have been because processing of the longitudinal control task had become automatic (i.e., completely attention-free) for the experienced drivers used in these studies. Perhaps, then, the task used – following a constant-speed lead vehicle – was not appropriate to highlight any MWL effects when using ACC, as it did not test the 'adaptiveness' of the ACC system and was more akin to using standard cruise control. Alternatively, the much heavier load imposed by steering during these tasks could have masked any MWL advantage of using ACC. This explanation would account for the fact that, when the steering load was no longer a factor (i.e., steering had been automated), ACC did significantly reduce MWL.

In order to test these explanations, we (Young & Stanton, 2004) designed a study using four automation conditions: manual (participant controls speed and steering), ACC (participant controls steering only), LC (participant controls speed only), and ACC+LC (both speed and steering are automated – essentially a fully automated drive). The two manipulations – minimising steering load and increasing longitudinal load – were varied one at a time, to isolate their effects and evaluate each explanation independently.

Experiment 1 used a constant-speed vehicle-following task, as per Young & Stanton (2002b), but on a straight road. As such, the lateral demands of steering the vehicle were minimised. This is similar to using LC, so this experiment would predict reduced MWL in the ACC and ACC+LC conditions (which are similar to each other), but no difference between manual driving and using LC. These predictions are illustrated in Figure 5.1.

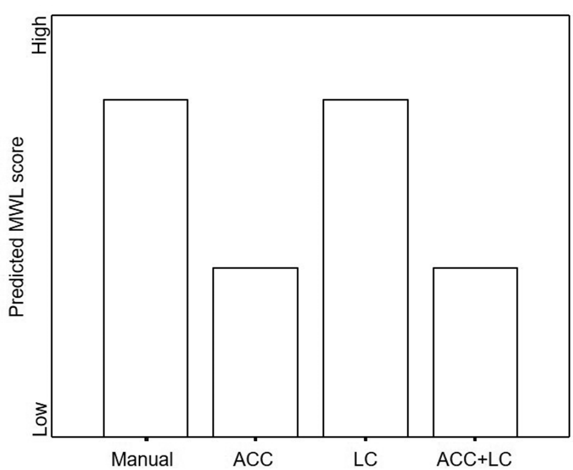

Figure 5.1 Predicted MWL scores across automation conditions, experiment 1. These predictions are based on the hypothesis that ACC will only reduce MWL if steering demands are minimised.

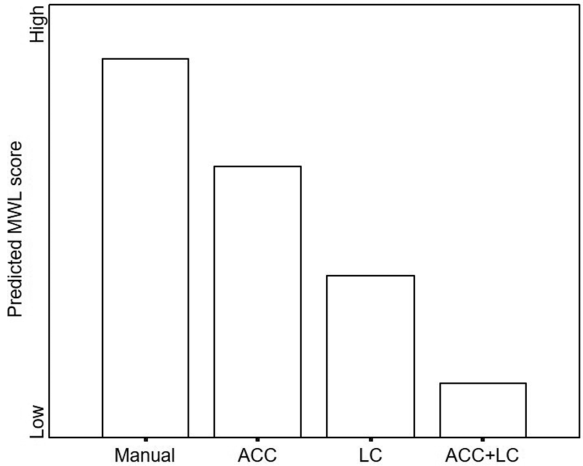

Figure 5.2 Predicted MWL scores across automation conditions, experiment 2. These predictions are based on the hypothesis that ACC will only affect MWL if longitudinal demands are nontrivial.

Experiment 2 used the original (Young & Stanton, 2002b) mixed course with curved and straight sections, but now with a variable-speed lead vehicle. This imposes additional longitudinal demand, so the prediction of experiment 2 was a stepwise reduction in MWL across the manual, ACC, LC, and ACC+LC conditions (assuming that steering is still more demanding than the additional longitudinal task). These predictions are represented in Figure 5.2.

EXPERIMENT 1: STRAIGHT ROADS

Method

Experiment 1 was conducted in order to determine whether the effect of ACC on MWL has previously been masked by the dominant influence of steering. Therefore, participants were required to drive on a simple straight road for 10 minutes in each of the four automation conditions (manual, ACC, LC, and ACC+LC). This removes most of the steering demand, presumably making the MWL measurements more sensitive to longitudinal demands. If there is an effect of ACC at constant speed, it should be revealed here.

The design was within-subjects, with 12 experienced drivers (i.e., those with a full UK driving licence) as participants. Dependent measures (see Chapter 4) included the primary task measures of longitudinal and lateral control, the visual-spatial secondary task, and the NASA-TLX (Hart & Staveland, 1988) in order to compare with previous studies using this subjective MWL scale (Nilsson, 1995; Ward et al., 1995).

In all of the experimental conditions, participants were faced with a single-carriageway road. The course was a simple straight road, with no hills or wind gusts to disturb longitudinal or lateral control. Participants were instructed to first catch up and then follow a leading vehicle, which was travelling at a constant 70 mph (113 km/h), for the 10-minute duration of the trial. There were no other vehicles in the participants' lane (so no overtaking was necessary), although oncoming traffic was encountered infrequently, encouraging participants to remain in their own lane. Participants were required to maintain a constant distance from the lead vehicle, although the choice of that distance was left to the individual. There were a number of advantages to this approach. Firstly, it meant that participants did not have to disengage the automatic devices (for instance, in order to overtake), thus avoiding contamination of conditions. Secondly, following a car motivated participants to drive at a relatively constant speed, thereby controlling objective demand across conditions. Otherwise, participants may have compensated for increased workload by reducing speed, which again would contaminate results. Finally, a constant speed implied that participants all drove approximately equal distances, again controlling for workload and attention differences which may otherwise have been incurred.

Results

In terms of driving performance data, using LC unsurprisingly resulted in dramatically better (that is to say, perfect) steering performance when LC was engaged. The more interesting comparison for lateral control was between manual and ACC conditions, as both involved manual steering, but there was no significant difference in lane excursions nor time spent out of lane between these conditions.

Despite the fact that lateral control demands were minimised on the straight road design of this experiment, then, there was still some variability in manual control of steering. Moreover, it seems that using ACC has no effect on human lateral control. In other words, steering performance was equivalent whether or not automation was used to relieve the subtask of longitudinal control.

The results for longitudinal control were less clear, with some spurious results muddying the waters. On the whole, though, it appeared that – on this straight road, at least – humans were equally capable of maintaining constant speed and headway as ACC.

For MWL, automation had a significant effect on secondary task scores, with no difference between manual and ACC conditions, but stepwise increases (i.e., decreases in MWL) with LC and again with ACC+LC (see Figure 5.3).

As for subjective MWL on the NASA-TLX, the overall workload (OWL) scale was significantly affected by automation, with a stepwise reduction from manual to ACC, from ACC to LC, and from LC to ACC+LC (Figure 5.4).

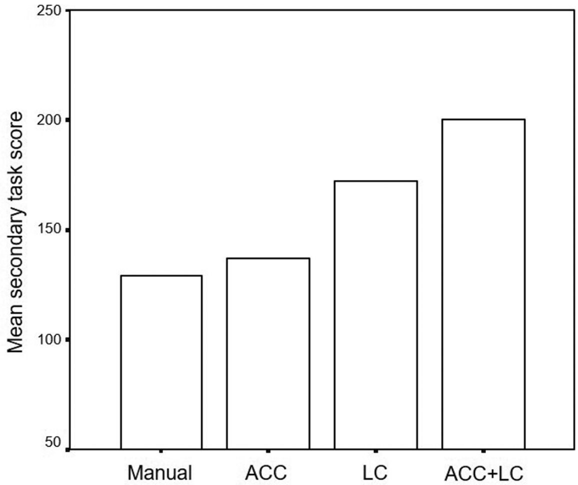

Figure 5.3 Secondary task scores across automation conditions. Higher scores reflect lower MWL.

Discussion

From the primary and secondary task performance data, it was apparent that minimising lateral demands does not release any extra spare capacity when using ACC. The hypothesis that the heavy demands of steering may have masked a MWL effect of ACC was therefore not supported, at least as far as the performance data are concerned. The secondary task scores also fit well

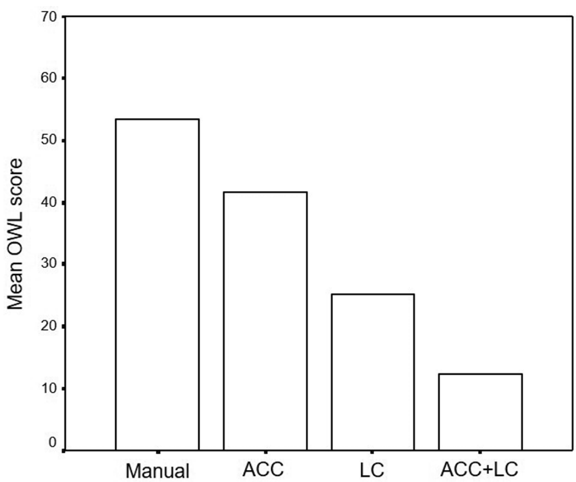

Figure 5.4 Overall workload ratings across automation conditions. Higher scores reflect higher MWL.

with the primary task data. Longitudinal control was no better when ACC was engaged than if speed was controlled manually. As such, relieving the driver of this task did not decrease the driving demands, supporting the notion that constant-speed driving is processed in a fully automatic way for experienced drivers. However, there was still a puzzling increase in spare capacity in the ACC+LC condition. Perhaps, in the LC condition, participants were periodically checking the speedometer or road view as uncertainty built up about the road situation (cf. Senders et al., 1967). Even occasional glances could sufficiently disrupt secondary task performance. Lateral control, on the other hand, was worse for humans than the automated system. Therefore, some improvement on this control dimension can still be made, and that is reflected in the additional spare capacity which is observed when steering is automated.

Interestingly, participants did perceive a reduction in MWL when ACC was engaged, despite the fact that objectively (i.e., as determined from the secondary task data) the demands did not change. So the masking hypothesis, initially rejected on the basis of the secondary task data, could apply to these subjective data. Actual spare capacity is not influenced by ACC, purely and simply because it does not relieve the experienced driver of any demands when the longitudinal control task is to maintain a constant speed. When other demands (i.e., steering) are high, participants understandably do not perceive a difference between the manual and ACC conditions. However, when the steering demands are minimised, drivers do become sensitive to the absence of driving subtasks, even though those subtasks were ostensibly automatic (cognitively speaking) for this group of participants. In that respect, these results are consistent with the findings of Liu & Wickens (1994), in that the subjective metric is sensitive to the presence of automation, while the secondary task revealed automatic performance.

Overall, the results from this experiment showed that a constant speed longitudinal control task does not pose any additional demands for experienced drivers, presumably because automatic processing of this task has virtually reached its ceiling. In the absence of a demanding lateral control task, participants did perceive a difference in MWL between the manual and ACC drives. The possibility that the subjective demands of longitudinal control are masked by the much greater demands of steering therefore remains credible.

Despite these encouraging results, the pattern of MWL data did not accurately reflect the predictions made for this experiment. In particular, there was a substantial MWL decrease when using LC, even though steering demands were minimised. Taking this result alongside the lateral control performance data (which showed some lane excursions under manual control), it seems clear that steering was not a cognitively automatic task even on a straight road. Furthermore, a significant increase in spare capacity was observed in the ACC+LC condition, yet it had been concluded that longitudinal control in these task conditions did not draw any attentional demands. Therefore, the next step was to investigate the alternative approach – increasing the longitudinal demands.

EXPERIMENT 2: VARIABLE-SPEED LEAD VEHICLE

Method

In the light of the results from experiment 1, it was apparent that minimising the steering load did not reveal any advantages for ACC in terms of spare attentional capacity. Experiment 2 therefore considered an alternative hypothesis – that the task of following a constant-speed lead vehicle is not really a test of longitudinal control, and does not exploit the functionality of the ACC system. As with experiment 1, the design was completely within-subjects, with 12 experienced driver participants.

In experiment 2, we used a course comprising a mix of curves and straight sections, and a change was made to the characteristics of the lead vehicle. At pseudo-random intervals and without warning, the lead car would firmly brake (with brake lights illuminated) until it reached a speed of about 30 mph (48 km/h), when it would accelerate again to its default speed of 70 mph (113 km/h). The participant's task was to match the speed of the lead vehicle, staying behind it and trying to maintain a constant headway as before. In this case, the additional longitudinal demands should theoretically lead to a MWL reduction when ACC relieves the participant of this task. Furthermore, car-following performance in these conditions also offers a measure of attention (Zhang et al., 2021).

The same primary task, secondary task, and subjective MWL measures as before were used as dependent variables. Primary task variables included the evaluative performance measures of longitudinal and lateral control, while the secondary task and NASA-TLX were as used in the previous experiments.

Results

Starting with driving performance, as with experiment 1 LC was significantly better in terms of both time spent out of lane and number of lane excursions than manual steering, with or without ACC engaged. There was no difference in steering performance between the manual and ACC conditions.

The longitudinal control data revealed some interesting results, with speed instability apparently getting worse in the two ACC conditions (ACC, ACC+LC) compared to manual control of accelerating and braking, while headway instability was significantly better with ACC engaged. There were no differences between the manual and LC conditions (that is, when longitudinal control was manually performed).

Turning to MWL, automation significantly increased spare attentional capacity as measured by the secondary task, with stepwise increases in correct responses from manual to ACC, from ACC to LC, and from LC to ACC+LC (Figure 5.5). This pattern of responses differs from those in experiment 1, and fulfils the prediction made for the present study.

For subjective workload, the OWL scores on the NASA-TLX exhibited a similar pattern, except there was no difference between the ACC and LC conditions; other comparisons were significant (Figure 5.6).

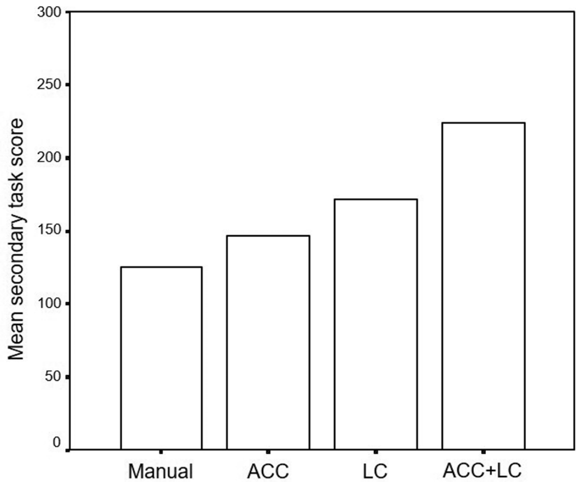

Figure 5.5 Secondary task scores across automation conditions. Higher scores reflect lower MWL.

Discussion

As in experiment 1, the lateral performance data simply indicate that LC is better than the human at maintaining lane position. This result is less surprising in the current study, for which steering demands were relatively high, than in the previous experiment, when the only task was to keep the vehicle in a straight line. It was, however, notable that the longitudinal demands were

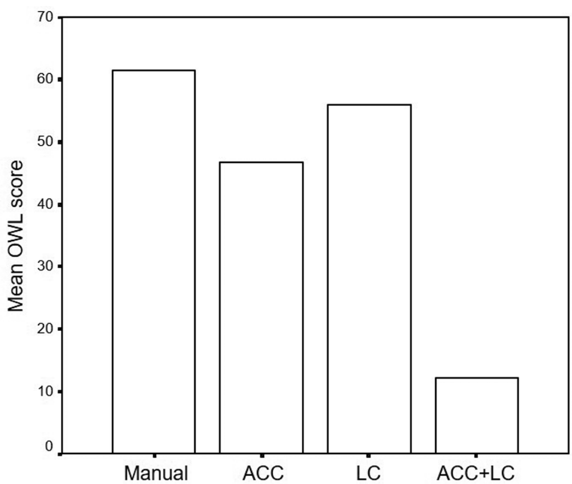

Figure 5.6 Overall Workload ratings across automation conditions. Higher scores reflect higher MWL.

nontrivial in experiment 2, yet the use of ACC did not improve participants' steering ability.

In our previous experiment (Young & Stanton, 2002b), longitudinal instability was generally reduced only in the ACC+LC drive. From this, it might be concluded that driving on a curved course increases longitudinal instability. Drivers were probably slowing down for corners or, in the case of the ACC condition, either disengaging ACC or drifting out of lane such that the system lost its target and attempted to reacquire set speed.

In the present study, ACC appeared to increase speed instability, while reducing headway instability. This apparent contradiction is explainable, though, when considering the nature of the ACC system. ACC was designed (in the simulator at least) to maintain set speed until a lead vehicle impeded progress. Once a lead vehicle was detected, speed was adjusted to match that of the target as closely as possible. Therefore, fluctuations in speed of the lead vehicle were almost exactly matched by the ACC car. In the present experiment, this feature served to maintain a more consistent headway, but at the same time increasing speed instability due to the designed oscillations in speed of the lead vehicle. Manual control, on the other hand, dampened these speed oscillations by adopting a greater following distance – a kind of behavioural adaptation in action. When the lead vehicle slowed down, it was not necessary to adjust speed a great deal, but distance headway was compromised. Such a driving style suggests that participants were economising on their physical demands (i.e., repeatedly slowing down and speeding up) to create a smoother drive, but perhaps at the expense of increased headway monitoring demands.

For spare attentional capacity, it is clear from these results that ACC can actually have a beneficial effect when longitudinal demands are increased. Therefore, whilst automaticity may dominate the task of maintaining a constant speed, following a variable-speed lead vehicle requires much more controlled processing. However, the steering demands of the present course are evidently still greater than those imposed by the car-following task. Nonetheless, the results show that experienced drivers can in fact be relieved of attentional demands by ACC under the right conditions. The stepwise pattern for the secondary task score perfectly matches the prediction for this study.

Similarly, the pattern of subjective MWL data is consistent with the predictions made for this study. Rather than stepwise reductions in subjective MWL, though, it seems the new longitudinal task imposed similar levels of perceived demand as the steering task. The pattern of TLX ratings further dissociates the subjective and secondary task measures of MWL, adding weight to the argument that subjective ratings are not sensitive to differences due to automaticity.

In sum, the hypothesis that ACC would only reduce MWL when longitudinal demands were high was consistently supported by the results of experiment 2. In particular, the predicted pattern of MWL was exactly matched by the secondary task data, and supported by the subjective data.

One particularly notable finding from this study was the lack of a difference in lateral control performance between the manual and ACC conditions. In spite of the decreased demands when driving with ACC, participants did not translate this into a performance improvement for their steering. This could represent a ceiling of performance for human lateral control, or it could be indicative of a MWL homeostasis effect, with participants adjusting their performance to maintain a consistent level of MWL (cf. Buck et al., 1994; Zeitlin, 1995).

GENERAL DISCUSSION

Summary of results

In both experiments, LC was naturally better at maintaining lane position than the human driver. Similarly, participants tended to drive more slowly and with longer headways than the ACC system. The instability scores, a judgemental measure of performance, were mostly equivalent across automation conditions if the task was to maintain constant speed on a straight road (experiment 1). Under more demanding task conditions, the ACC system was significantly better at maintaining a constant headway from the variable-speed lead vehicle.

In experiment 1, driving on a straight road with ACC did not free up any more attentional resources than maintaining a constant speed manually. However, participants did perceive a reduction in MWL. Meanwhile, driving on the mixed course with a variable-speed lead vehicle (experiment 2) did affect spare capacity in the stepwise fashion as predicted. Subjective MWL did not decrease in quite the same way, as there was no difference between ACC and LC, but the results were still arguably consistent with the predictions, while indicating that the variable-speed task imposes similar levels of MWL as steering demands for this type of road. In both cases, the lowest MWL on both measures was in the highly automated drive (ACC+LC). In that condition, drivers were able to divert their attention to the secondary task, whereas with just ACC the driver still has to pay attention to the roadway – the remaining steering task requires drivers to visually sample the road at least every three seconds (de Winter et al., 2014).

Taking the results of experiments 1 and 2 together, it can be concluded that our previous research with a constant-speed task (Young & Stanton, 2002b) has not exploited the functionality of the ACC system, hence the conflicting findings about the effect of ACC on MWL. Although perceptions of demand may have been masked by the extra steering load (which, as evidenced by the MWL data in the LC conditions, was quite substantial), the level of automaticity achieved by experienced drivers in constant-speed driving meant that ACC could not relieve any attentional demands for that task. Forced variable-speed driving, on the other hand, is subject to more controlled (rule-based) processing, providing the opportunity for ACC to relieve this element of driver MWL.

Implications: mental workload and adaptive cruise control

The results in these two related experiments support the idea that ACC can relieve experienced drivers of MWL, but only in cases where the traffic flow is variable. At a constant speed, processing of longitudinal control is fully automatic for these drivers, and they only perceive a benefit when other demands (i.e., steering) are minimised. Even in this case, though, objective demand (i.e., spare attentional capacity) does not increase over and above that when driving normally. Steering, being a second-order tracking task, is naturally more demanding than longitudinal control (Wickens et al., 1998), so LC reduces MWL even on a straight road.

A general conclusion to emerge from these experiments is that steering is a primary determinant of driver MWL. Objectively speaking, ACC does not actually relieve demand significantly unless the longitudinal demands are already high. Since ACC is essentially a coarse form of static automation, using it when actual demands are low will not significantly increase spare attentional capacity (indeed, in the constant-speed case, it is acting in a manner akin to conventional cruise control).

From the applied viewpoint, these conclusions support the contention of vehicle manufacturers that ACC systems can offer added comfort and convenience to driving (Richardson et al., 1997). Indeed, the point of ACC is its adaptive nature: whereas standard cruise control has traditionally been more suited to highways that tend to be long, straight, and relatively empty, ACC is designed for roads with an increased traffic density and less consistent speed profiles. Using standard cruise control would not provide any benefit in such an environment, and indeed may even increase workload and frustration, as it would be necessary to continually disengage and reengage the system. An ACC system, on the other hand, can cope with fluctuations in traffic flow, and thus lead to a reduction in MWL, as seen in experiment 2.

In addition, the results of these experiments indirectly support one of the presumptions made in this book: that such vehicle technologies can relieve driver load at a psychological level. Orthodox systems, such as conventional cruise control, are not thought to relieve the driver of any MWL, as there is little information processing involved in maintaining a constant speed. The results of this experiment indicate that this is indeed the case, at least as far as experienced drivers are concerned.

CONCLUSIONS

Findings from both this study and previous literature are in conflict about the effects of ACC on MWL. It was found that this conflict is mostly likely due to the design of the task used. Simple car-following at a constant speed does not exploit the 'adaptiveness' of the ACC system, whereas following a variable speed vehicle does. However, there was also some evidence that effects of ACC on subjective MWL may have been masked by the much greater demands of steering the vehicle.

One particular finding in experiment 2 also provides some further evidence supporting malleable attentional resources theory (MART). For the leftover human tasks in partial automation conditions (i.e., steering when ACC is engaged, longitudinal control when LC is engaged), there was no improvement in performance compared to fully manual driving, despite objective and subjective workload reductions. It could be the case that human performance was already at ceiling in the manual condition, and could not improve any further. Nevertheless, there is obviously room for improvement as the automated systems consistently exhibited superior performance over human control. If performance could improve, but did not, MART would suggest that the reduction in attentional capacity has consequently limited that performance ceiling – in other words, performance has matched the available resources.

An alternative perspective on this considers the effects of skill. In this chapter, we have toyed with the notion that the constant-speed following task is cognitively automatic for this experienced driver sample, as an explanation for the findings. Furthermore, in Chapter 3 we learned that automaticity in information processing reduces an operator's dependence on attentional resources. Clearly, then, there is an interaction between automation and automaticity. The next question to be addressed is, therefore, how the effects of automation might relate to automaticity, in terms of driver skill level. Possibly, a high level of automaticity might exacerbate underload, since there are very few demands on the driver's attentional resources. On the other hand, the very nature of automatic processing might ameliorate the performance impacts of mental underload. In the next chapter, we compare the results of the previous study alongside data for three other levels of driver skill.

KEY POINTS

- Adaptive cruise control (ACC) is largely marketed as a comfort and convenience system, but it has the potential to affect driver mental workload.
- However, the research jury is out in terms of the effects of ACC on workload; these effects are likely dependent on task context.
- A simulator study demonstrated that the impact of ACC is most pronounced in a variable-speed car-following task, which exploits the 'adaptive' element of the system (since a simpler constant-speed task is more cognitively automatic anyway).

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Chapter 6

What's skill got to do with it?

OVERVIEW

We are making good progress now and, having established that some levels of automated driving reduce workload and attention for experienced drivers, this chapter considers how the development of automaticity within the driving task may influence performance in underload situations. In an extension of Young & Stanton's (2002b) simulator study (presented in Chapter 4), driver skill was manipulated alongside driving automation, each with four levels. Driving performance, mental workload and attentional capacity were measured. The data suggested that driver skill had little effect on subjective mental workload, but a secondary task measure did reveal an interaction between skill and automation, with distinct patterns of attentional demand observed at extreme levels of each variable. As before, though, the most intriguing results were from the attentional capacity data, which showed that – with little exception – capacity and mental workload were directly related at all levels of driver skill, consistent with earlier studies. The results are discussed in the light of research on applied cognition and automation, further fleshing out the theory of malleable attentional resources.

INTRODUCTION

In the last two chapters, we have explored the intimate relationship between automation and mental workload (MWL), via the mediator of attention. So far, we have learned that some levels of automation can reduce MWL, and that there are some curious effects of combining automated systems which may be related to driver skill. Now, then, we are going to add that factor into the mix.

Skill and MWL are already intertwined, as the level of MWL, or attentional demand operators experience, very much depends on their level of skill. As we learned in Chapter 3, skilled processing – or automaticity (e.g., Anderson, 1995; Underwood & Everatt, 1996) – is characterised by being free of attentional resource limitations (Schneider & Shiffrin, 1977; Shiffrin

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& Schneider, 1977). As skill develops on a task, performance becomes more automatic and attentional resources are gradually released for other tasks, with a resulting decrease in MWL (cf. Chi et al., 2019; Gopher & Kimchi, 1989; Liu & Wickens, 1994). Thus, there is an inverse relationship between skill and MWL, as skilled operators experience less MWL than novices (Hancock & Chignell, 1988). At the highest skill levels, when task performance becomes automatic (skill-based), the demand on attentional resources is very low (although not entirely absent; Chi et al., 2019; Huey & Wickens, 1993).

In driving, skill acquisition can occur relatively quickly (Helander, 1978; Verwey, 2000) at lower, operational (i.e., vehicle control) levels of the task (cf. Ranney, 1994; Rasmussen, 1986), which become cognitively automatic for the skilled driver who operates at higher (strategic) levels of the control hierarchy (Stanton & Marsden, 1996). Although skill continues to develop at tactical and strategic levels of control, some researchers (e.g., Groeger & Clegg, 1997; Harms, 1991; Rumar, 1990) maintain that the variability of these tasks means that they might never develop automaticity. Thus, these aspects of driving will always impose higher workload (Huey & Wickens, 1993). But, in another irony of automation (see Chapter 2), it is often the operational, skill-based tasks that are automated first (think of the automated lateral and longitudinal control we have been studying in the last couple of chapters), because they are the tasks that are technologically easier to automate. But this reduces workload where it was already low, while leaving the higher-workload, knowledge-based tasks entirely in the human's hands (Huey & Wickens, 1993).

Since these operational tasks are more amenable to the development of automaticity, it is conceivable that automation may provide an alternative to the skill development process. It has been shown that automation can reduce the skills gap in driving (Shinar et al., 1998; Ward, 2000), allowing novices to exhibit performance more like their expert counterparts. There is thus a parallel between automaticity and automation, since all operators – novices and experts alike – process the task in a fast, attention-free, and unconscious manner when using automation. Bainbridge (1978) makes the point that increasing task demands can basically transform an expert into a novice (cf. Beilock et al., 2002). It is plausible that the reverse could be true in a situation of unusually low demand – a novice using automation is essentially thinking (or rather 'unthinking') like an expert (at least in terms of MWL). Nevertheless, the novice is undoubtedly using different underlying cognitive mechanisms, even at these low-level operational aspects of driving.

Meanwhile, for skilled drivers, there is a potential paradox associated with the underload problem. A highly developed skill essentially looks after a task in the same way as automation. With very little conscious control, an experienced driver may actually be faced with similar conditions of underload as someone with less skill would if using automation. Therefore, performance in an unexpected critical situation – which arguably depends more on rule- and knowledge-based processing – might suffer due to the lack of any controlled processing on the normal task. Over time, this may be exacerbated by the 'catch-22' (cf. Reason, 1990) of skill degradation with automation.

We may therefore ask what the implications are for mental underload with groups of different skill levels – will experts be more prone to underload due to the already low level of MWL in the task, or will novices suffer because they do not have the knowledge base to support the task (cf. Bainbridge, 1978)? Extrapolating from an early study to try and start answering this question, Blaauw (1982) imposed ACC-like conditions on participants by using forced longitudinal control. The performance of inexperienced drivers was found to be more variable in terms of velocity and lateral position than that of experienced drivers. This might suggest that when using ACC, less experienced drivers will be worse at steering control than those with more developed skills. However, this is a tentative prediction as, in their study, all participants had to control speed as well as steering. Relieving drivers of the longitudinal element may have different effects than imposing a fixed speed task.

In another related study, Yanko & Spalek (2013) tested drivers in a simulator with a variable-speed lead-vehicle following task (similar to the one we used in Chapter 5) on familiar and unfamiliar routes. On familiar routes, drivers followed the lead car more closely and also reacted more slowly to pedestrians approaching the road. Yanko & Spalek (2013) argued that the automaticity associated with the familiar route resulted in mind-wandering – but they also floated the possibility that malleable attentional resources theory (MART) might be an explanation, on the basis of the low workload of the familiar route.

Examining the performance of drivers from a range of skill groups with automation allows us to explore the relation between MART and automaticity. These perspectives are not mutually exclusive, as automatic processes are by definition resource-free. Other sources of variation in resource capacity (age, arousal, mood) only affect effortful processes. Automatic performance, not being dependent on resources, is unaffected by such variables (Hasher & Zacks, 1979). It would be interesting to find out if any resource fluctuations due to task demands follow the same pattern.

In the current chapter (which is based on Young & Stanton, 2007c), then, we explore these issues by extending the study presented in Chapter 4 (Young & Stanton, 2002b). That study tested experienced drivers under four levels of automation (manual, adaptive cruise control (ACC), lane centring (LC), and ACC+LC) in the Southampton Driving Simulator (SDS). As a reminder, it was found that MWL (on subjective and secondary task measures) decreased significantly in the LC and ACC+LC conditions, but not with ACC on its own. A similar pattern was observed for our metric of attentional capacity, the attention ratio, in support of MART.

We now compare those data with the performance of drivers at three alternative levels of skill (novice, learner, and advanced) in the SDS to determine the relationships between skill, automation, performance, MWL, and attention. We expect that the general pattern of reduced workload with increased automation (as observed by Young & Stanton, 2002b) will be replicated. However, given the discussion above, and based on the arguments of Bainbridge (1978), this effect may be moderated by skill level. One possibility is that lower skill groups will experience higher MWL when driving manually but, as more levels of automation are introduced, the MWL data will equalise across skill groups. Similarly, we may expect the manual element of driving performance to be worse for the less skilled drivers (cf. Blaauw, 1982), but again that this skills gap may be attenuated as more levels of automation are introduced (cf. Anderson, 1995; Shinar et al., 1998; Ward, 2000). Meanwhile, the secondary task performance data should show a similar interaction pattern, as this is as much a measure of MWL as it is of automaticity (Liu & Wickens, 1994). That is, there should be significant differences in secondary task score at low levels of automation, when skilled drivers have more spare capacity than unskilled participants. At higher levels of automation, skill becomes less of an issue as far as spare capacity is concerned, and differences in secondary task score should be no greater than chance. Subjective MWL, on the other hand, should show a main effect of automation without any interaction, as this responds to task demands but is insensitive to level of skill (Liu & Wickens, 1994). In other words, automation will have a bigger impact on MWL and performance for less skilled drivers, reducing the gap to skilled drivers as more automation is used. These predictions are illustrated in Figure 6.1. Finally, MART (Young & Stanton, 2002a; 2002b) predicts that attentional capacity will diminish when MWL is reduced. What we do not know, however, is how this underload effect will be influenced by skill, and how this interacts with the performance of drivers in the different skill groups at the operational level of driving.

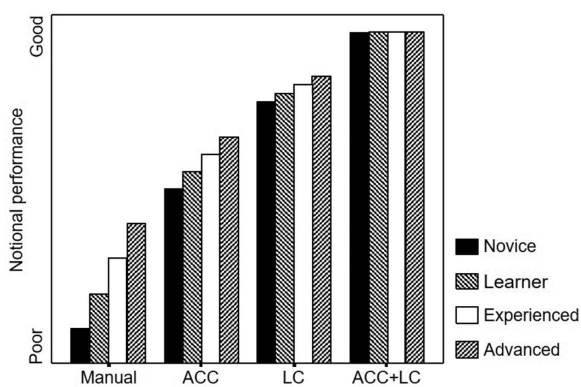


Figure 6.1 Notional representation of performance across skill groups and automation conditions, where a higher value indicates better performance.

METHOD

Design

Essentially, this experiment was an extension of that conducted by Young & Stanton (2002b) presented in Chapter 4, but with the additional between-subjects variable of driver skill. A mixed design was therefore used, comprising the same four levels of automation for the within-subjects independent variable, and driver skill level as the between-subjects factor, again with four levels: novice (never driven before), learner (currently learning but does not hold a full licence), experienced (held a full licence for at least one year), and advanced (having passed a nationally recognised advanced driving qualification in the UK). Learner drivers are assumed to be somewhere between knowledge- and rule-based processing on the automaticity continuum (cf. Chi et al., 2019), with novices operating at a purely knowledge-based level, while the experienced and advanced groups represent automatic processing (though, as we have previously noted and discuss further later, there is something of a paradox with advanced driving techniques in this regard).

Since the experimental tasks were focused at the operational level of driving, and it has been shown that automaticity at this level can develop within one month (Helander, 1978), a novice group was chosen as an absolute baseline for unskilled performance. The advanced group was included as a high-level skill group because these drivers have undertaken further coaching based on police driving skills which, it is claimed, makes them statistically 75% less likely to be involved in a collision than other drivers without such training. There is evidence that this kind of coaching does significantly decrease the collision risk (Hoinville et al., 1972) as well as improving driving skills – even for operational tasks such as steering and headway (Stanton et al., 2007).

As before, the dependent measures were divided into primary task performance (longitudinal and lateral control), driver MWL (as per subjective and secondary task measures), and attentional capacity (the derived attention ratio).

There were 24 novice drivers in this experiment, and 30 participants in each of the learner, experienced and advanced conditions. The sample of experienced drivers in this experiment was the same as that used by Young & Stanton (2002b), and the results for this group in the present chapter are the same as those reported in Chapter 4. Although an attempt was made to balance age and gender across groups as far as possible, participant availability and population demographics made this difficult (e.g., the advanced driver population tends to be skewed towards older males).

Procedure

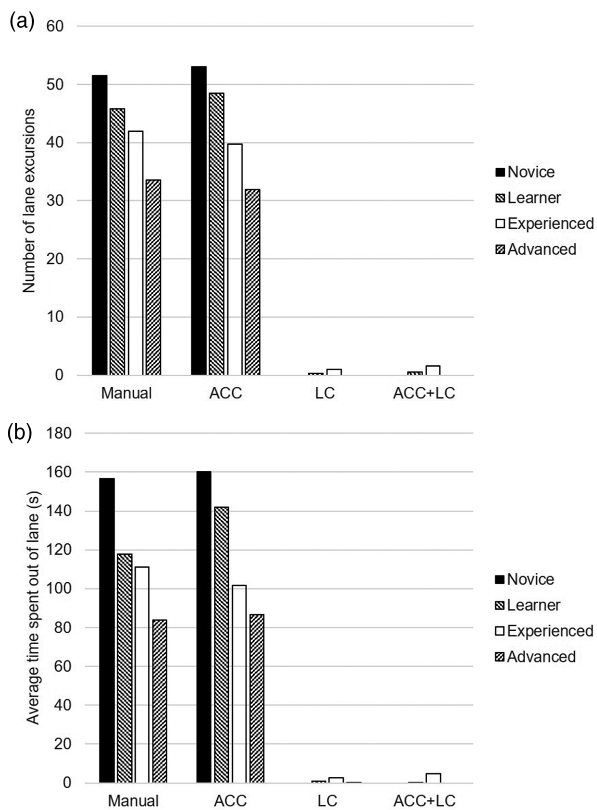
The procedure was the same for all participants, and followed that of Young & Stanton (2002b). Participants were given a minimum 15-minute practice run before full instructions were given and the experimental trials began. The four experimental conditions lasted 10 minutes each, and were presented in a counterbalanced order to preclude practice effects.

As before, the driving task used the ‘follow-that-car’ paradigm, with a lead vehicle travelling at a constant 70 mph (113 km/h). While driving, participants were expected to attend to the secondary task when they felt able to do so.

RESULTS

Driving performance data

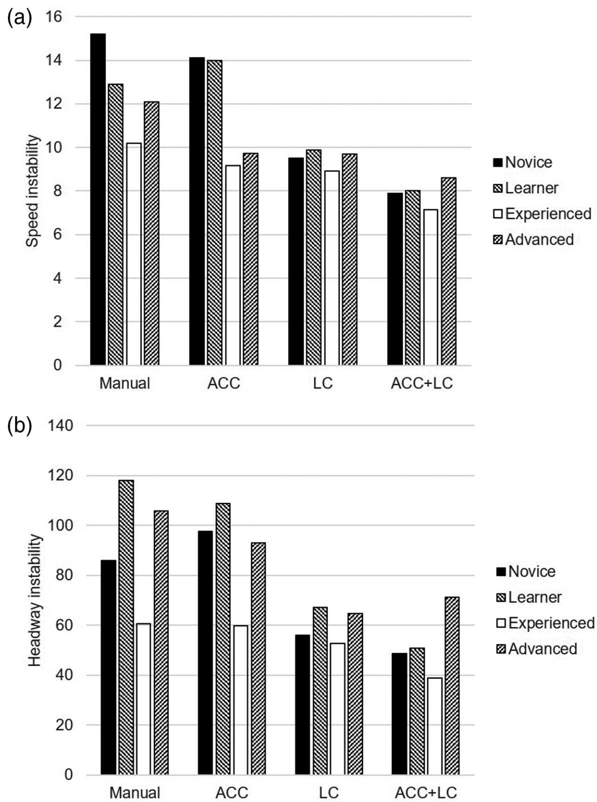
Lateral control was significantly affected by both automation and driver skill, with main effects for number of lane excursions and time spent out of lane. In all skill groups, there was no difference between manual and ACC conditions, but lateral control significantly improved when LC was switched on (see Figures 6.2a and 6.2b). Furthermore, holding a driving licence improved



Figures 6.2a (top) and 6.2b (bottom) Lateral control performance measures across skill groups and automation conditions.

lateral control, as both experienced and advanced drivers maintained better lane position than novices and learners.

Longitudinal control showed a similar pattern of results, as both independent variables affected speed and headway instability. Significant interactions were observed for both these variables as well. Compared to manual driving, speed instability with ACC decreased for advanced drivers only. Speed instability for novice and learner drivers decreased significantly in the LC condition, while a marginal decrease was observed for experienced and advanced participants. Finally, there was a reduction in speed instability for all drivers in the ACC+LC condition. Headway instability was reduced in the LC condition for novices, learners, and advanced drivers, but not for the experienced group – most probably because their headway instability was already low in manual driving. There were no differences between the manual and ACC conditions, while all drivers found their headway instability was lower in the ACC+LC condition. Between-subjects differences generally manifested themselves in lower instability for the experienced group (see Figures 6.3a and 6.3b).



Figures 6.3a (top) and 6.3b (bottom) Longitudinal control performance measures across skill groups and automation conditions.

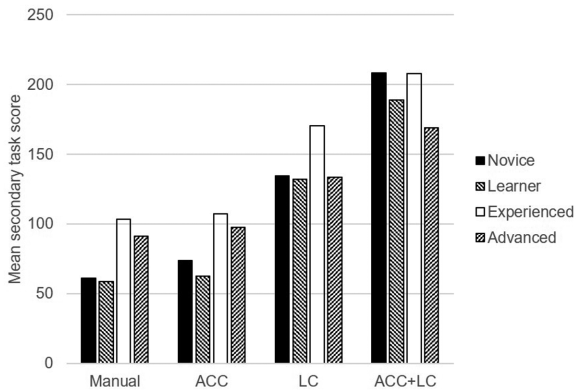


Figure 6.4 Mean number of correct responses on secondary task across skill groups and automation conditions.

Mental workload data

Automation significantly affected secondary task performance. Generally, significantly more correct responses were made (that is, primary task demands were lower) in the LC and ACC+LC conditions (see Figure 6.4). Whilst the effect of skill was only marginal, there was an interaction between skill and automation. The reason for this interaction lay in the comparisons between the manual and ACC conditions. Novice drivers made significantly more responses with ACC than in the manual condition, while the learner, experienced, and advanced groups did not show a difference between these conditions.

On the NASA-TLX, the overall workload (OWL) score differed across the four automation conditions within each skill group, with stepwise reductions in OWL across automation conditions in each of the novice, learner, and advanced groups from manual, to ACC, to LC, to ACC+LC. However, in the experienced group, the difference between manual and ACC conditions was nonsignificant, although there were still significant reductions from ACC to LC, and from LC to ACC+LC. There was also an indication that overall workload in the ACC+LC condition increased with higher skill levels, as the advanced group reported higher subjective MWL than novices. OWL scores are summarised in Figure 6.5.

Attention ratio data

The attention ratio analyses were performed on a subset of participants from each of the driver groups (20 novices, 17 learners, 20 experienced and 15 advanced), as the video data on which the measure is derived were not clear enough for all participants to code reliably (e.g., due to the participant wearing glasses).

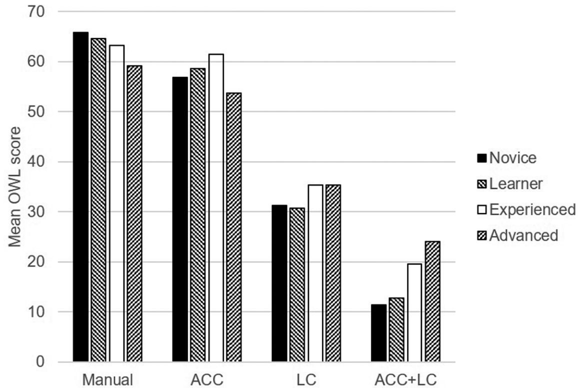


Figure 6.5 Overall workload ratings across skill groups and automation conditions.

A significant main effect of automation was found in each skill group, with no differences between manual and ACC conditions, but all groups showed a significant reduction in attention ratio from ACC to LC. Furthermore, a significant reduction between AS and ACC+AS was observed in the novice, experienced and advanced groups, although this difference was not significant for learner drivers (see Figure 6.6). In other words, these decreases in attention ratio mean that time spent on the secondary task is increasing disproportionately with number of secondary task responses – participants were being slower per response, which is indicative of reduced capacity (Grimes, 1991). Note also that these results are not due to any trade-off between accuracy and speed, since error rates on the secondary task were quite consistent (around 5%) across all conditions.

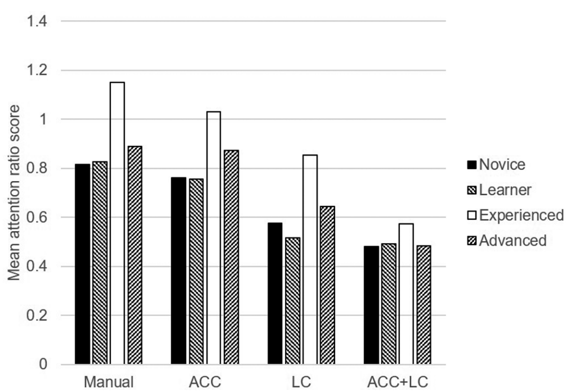


Figure 6.6 Mean attention ratio score across skill groups and automation conditions.

DISCUSSION

Implications: mental workload and performance

The effects of automation on MWL observed in the present study were largely robust across skill groups, and a consistent pattern is emerging in these studies. Apart from novice drivers, ACC seems to have little effect on spare attentional capacity (cf. Nilsson, 1995; Ward et al., 1995; Young & Stanton, 1997; 2002b), while LC and ACC+LC do reduce MWL for all skill levels (cf. de Waard et al., 1999; Young & Stanton, 1997; 2002b). Subjective MWL, on the other hand, was sensitive to ACC for all except the experienced group. Clearly, there is a perceived impact of ACC on the driving task, even if it does not necessarily translate to an objective reduction in MWL; this is consistent with the notion that subjective MWL scores are sensitive to the presence of automation irrespective of automaticity (Liu & Wickens, 1994).

Interestingly, the only difference in subjective workload across skill groups was in the ACC+LC condition, being significantly higher for advanced drivers when compared to novices. There are two ways of interpreting this finding. One is simply a consequence of the advanced training regime, which encourages drivers to maintain a conscious focus on the task at all times. So while the lower skill groups may have been content to trust the automation, perhaps the advanced drivers were less willing to do so. The second explanation is in terms of the automaticity theories outlined earlier. Under normal circumstances, an increase in skill should result in a decrease in perceived workload, providing that the task and goals remain constant. However, the ACC+LC condition is somewhat unusual, in that vehicle control is essentially fully automated. For novice drivers, this situation is as familiar as regular driving. It is, however, a novel scenario for the more experienced driver. Consider Bainbridge's (1978) point that uncertainty increases demand and impairs skilled behaviour. The dramatic change in task situation for advanced drivers could introduce that uncertainty and hence increase subjective levels of demand.

In terms of performance, there was a clear divide between drivers (i.e., experienced and advanced) and non-drivers (i.e., novices and learners), particularly for lateral control. When using automation, the interesting comparisons are between the manual subtasks when part-task automation is used (i.e., manual steering when ACC is used, or longitudinal control when LC is used; unsurprisingly, the automated systems were consistently better than humans in controlling the vehicle). Here, this had an influence on longitudinal control, with a greater improvement in speed maintenance when LC was engaged for novices and learners than for experienced and advanced drivers. It seems, then, that reductions in MWL are associated with improved performance, particularly for non-drivers.

Implications: malleable attentional resources theory and skill

As with the MWL data, a robust and consistent pattern has emerged regarding attentional capacity, in that all skill groups appear to show a reduction in resources in line with changes in MWL. Thus we see that everyone, regardless of skill level, is susceptible to malleable attentional resources in the face of underload.

For automaticity, the results support the significant role of attentional resources in controlled processing, reflecting previous research in driving (e.g., Lansdown, 2002) and other domains (e.g., Beilock et al., 2002). With the clear MWL and performance differences between skill groups, it seems that performance is very much resource-limited for non-drivers, but data-limited for the skilled participants (cf. Norman & Bobrow, 1975). The fact that experienced drivers did not reap any performance benefits of automation is probably due to the resource-free nature of their processing. To a certain extent, these conclusions are also supported by the secondary task data. Novice drivers actually differed in spare capacity between manual and ACC conditions, reflecting their lack of skill in the total driving task. The fact that this difference disappeared in the learner group may be indicative of the speed with which the physical skills of vehicle control are acquired – it has been found that these can develop within one month (Helander, 1978; Verwey, 2000). Thus, it might be said that the learner drivers had developed an intermediate level of automaticity (or rule-based processing, after Rasmussen, 1986), at least as far as longitudinal control was concerned. The higher skill groups had presumably developed their skills such that longitudinal control did not demand a great deal of attention – this component of the driving task had become automatic or skill-based. Clearly, though, the driving task as a whole was not fully automatic even for skilled drivers, or there would be no MWL differences at all between automation conditions. These findings therefore support the view that automaticity is both resource-based and lies on a continuum, as with Rasmussen's (1986) skill-rule-knowledge framework and reflected in the hierarchy of driving skills (operational, tactical, strategic; Ranney, 1994).

Overall, the predictions of this study appear to have been generally upheld, in that non-drivers exhibited inferior performance than more skilled drivers, but the skills gap was attenuated as more levels of automation were introduced (cf. Shinar et al., 1998; Ward, 2000). Contrary to conventional wisdom on underload, then, reductions in MWL were associated with *improvements* in performance for unskilled drivers – despite the fact that all skill groups were susceptible to resource shrinkage in underload conditions. Rather than facing a possible adverse situation of underload with automation, then, drivers with less skill are evidently being overloaded under normal (manual) conditions, and could thus ostensibly benefit from the introduction of automation.

However, consider the nature of the task used here – a highly controlled, *normal* driving scenario. That is, there were no emergency or abnormal events. Task demands were thus stable within each condition, and so by definition did not exceed the shrunken capacity predicted by MART. Earlier research into performance with automation had only found detrimental effects when there is a sudden increase in demand, such as an emergency scenario (Nilsson, 1995; Stanton et al., 1997). Such findings are consistent with MART, since the sudden increase would be beyond the operator's (shrunken) capacity, yet are difficult to resolve with fixed-capacity models (when full resources should always be available). A replication of the present study incorporating an emergency event would allow a direct test of MART's predictions for performance within the current design. Moreover, such a design would also elucidate the qualitative difference between novices using automation and experts using automaticity, since the former would not be expected to have the knowledge base to support such performance. Of course, all of this assumes that the reductions in MWL evinced in the present study do actually represent underload (as opposed to just reduced MWL). We may be cautious about the conclusions in this regard until a study involving an emergency scenario reveals otherwise (spoiler alert: we present such a study in Chapter 7). Nonetheless, the potential for such a study to elucidate the level of shrinkage which impairs performance – that is, the underload 'redline' – is immensely valuable.

One final note here on the perplexing anomaly in secondary task scores for advanced drivers as alluded to earlier – that they were more akin to those for non-drivers than experienced. Although the advanced group was assumed to be more highly skilled than the experienced drivers, there is a certain irony in the training techniques for advanced drivers. Advanced driving techniques attempt to maintain conscious awareness of the driving task at all levels. Whilst this helps to maintain a high level of performance and situation awareness (Stanton et al., 2007), it is paradoxical in that such controlled processing does not by definition equate with expert performance. In essence, then, such a level of skill brings cognitive processing full circle, and it is therefore possible to explain why the results of less skilled drivers should be similar to the advanced group (this might also account for their primary task performance data being apparently worse than experienced drivers). Rather than relying on open-loop, anticipatory control, advanced drivers deliberately force themselves to be aware of environmental feedback (cf. Bainbridge, 1978). In doing so, the benefits of controlled processing (i.e., adaptable in novel situations) are combined with the extended knowledge base of the skilled driver – with a concomitant reduction in collisions and 'actions not as planned' (Reason, 1979). With such resource-demanding processing, a decrease in objective demand through automation should improve performance. Whether or not this higher MWL is a cost (in terms of overload) or a benefit (in terms of underload) remains to be seen.

CONCLUSIONS

The data presented in this chapter (Young & Stanton, 2007c) are consistent with the idea that automation and automaticity can overlap, as unskilled drivers effectively behaved in an automatic manner when automation was used. There are a number of implications arising from these results. It seems that increasing levels of automation does indeed attenuate observable differences in performance between skill groups, as suggested earlier (cf. Shinar et al., 1998; Ward, 2000). That is, the performance of inexperienced drivers on speed control benefits more from lateral control being automated, bringing them in line with their more experienced counterparts.

On the face of it, this is a promising finding – everybody will apparently drive better with more automation. But, as we have discussed in earlier chapters, we would not necessarily expect performance differences if the situation with the automation is nominal, even with reduced MWL, because the reduced demand is within the reduced capacity of the operator. But we have also predicted that, if workload should suddenly increase, then performance problems are likely – so what happens when the driver has to take over from the automation? Presumably the automatic behaviour of experts will quickly resume, save for any skill degradation (Stanton & Marsden, 1996). Those with less experience, though, may have more trouble recalling stored routines and responding in a controlled manner. The next study in this series explores this very question.

KEY POINTS

- Skill and mental workload are intertwined, as expert performance (automaticity in cognitive processing terms) is characterised by being largely free of attentional resource limitations, thus reducing workload.
- The driver's level of automaticity has the potential to interact with level of automation, as the workload experienced by an expert is already low, while a novice does not have the background knowledge base to support the task.
- Data from a simulator study showed that automation can to some extent attenuate performance differences between driver skill levels, lending weight to the suggestion that automation can have a parallel (but qualitatively different) impact to automaticity.
- The study also confirmed that adaptive cruise control and lane centring systems had similar effects on driver mental workload and attentional resources across all skill levels, from novice to advanced.

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Chapter 7

I thought you were driving!

OVERVIEW

Having covered a lot of ground, it is nearly time for another rest stop on our journey. The final chapter for this stage presents the culmination of our series of experiments developing malleable attentional resources theory (MART). Building on the work so far, which has shown that attentional capacity shrinks in line with reductions in mental workload, we now examine the consequences of such shrinkage for performance by testing responses to an automation failure event. Research on reaction times to failures of different levels of automation is reviewed before going on to describe a study comparing learners and experienced drivers in the Southampton Driving Simulator. Participants faced a failure of driving automation in two different workload conditions. Reaction times to the automation failure were increased when compared with analogous responses in manual driving from other research. Moreover, when participants had already been through an automation failure (and could therefore reasonably expect another failure), learner drivers were worse at recovering control than experienced drivers. Although the conclusions for MART were tempered by evidence of vigilance and physiological arousal playing a part, on the whole there was support for the notion that all drivers would experience resource shrinkage, but the automaticity of experienced drivers confers some immunity to the effects of such shrinkage.

INTRODUCTION

In the last few chapters, we have revisited a series of papers that built a case for an explanatory theory of the effects of mental underload on performance. Malleable attentional resources theory (MART) offers a solution by drawing on existing capacity theories of attention (Kahneman, 1973; Wickens, 1984; 2002). MART challenges conventional assumptions by stating that resource size is not fixed, and can actually shrink with reductions in mental workload (MWL). In underload situations, it is hypothesised that resources shrink to such an extent that performance levels in otherwise normal situations are no

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longer within the capacity of the operator. Young & Stanton (2002a, 2002b) established theoretical and empirical evidence for MART, while Young & Stanton (2007c) developed the theory by relating it to issues of skill and automaticity.

Young & Stanton (2002b) tested participants in a driving simulator under different levels of driving automation to provide support for MART. Although they found that reductions in MWL associated with automation were also reflected in a shrinkage of attentional resources, this did not translate into a detrimental effect on normal driving performance. Young & Stanton (2002b) concluded that this was because participants had adapted well to the reduced demands, matching resource capacity to objective demands. However, as we described in Chapter 3, the 'problem' with underload is manifest in workload transitions (Huey & Wickens, 1993; Young et al., 2015) – that is, sudden increases in demand that are above the shrunken capacity limit. Whilst automation can actually improve performance in routine tasks, people struggle to recover if something unexpected happens (Onnasch et al., 2014). MART assumes that underload has caused attentional resources to shrink below a level at which coping is ordinarily possible (refer back to Figure 3.5 for an illustration).

In the context of automated driving, these sudden workload transitions can occur when manual takeover of control is required. We might consider these situations as 'failures' of automation, but it is worth reminding ourselves that they may not be technical failures at all; even the latest technology cannot deal with all unforeseen events, so it could just be a non-routine scenario that the automation has not been programmed to deal with (Endsley, 1987). And on the road, when the driver is required to step in, they have very little time to do so (Hancock, 2019; 2021); at highway speeds, the car will travel a great distance even in a few seconds. The fact that automation is becoming ever more reliable only exacerbates the problem – 'failures' might be rare but they will eventually happen, leaving the driver facing 'hours of boredom followed by moments of terror', with very little to do until things go very wrong, very quickly (Hancock, 2019; 2021).

Numerous studies have demonstrated that, in these critical situations, drivers exhibit worse responses with automation and are unable to reclaim control in a safe and timely manner (see e.g., de Winter et al., 2014, and Victor et al., 2018 for reviews). To set the context for the study we present in this chapter, we now go on to review such research addressing two broad questions: whether (and how) drivers respond at all to critical events, and what effect the automation has on their reaction times to such events.

Responses to automation failure

Several studies have used driving simulators to explore the effects of automation failure on driver performance. These have consistently demonstrated performance in the automated conditions to be inferior to that in manual control, as well as being generally associated with reductions in MWL.

One of the first such studies (Nilsson, 1995) compared critical situations between drivers using adaptive cruise control (ACC) and those driving manually, and found dramatically worse performance in the ACC condition. Of those who crashed (in a scenario when the car approached a stationary queue), participants were four times more likely to have been using ACC than driving manually. Later, Desmond et al. (1998) also compared failures of automation to a manual control condition. Participants drove a simulated vehicle under manual and level 2 automated (i.e., lateral and longitudinal) control. Lateral failure in the automation condition was balanced with simulated wind gusts to affect vehicle dynamics in the manual condition. Once again, recovery from these situations was better in the manual condition. The authors concluded that this was due to a misperception of task demands leading to an inappropriately low investment of effort in the automated case, although there were no differences in subjective MWL between the conditions.

Like Nilsson (1995), others have found startling proportions of drivers failing to respond effectively in automation failure scenarios. Stanton et al. (1997) used the Southampton Driving Simulator (SDS) to explore the effects of ACC failure on driver performance. Participants were required to follow a lead vehicle with ACC engaged. At a predetermined point, the ACC system would fail to detect the lead vehicle braking, necessitating participant intervention to avoid a collision. It was found that one-third of all participants collided with the lead vehicle when ACC failed. In addition, the use of a secondary task demonstrated that under normal circumstances, workload is significantly reduced when ACC is engaged. Similarly, another simulator study of an emergency situation involving level 2 driving automation found that only half of the drivers reclaimed control effectively (de Waard et al., 1999), with the remainder facing a distance headway as low as 10 centimetres. The authors even claimed that this was an optimistic estimate, with demand characteristics in the simulated environment essentially getting the best performance out of their participants.

More recently, in an on-road study of drivers' responses to a system takeover warning, Banks & Stanton (2016) found that nearly one-quarter of drivers did not regain complete control of the vehicle. In a series of related papers, Ljung Aust (2020) and colleagues (Tivesten et al., 2019; Victor et al., 2018) reported on a test track study in which drivers used a perfectly reliable automated driving system for 30 minutes before facing a critical event that required manual intervention. Despite drivers' visual attention largely being on the road ahead, nearly one-third still crashed in the critical event. Victor et al. (2018) pointed out that just because drivers were looking at the road, this is not the same as being in the loop – it requires recognition and a decision to act. Whilst the results were attributed to drivers' expectations of and trust in the system (Ljung Aust, 2020), there was no 'first failure' effect in that experiencing one crash did not necessarily mitigate subsequent conflicts (Victor et al., 2018), contrary to results elsewhere (Seppelt & Lee, 2007, found that drivers relied less on ACC after a failure). In fact, drivers' glance behaviour was a stronger predictor of whether they crashed than their reported trust (Tivesten et al., 2019).

There are exceptions to the rule. One is in a study by Eriksson et al. (2018), who devised a driving simulator study to test participants' responses to a steering deviation while the driver was distracted with a secondary task. The 'jerk' response in trying to recover control was ostensibly worse under manual, distracted driving than in the parallel situation of recovering control from failure of a lane centring (LC) system. Similarly, Gold et al. (2018) reported evidence of improved performance in a takeover situation from level 3 automation when carrying out a non-driving secondary task, which they suggested may be a demonstration of MART since the additional workload activated attentional resources.

Reaction times to automation failure

A number of studies have examined brake reaction times to a lead vehicle decelerating when driving manually. In these studies, one of the main factors that can affect reaction time is whether the driver is aware of, or expecting, the hazard; responses are generally slower where the driver is not expecting the hazard (Schweitzer et al., 1995; Sohn & Stepleman, 1998; van der Hulst et al., 1999; Warshawsky-Livne & Shinar, 2002). Reaction times are also longer if the lead vehicle decelerates more slowly, or with increased headway between the two vehicles. Table 7.1 summarises the data on reaction times found in these studies (note that the longer reaction times in the study by van der Hulst et al., 1999, were apparently due to the relatively slow rate of deceleration used compared to other research).

When adding automation into the mix, various studies have found increased brake reaction times in critical situations when using ACC (e.g., Hogema & Janssen, 1996; Hogema et al., 1997) as well as with conventional cruise control (Vollrath et al., 2011). A test track study by Rudin-Brown & Parker (2004) looked at reactions to critical events when using an ACC system. These critical events included responding to the lead vehicle braking and, towards the end of one condition, a failure of the ACC system in which it would lose detection of the lead vehicle and gradually accelerate to its set speed. If drivers did not intervene, this would result in a collision at least 33 seconds later, depending on the exact speed of the vehicles. Rudin-Brown & Parker (2004)

Table 7.1 Summary of brake reaction times (in seconds) from the studies reviewed

	Aware	*Partially aware*	*Unaware*
Warshawsky-Livne & Shinar (2002)	0.540	0.565	0.590
Schweitzer et al. (1995)	0.550	0.632	0.739
Sohn & Stepleman (1998)	1.290		1.360
van der Hulst et al. (1999)	4.200		6.300

found that whilst ACC reduced workload (as measured by a secondary task), it increased the reaction times to a lead vehicle braking, particularly when the ACC was set with a longer headway (2.4 seconds time headway compared to 1.4 seconds). Average reaction times were 2 seconds for manual driving, 2.6 seconds for the short headway ACC, and 2.8 seconds for long headway ACC. There were also around one-third fewer safe braking events (defined as braking within 2 seconds) with ACC than when driving manually. In short, drivers braked later, harder and more often than was necessary. Moreover, when faced with the ACC failure, drivers took an average of 23 seconds to respond. Interestingly, drivers waited until the average headway was 0.6 seconds before intervening, a value similar to the kinds of headways that a substantial minority of drivers adopt in other research (Taieb-Maimon & Shinar, 2001) and of the same order as the lower end of brake reaction times summarised in Table 7.1. So this kind of headway might seem to be a minimum threshold that drivers use to decide whether to brake manually. Rudin-Brown & Parker (2004) also found that ACC resulted in more lane position variability, concluding – with some echoes of MART – that the reduction in workload led to the decrements in performance and reaction time, as the spare attentional capacity was diverted to other, non-driving, tasks.

Going beyond ACC, other research in highly automated vehicles has also demonstrated delayed responses to emergency situations that are outside the system's operational design domain (Navarro et al., 2018). Considering the case of manual takeover from automation (emergency or otherwise), a review by Eriksson & Stanton (2017b) found a range of reaction times between 1 and 15 seconds, with most studies agreeing on somewhere around 3 seconds. These reaction times may be affected by factors such as traffic, speed, or the presence of a secondary task – if drivers are engaging in something other than driving (which drivers using automation are wont to do), we might expect reaction times closer to 15 seconds than to 1 second (more on distractions from secondary tasks in the next chapter). Furthermore, the quality of the takeover response (in terms of lateral deviation) may also be worse when drivers are distracted, even if reaction time is not (Zeeb et al., 2016).

Eriksson & Stanton (2017b) also conducted a simulator study of their own on planned transitions from automated to manual control, with drivers taking between 2 and 26 seconds depending on task engagement. Reaction times to warnings can also be slower when both longitudinal and lateral control are automated (Seppelt & Victor, 2016). A similar study by Merat et al. (2014) examined driver behaviour when resuming control from a highly automated vehicle, where these transitions were designed into the system (either at regular time intervals or if the driver looked away from the road). Although performance was better if the transition was predictable (i.e., time-based), drivers did not begin to resume control until at least 10 seconds after the system disengaged, while both their steering performance and visual attention took up to 40 seconds to stabilise. Performance was also worse when workload was higher. There are echoes of this in the study by Zeeb et al. (2016), who observed that drivers' motor response (i.e., placing their hands back on the steering wheel) was relatively unaffected, but their 'cognitive readiness' was susceptible to distraction and adversely affected their performance in the immediate aftermath of the takeover.

The experiment

Following similar research elsewhere, then, this final study in the MART series (see also Young & Stanton, 2001b) centred on the performance of underloaded participants in response to an automation failure event. As with the Rudin-Brown & Parker (2004) test track study, the ACC system in our simulator was programmed to lose the target it was following and resume its set speed, accelerating towards the car in front. Participants had to respond by braking or steering if they were to avoid a crash.

Furthermore, as we reviewed in Chapter 6, the interaction of skill with MWL and automation has been relatively neglected in the applied literature. Automation has been demonstrated to reduce the performance gap between those of differing skill levels (Badham, 1992; Shinar et al., 1998; Ward, 2000). Whilst this may be true under normal circumstances, the reactions of different skill groups when faced with automation failure are less well researched. One study in an aviation context (Mohrmann et al., 2015) suggested that inexperienced pilots were overconfident with a highly reliable automated subsystem, which adversely affected their reactions when the system failed. More specifically, Larsson et al. (2014) demonstrated that reactions to a critical situation using either level 1 (ACC) or level 2 (ACC+LC) automation were around 2 seconds slower than the same scenario while driving manually – but those experienced with using ACC were about half a second faster than novices. They put this down to knowledge of the system's limitations (i.e., braking hard in response to a vehicle cutting in front) rather than anything to do with response to the hazard. This echoed earlier research that showed drivers' reactions to ACC failure depended on the context, with more (over)reliance in a traffic situation that exceeded the ACC's braking limits than in rain that had degraded the ACC's sensors (see Seppelt & Lee, 2007). Moreover, drivers continued to rely less on the ACC after a failure. So, to some extent, drivers' responses to ACC failure may depend on their appreciation of its limitations (cf. Pampel et al., 2020).

Nevertheless, in terms of the workload effects between different skill groups, we have little evidence to go on. On the one hand, the enhanced knowledge base of experienced drivers may facilitate their responses; on the other, the sudden increase in demand might cause them to revert to a novice strategy (cf. Bainbridge, 1978; Beilock et al., 2002). The research in our laboratory found that automation had similar effects on attentional capacity regardless of skill level (Young & Stanton, 2007c), suggesting that automaticity does not prevent the resource shrinkage associated with underload. By examining the performance of drivers and non-drivers in critical automation failure scenarios, we may further elucidate the effects of underload on performance.

The study in this chapter was therefore designed to investigate whether different levels of automation or driver skill would affect reactions in recovering control of the vehicle in an automation failure scenario. The combination of MART with the theory of automaticity when using automation suggests that responses to failure would vary according to levels of skill and MWL. MART would predict decreased MWL accompanied by impaired responses to automation failure under high levels of automation, when compared to low automation conditions. There should also be a main effect of skill, such that experienced driver performance is generally better than the less skilled drivers. Furthermore, the influence of automaticity is predicted to interact with level of automation. Unskilled drivers should suffer greater performance degradation than their skilled counterparts when responding to failures in the high automation condition. The main predictions are illustrated in Figure 7.1.

There is, however, an elephant in the car that we have not properly addressed so far. The essence of MART hinges on the direct relation between mental demands and attentional capacity. It predicts that, in addition to being affected by contextual factors such as physiological arousal, age, or mood (Hasher & Zacks, 1979), the size of resource pools can alter purely because of task intrinsic factors which reduce MWL. One problem with this explanation is that it is difficult to separate the effects of task demands from arousal – the two tend to be associated. Research has related decreases in arousal (as measured by heart rate) to subjective states of underload and boredom (Braby et al., 1993) as well as automation (de Winter et al., 2014). Meanwhile, arousal has been linked to the deployment of attentional resources, such that there is a positive relation between arousal and attentional capacity (Hasher & Zacks, 1979; Humphreys & Revelle, 1984; Necka, 1996). In the original formulation of a capacity theory of attention, Kahneman (1973) put these two aspects together, suggesting that task demands affect arousal, and that arousal in

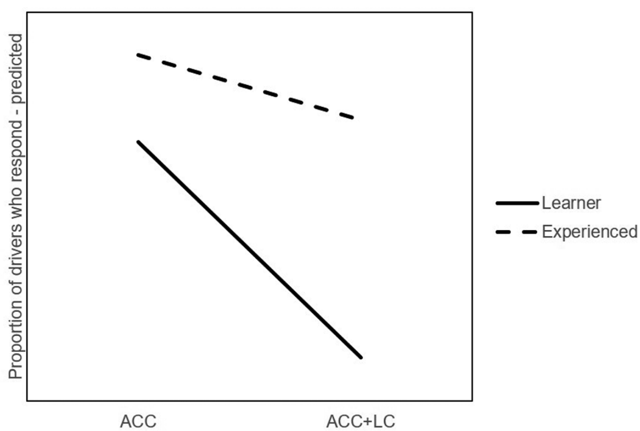

Figure 7.1 Predicted levels of response to automation failure across skill groups and automation conditions.

turn is positively correlated with capacity, particularly at low arousal levels (although the concept of flexible capacity proved difficult to test; Huey & Wickens, 1993). Finally, we have also known for a very long time that arousal and performance are related on the classic inverted-U curve (Yerkes & Dodson, 1908). Moreover, for simple tasks at low levels of MWL, the optimal arousal 'peak' of the inverted-U curve is higher than for a complex task (i.e., higher arousal is needed for optimal performance of a low MWL task); this has been linked to the mobilisation of attentional resources and a momentary shrinking of capacity similar to the effect of fatigue (Lee et al., 2020).

The detrimental effects of underload on performance may not, therefore, be a direct consequence of the mental demands. Instead, it could simply be the case that the arousal level of the operator has dropped, adversely affecting attention. As well as testing MART in an automation failure scenario, then, the present study attempts to dissociate physiological arousal from MWL to provide support for MART.

METHOD

Design

In a lot of previous research, the contrast has largely been drawn between manual and ACC-supported driving (see also de Winter et al., 2014). The problem with this approach, when investigating the effects of automation failure, is establishing equivalence between the two conditions – for instance, comparing an ACC failure with an analogous emergency situation in manual driving. Moreover, the main point of the present study is to try and isolate MWL (specifically, underload) as the key factor affecting performance in an automation failure scenario.

Therefore, we did not need to test all four levels of automation as in our previous studies, but we only needed two conditions which *differed* in their level of MWL. Comparing ACC against ACC+LC met this requirement, since we had already established that the MWL associated with using ACC+LC is significantly lower than with ACC (Young & Stanton, 2002b; see Chapter 4). As both conditions use ACC, we could then present the critical automation failure with the ACC system each time, meeting the equivalence requirement that we sought. As the point of the experiment was to try to prove that reduced MWL is the factor which affects performance, a control condition of manual driving was not necessary. This has the added advantage of mitigating against any automation-specific explanations for performance effects, such as situation awareness or out-of-the-loop performance (cf. Endsley & Kiris, 1995; Kaber & Endsley, 2004). Some research has shown that reactions to critical events with such highly automated driving are worse than with ACC (de Winter et al., 2014).

Furthermore, by presenting the automation failure twice (once in each condition), the possibility of different levels of anticipation (Huey & Wickens, 1993), effort or voluntary allocation of attention can be assessed (cf. Desmond et al., 1998; Kahneman, 1973), comparable with previous studies on driver awareness of an impending critical event (e.g., Dingus et al., 1998; Schweitzer et al., 1995; Sohn & Stepleman, 1998; van der Hulst et al., 1999; Warshawsky-Livne & Shinar, 2002). Presumably, participants who were once naïve to the possibility of automation failure may then invest more effort in monitoring or recovering from a failure if they thought it could happen again, and we may see performance improve on the second trial. If, instead, responses to failures do not differ from first to second presentation, then this may point to an inability (rather than an unwillingness) to respond, in line with MART.

The automation failure occurred 51 seconds from the end of the run, and involved ACC disengaging without warning at the same time as the lead car braking. Participants had to intervene if a collision was to be avoided. If no action was taken, collision with the lead vehicle occurred approximately 4 seconds after the failure. Minimal feedback was given about the failure, except for the 'CC' icon on the screen extinguishing, and a very slight change in engine note.

Two groups of driver skill were compared as a between-subjects factor: learner (i.e., currently learning but does not hold a full licence), and experienced (holds a full UK driving licence). These groups were selected on the basis of previous research in the SDS (Young & Stanton, 2007c; see Chapter 6), which suggested a clear performance divide between skilled drivers (i.e., those with a full UK driving licence) and non-drivers (those without a licence), particularly for longitudinal control (Blaauw, 1982, found similar results in non-automated driving). There were 20 learners and 24 experienced drivers who took part in this study.

In keeping with the experimental design used previously, the simulated road was a mixture of straight and curved sections. Other research in our laboratory (Young & Stanton, 2004; see Chapter 5) provided the choice of experimental task. Mental workload differences with ACC were found to be most sensitive when following a variable speed lead vehicle, rather than one at constant speed. Thus in adopting the design of Young & Stanton (2004), participants were required to follow a lead vehicle which was programmed to travel at a maximum 70 mph (113 km/h), but at pseudo-random intervals would brake to around 30 mph (48 km/h) before accelerating back up to 70 mph. This task also provided face validity for the failure event. It is feasible that in certain situations, ACC may not detect the braking of a lead vehicle, therefore this is a realistic failure scenario to use. Time headway of the ACC system was set at approximately 1.75 s.

Given the criticality of inducing an underload state for this experiment, we decided not to use a secondary task as there is evidence that it can affect both subjective workload ratings (Liu, 1996; Meshkati et al., 1990; Nees & Sampsell, 2021) and driving performance (Brouwer et al., 1991; Foy & Chapman, 2018; Verwey & Veltman, 1996). The intrusiveness of a secondary task on performance can be especially pronounced at low workload levels (Rudin-Brown & Parker, 2004; Wierwille & Gutmann, 1978), even in spite of instructions emphasising that priority should be given to the primary task (Kantowitz, 2000). In a separate study in the SDS (Young & Stanton, 2007b), we also found that our secondary task interfered with steering performance as well as inflating scores on the NASA-TLX. Whilst the effect on steering may simply have represented manual response competition, since the secondary task buttons were on the steering column, this is still a concern for a study which is attempting to determine the 'pure' effects of underload on performance.

If the performance of a secondary task contributes to mental workload, it may not be possible to induce an underload state, regardless of the primary task demands (Liu, 2003, found that a mobile phone task actually improved driving performance in otherwise low workload situations). In that case, we might not be able to attribute differences in performance with automation (if any) to mental underload. Once we discovered that the secondary task can inflate overall workload, we decided it was probably sensible not to use it in experiments investigating the effects of underload on performance. Moreover, in Chapter 4 we also concluded that the secondary task may have been serving to draw attention away from the driving task, let alone interfering with workload. In that case, the underload explanation for any performance effects in recovering control would be confounded.

Therefore, we took the decision not to use the secondary task in this automation failure experiment. A small pilot study was used to test subjective MWL with the proposed experimental design – a variable-speed lead vehicle but with no secondary task – though without the automation failure as this may have influenced the subjective responses. This pilot study confirmed that subjective MWL on the NASA-TLX still significantly reduced from ACC to ACC+LC in both skill groups, and the data compared well to those gathered by Young & Stanton (2002b). We could therefore be confident that there was still a significant MWL reduction in the ACC+LC condition compared to driving with ACC only.

In terms of dependent variables, reaction times to the failure event and/or time until the collision occurred were recorded. Whether or not the participant reacted and/or collided at all were also dependent variables. All of these data were analysed within each trial (i.e., failure-naïve vs. failure-primed – analogous to the 'unaware' and 'partially aware' conditions used in the other studies of brake reaction times reviewed earlier) to determine whether experience of a previous failure event affects behaviour in subsequent trials (see Young & Stanton, 2007a, for a more detailed analysis of this part of the study).

For all participants who reacted to the failure, three reaction time variables were calculated: brake reaction time (BRT), foot movement time (MT), and total braking time (TBT). The simulator recorded data on TBT (i.e., time from onset of the automation failure to first pressure on the brake pedal), and an infra-red camera in the footwell was used to record MT (i.e., time to move the foot from its resting position to the brake pedal – note that the foot was resting on the floor since ACC made pedal inputs redundant). BRT was then calculated by subtracting MT from TBT (cf. Liebermann et al., 1995).

Therefore, BRT is the participants' thinking time (i.e., time from the failure event to first reaction), while TBT is the time required to process information from the environment as well as implement the appropriate response.

To address the question of whether attention shrinks purely in response to MWL (as MART predicts) or via the moderator of physiological arousal, an appropriate measure of arousal was needed. A simple and reliable measure of arousal is heart rate (Humphreys & Revelle, 1984; Roscoe, 1992), measured in beats per minute (bpm). Whilst it is true that heart rate (HR) has been used to measure MWL (and, indeed, has tentatively been linked with reduced MWL of automated driving; de Winter et al., 2014), it has a much longer association with physiological arousal (Humphreys & Revelle, 1984; Jorna, 1992; Roscoe, 1992). Derivative measures, such as heart rate variability, are better indicators of MWL (Jorna, 1992); the simpler HR measure was used here purely to gauge arousal rather than MWL. Heart rate was recorded using a nonintrusive sports monitor with a chest belt sensor. For the purposes of analysis, the HR data were divided into six time blocks, which included a block for baseline data, and five two-minute blocks during the experimental trial; average HR was used as the dependent variable within each of these blocks.

Procedure

Participants were given a 5-minute practice run in the simulator, to allow them time to acclimatise to the controls. Following the practice run, the two automation conditions were explained to participants and operation of the automation controls was demonstrated. Participants then put on the chest belt for the heart rate monitor, which started recording before each condition to allow for baseline data to be collected.

The two experimental conditions, each of 10 minutes duration, were then presented to the participant in a randomised and counterbalanced order. In the experimental trials, participants were required to follow a lead vehicle travelling at a maximum speed of 70 mph (113 km/h). Participants were told that the lead vehicle would brake periodically, and they were instructed to stay behind it, relying on the ACC system to maintain headway as much as possible. However, participants were also informed that if they felt the need to intervene, they should do so, treating the drive as much like a real situation as possible.

Prior to the first condition, participants were given no specific instructions with regard to automation failure. They were simply told to treat it as much as possible like a real road situation, and to behave accordingly. However, after the failure in the first trial, participants were informed before the second trial that the automation was not perfect (as had been observed in the first run) and, should it fail again, they were to take over manual control as quickly and effectively as possible. This was to test whether participants who were motivated to invest effort in monitoring for a failure were more effective than those who were naïve (cf. Desmond et al., 1998; Matthews & Desmond, 2002).

RESULTS

Reaction frequencies

One of the key dependent variables was whether or not participants reacted at all to the failure event. In the learner driver group, 12 participants out of 20 responded to the failure event in the ACC condition, while only 7 out of 20 did so in the ACC+LC drive. Neither of these figures was significantly different to chance responding.

Experienced drivers, on the other hand, performed slightly better. Of the 24 experienced participants, 15 attempted to regain control in the ACC condition, and 18 reacted when using ACC+LC. The latter statistic was significantly more than would have been expected due to chance. These response frequencies are illustrated in Figure 7.2.

In the light of this unexpected result, we decided to examine the data more closely. Some of the studies reviewed earlier distinguished between ‘aware’ and ‘unaware’ participants when it came to reactions to a critical event. So we explored the possibility of a learning effect from trial 1 to trial 2, comparing reactions across the two trials, collapsing the automation variable. In trial 1, only five learner participants reacted, which was significantly less than expected due to chance. This effect disappeared in trial 2, although the trend reversed with 14 participants making an effort. For experienced drivers, the 11 who responded in trial 1 was no different to a chance result. On the second trial though, a significantly high number of 22 attempted a recovery.

Given that there is apparently a strong learning effect in each group, examinations of the automation effect were repeated, this time within each trial. In trial 1, when participants were expected to be naïve, there were no significant effects of automation in either skill group. However, by the second trial, all 12

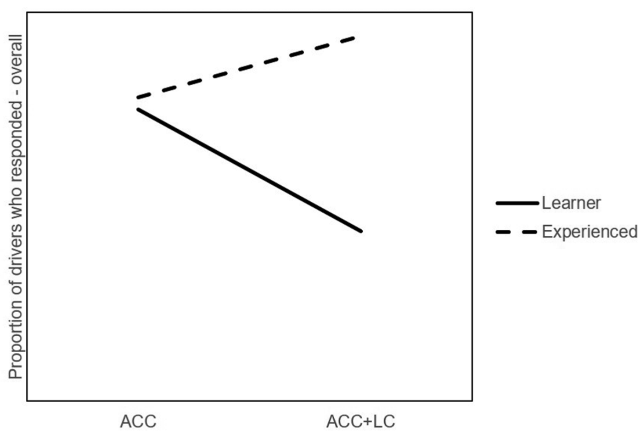

Figure 7.2 Proportion of drivers who responded overall, across skill groups and automation conditions.

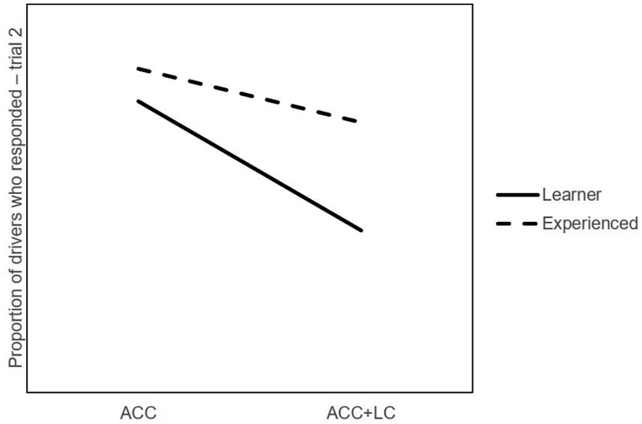

Figure 7.3 Number of drivers who responded in trial 2 (failure-primed), across skill groups and automation conditions.

experienced drivers who used ACC reacted to the failure, and 10 of the 12 in the ACC+LC condition responded – significantly higher than a chance level of responding. The effect of automation for learners was especially pronounced, with nine out of the 10 learners using ACC attempting to respond (significantly greater than chance), while exactly half responded in the ACC+LC condition (see Figure 7.3).

Figure 7.3 is quite an accurate reflection of the predictions for this study. The performance of experienced drivers is virtually at ceiling, with responses in both automation conditions being significantly higher than those which would be expected due to chance. However, the pattern for learner drivers is most supportive of MART. When naïve, all participants have a roughly equal chance of responding to automation failure. If a failure has already been presented, though, the responses of learner drivers only improve if task demands are high. In other words, mental underload has had a detrimental effect on the responses of unskilled participants. This result epitomises MART while incorporating the factor of automaticity with automation. When combined with the data collected by Young & Stanton (2007c), it is apparent that the low mental workload of the ACC+LC condition has shrunk the attentional capacity of all drivers. However, only learners suffer a consequent performance decrement, probably due to the automatic nature of processing for experienced drivers.

Reaction time data

Not all participants reacted to the automation failure; for those participants who actually did react, there was no effect of automation on brake reaction time in either skill group. Again, a further analysis by trial was carried out in order to determine if there were any learning effects from trial 1 to trial 2.

Table 7.2 Means for brake reaction time (BRT) in seconds across skill groups and automation conditions.

	Learner			*Experienced*		
	BRT_1	BRT_2	$BRT_{overall}$	BRT_1	BRT_2	$BRT_{overall}$
ACC	2.99	2.16	2.37	2.33	2.08	2.13
ACC+LC	2.41	2.37	2.38	2.90	2.14	2.48
Overall	2.76	2.24		2.74	2.10	

Suffixes refer to experimental trial 1 or 2, or the overall statistics

In the learner driver group, differences in brake reaction time between trials were nonsignificant. Experienced drivers, however, were quicker to react in trial 2. On average, experienced participants took 2.7 seconds to react in trial 1 compared to 2.14 seconds in trial 2. This suggests a significant learning effect between trials for experienced drivers; however, this occurred irrespective of automation level, and therefore does not have a bearing on the hypotheses of this study. Descriptive data are summarised across all conditions in Table 7.2.

Physiological arousal

In order to determine what role (if any) physiological arousal played in these findings, the HR data were analysed across level of automation (two levels) and time block (six levels), referencing against the baseline HR recorded before the trial began. No between-subjects comparisons were made, as individual differences in HR responses are too large to make statistical comparisons sensible (Roscoe, 1992). Separate analyses were therefore carried out for each skill group.

For learner drivers, HR in the ACC condition was not significantly different from baseline HR, whereas in the ACC+LC condition every sector registered a significantly lower HR compared to the baseline. Mean heart rate in each sector across conditions is plotted in Figure 7.4.

Meanwhile, the analysis for experienced drivers only revealed an effect of time on task, with HR significantly decreasing in the second, third and fourth sectors of the experimental run (i.e., from the third minute to the ninth minute). Mean heart rate in each sector by automation condition is presented in Figure 7.5. Despite appearances from the graph, there was not a statistical difference between the automation conditions.

One final analysis was carried out which is relevant to MART. This experiment was an attempt to establish whether physiological arousal accounts for performance differences following automation failure over and above MWL. Given that the automation failure occurred in the final sector, it would seem logical to compare HR across automation conditions in the penultimate sector, immediately prior to the failure event. These analyses revealed a significant HR reduction in the ACC+LC condition for both learners and experienced

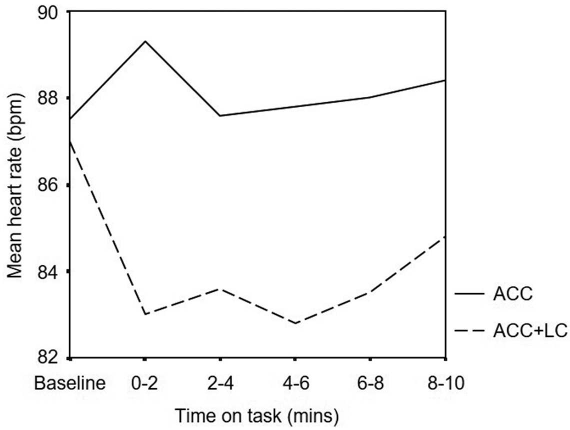

Figure 7.4 Mean heart rate across automation conditions and time sectors for learner drivers.

drivers. There were no differences in baseline HR prior to each trial, so it must be assumed that these differences were due to the driving condition. Mean heart rate values (bpm) across each of these conditions in the penultimate sector are presented in Figure 7.6.

Subjective mental workload

One advantage of the NASA-TLX is in using the subscales to diagnose the source of MWL. In an effort to rule out vigilance as a competing explanation for the results, we can analyse the subscales to look for the MWL signature

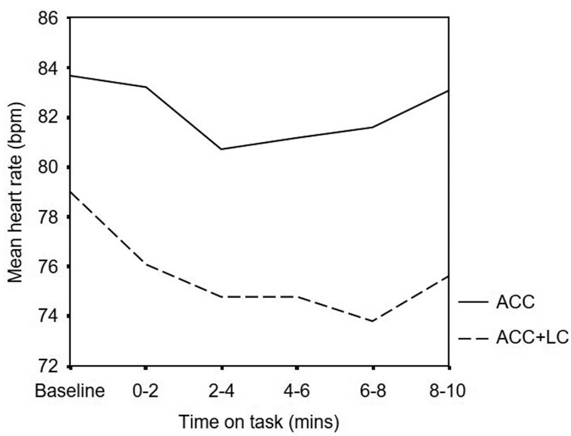

Figure 7.5 Mean heart rate across automation conditions and time sectors for experienced drivers.

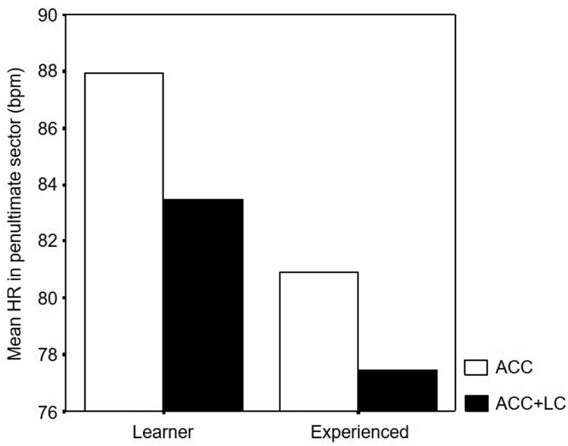

Figure 7.6 Mean heart rate prior to automation failure across skill groups and automation conditions.

for vigilance tasks which has been observed by Warm et al. (1996). They found that the TLX scales of Mental Demand and Frustration were the most significant contributors to overall workload for vigilance tasks. To determine whether this signature existed at all in the present study, a regression analysis was performed on the TLX data from the pilot study for learners and experienced drivers in both ACC and ACC+LC conditions. Overall workload was the dependent variable, and the six subscales were entered as the independent variables. The output, in terms of beta weights on each scale, is presented in Table 7.3.

As can be seen from these data, the vigilance footprint appears to be evident in the ACC+LC condition, particularly for the learner driver group. When one views the mean scores across all the NASA-TLX subscale ratings for that condition (Figure 7.7), it is clear that Mental Demand and Frustration

Table 7.3 Regression coefficients for NASA-TLX subscales across skill groups and automation conditions

	Standardised beta coefficients			
	Learner		*Experienced*	
TLX subscale	*ACC*	*ACC+AS*	*ACC*	*ACC+AS*
Mental Demand	0.203	0.313	0.193	0.203
Physical Demand	0.127	0.071	0.167	0.073
Temporal Demand	0.167	0.167	0.163	0.186
Performance	0.184	0.147	0.177	0.186
Effort	0.191	0.110	0.181	0.124
Frustration	0.162	0.391	0.173	0.324

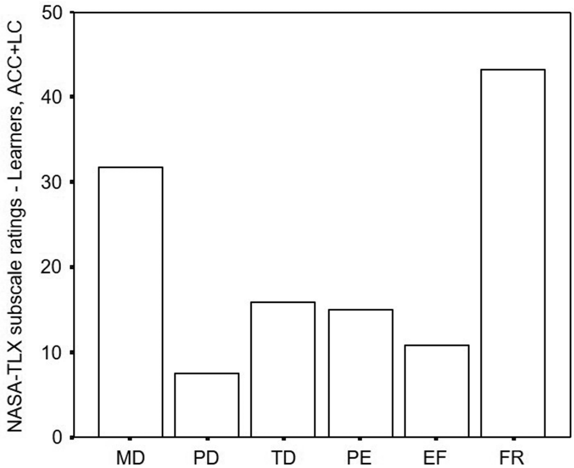

Figure 7.7 NASA-TLX subscale ratings for learners in ACC+LC condition.

are the overriding influences on MWL. Possibly, then, the vigilance decrement might play a part in any degradation of performance for learners when using ACC+LC.

DISCUSSION

Implications: malleable attentional resources theory and automaticity

We had to dig a little to figure out what was going on with the results in this study as, on the face of it, it looked like we did not have much support for MART. Surprisingly, and contrary to predictions, overall performance (in terms of responses to automation failure) did not decrease with the underload of ACC+LC. In fact, performance was actually better for experienced drivers in that condition (i.e., they were more likely to respond).

However, this result was mediated by a significant learning effect, as the responses of both groups were greatly improved in the second trial. A breakdown of analyses within each trial found that performance was generally at chance in each group when participants were naïve, but virtually at ceiling under most conditions when participants expected the failure. This is consistent with the research reviewed earlier showing better reactions for drivers who were aware of the possibility of failure, and is supported by other research (Ruscio et al., 2017) suggesting that the underload effect as predicted by MART only holds for unexpected takeover situations. In other words, when drivers are prepared to take over control, they may be priming their attentional resources to 'spin up' capacity in advance, thus negating the impact of a sudden increase in demand against their previously shrunken capacity.

The interesting exception to this rule was that learners did not improve their responses with ACC+LC even when they were aware of the possibility of failure. This represented the key finding from this study: that *learner drivers did not perform any better than chance in the low workload condition whether they were naïve or aware of the possibility of failure.*

This was a very interesting finding. It suggests that, just as other influences on capacity (such as arousal, mood, and age) only affect controlled processes (Hasher & Zacks, 1979), task demands only have a main effect on performance if the operator is unskilled. That is, the resource-free nature of automaticity allowed experienced drivers to bypass the underload decrement, since although resources have shrunk for skilled and unskilled alike, the performance of skilled operators is not dependent on those resources, so was relatively unaffected. In the present scenario, it seems that the emergency braking response is an overlearned reaction for experienced drivers (cf. Nilsson, 1995).

This finding was also contrary to the results of Kessel & Wickens (1982). Their experiment demonstrated that transfer of failure detection skill was better if a passive monitor had previously been an active controller, rather than vice-versa. That is, performance improves if the automated condition follows the manual condition, but not if the automated condition is presented first. Here, passive monitoring led to *worse* performance if the operator had been a prior controller. However, the situation is slightly different, as the system subject to failure (ACC) was never under active control. If participants were required to manually control speed and headway at some point, the results might have been more consistent with those of Kessel & Wickens (1982). As we explained earlier, though, such an experimental design would not have satisfied the aims of the study.

It was anticipated that resources would diminish in low workload conditions irrespective of voluntary strategies, such that participants would not be able to resume control even if they wanted to. The distinct improvements in performance for primed participants does not support this and implied an effect of effort. However, there is a qualification to this. Learner drivers only improved across trials in the ACC condition – no improvement was observed in the ACC+LC condition, despite the same effort manipulation, and despite there being evidence of better skill transfer from manual to automated (Kessel & Wickens, 1982). This is actually strong support for MART and sets it apart from some other explanations of mental underload. A maladaptive mobilisation of effort theory (e.g., Desmond & Hoyes, 1996; Desmond et al., 1998; Matthews et al., 1996) implies that there is some level of voluntary authority over investment of effort in performance – participants can consciously improve performance if motivated to do so (Matthews & Desmond, 2002). MART has no such mechanism – reduced capacity is an involuntary and inevitable consequence of reduced demands. Learner drivers were not unwilling to respond, they were simply unable to react.

Although these results were encouraging for MART, the heart rate data detracted from the picture somewhat. To rule out physiological arousal as the source of fluctuations in attentional capacity, ideally there would have been no difference in HR between the two conditions. This was not the case. In the learner group especially, HR was significantly lower in the ACC+LC condition than both the ACC condition and the baseline recordings. Overall, HR for experienced drivers did not statistically differ across automation conditions, although at the point when it most mattered (i.e., immediately prior to the automation failure), HR under full automation was significantly lower with full automation than with ACC. This result did not simply represent a time-on-task effect; therefore, the difference in HR between conditions in the penultimate time block must have been purely due to the level of automation. Moreover, the data collected in this series of studies suggests a reasonable correlation between physiological arousal and attentional capacity. In Chapter 4, we presented a timeline plot of the attention ratio variable as a decay curve of attentional resources. When comparing the parallel data from experienced drivers using ACC+LC in that study against the HR data in this study, attention ratio and HR appear to decrease along similar epochs.

It is possible, of course, that the physical activity of steering was at least partly responsible for the HR differences between the automation conditions. Nevertheless, the fact that arousal changes did occur is indisputable, and in a sense the source of this is irrelevant. The idea of a relationship between capacity and arousal is not new (e.g., Hasher & Zacks, 1979; Kahneman, 1973) and has been associated with rapid workload transitions (Huey & Wickens, 1993). Meanwhile, established attentional resource theory simply predicts that demands and arousal are positively associated (Kahneman, 1973), whereas MART sought to dissociate capacity from arousal and instead link it directly to demand. It seems, though, that underload, attentional resources and performance are indubitably related to physiological arousal (see also Young et al., 2015) and we cannot eliminate the possibility of arousal as an alternative explanation for the effects of underload on performance.

That said, we still believe there is value and validity in MART. In our opinion, the literature had not previously seen evidence of attentional resource shrinkage as convincing as the attention ratio data provided by Young & Stanton (2002b), nor had such shrinkage been explicitly attributed as the cause of mental underload performance problems. Furthermore, the influence of operator skill had not been addressed in past research. Combining the results of Young & Stanton (2002b) with the reactions to automation failure observed here provides strong support for the hypothesis that attentional capacity can shrink in line with reductions in MWL, and that excessive shrinkage can be detrimental to performance, especially for less skilled drivers. It could even be argued that the decrease in mental activity affects physiology, in an evolutionary efficiency of the cognitive system (cf. Adi-Japha & Freeman, 2000). However, such shrinkage might not be directly due to mental workload, given the associated effect of physiological arousal. Whether this effect is a cause, consequence, or simply coincidental with resource shrinkage, is a moot point.

Nevertheless, these are valuable findings from a practical perspective, since physiological arousal is more readily detected than mental underload. This factor may actually prove to be useful for purposes such as physiological monitoring of underload states (e.g., Brookhuis, 1993; Fairclough, 1993), which we will cover in Chapter 9. Moreover, it may even ultimately help us to define the elusive 'redline' of underload (or, indeed, overload) as arousal may help us to gauge the supply of resources against demands (cf. Young et al., 2015). Indeed, metrics of cerebral blood flow have been explicitly related to the supply of attentional resources in response to task demands, with direct reference to MART (Matthews et al., 2010). Such measures represent exciting developments in that quest for the 'holy grail' of identifying redlines in overload and underload. Rather than trying to dissociate the effects of mental demands from arousal, then, it may be more constructive to accept that the two are related.

Given the design of this study – a low demand situation, monitoring for a single failure – it could also be argued that a vigilance decrement might explain the differences in observed performance. Whilst vigilance decrements are less likely with dynamic signals such as driving (Parasuraman, 1987), two aspects suggest that vigilance may be important to the results obtained in this study. Firstly, there is evidence that vigilance decrements occur only for tasks involving controlled processing – automaticity is immune to problems of vigilance (Fisk & Schneider, 1981). The fact that performance decrements were only really evident in the learner driver group favours this explanation. The other aspect involves the MWL signature for vigilance observed in the TLX data (cf. Warm et al., 1996), which was particularly pronounced for learners in the ACC+LC condition, correlating with the distinctive performance effects in that condition.

However, these arguments may be countered by the fact that the experimental trials were still well below the timescales for vigilance problems – typically 20–30 minutes, as opposed to the 10-minute trials used here (see also Endsley & Kiris, 1995). Analogous results have been found with automated driving, as drivers 'switch off' from monitoring the road after 20 minutes with the automation engaged (Mueller et al., 2021). Finally, passive monitoring and vigilance have been characterised as high MWL tasks, rather than being associated with underload (Hancock, 2021; Hancock & Verwey, 1997; Metzger & Parasuraman, 2001). Given the reductions of MWL in the present task design (see also Young & Stanton, 2002b), we are reasonably confident that underload has played a greater part than vigilance in the effects on performance.

Another, related, explanation for performance decrements in automation involves situation awareness and the out-of-the-loop problem (Endsley, 1987). This is a general reference to the reduced ability of operators to detect or respond to critical events if the system had previously been under automated control (see e.g., Banks & Stanton, 2016; Mueller et al., 2021). The lack of interaction can reduce awareness of system states and can cause a decay of direct control skills (Kaber & Endsley, 1997). Endsley & Kiris (1995) found that participants attempting to recover from a system breakdown performed significantly worse when the task had been automated, than when they had been controlling the system manually. However, they found no differences in MWL, concluding that the lack of a MWL effect was due to the processing demands being shifted from control to monitoring (cf. Wickens & Kessel, 1981). The argument is that monitoring does not relieve workload, it just places different types of demands upon the operator. With no observed MWL differences across conditions, performance decrements were attributed to a loss of situation awareness, as participants' understanding of the situation was poorer in the fully automated condition than in the manual trials. In our study, there were indeed differences in MWL between conditions, and the automation failure occurred to the same system (ACC) in both conditions with no comparison to manual control.

In a series of studies (Gustavsson et al., 2018; Ljung Aust, 2020; Victor et al., 2018), drivers' (lack of) responses to critical scenarios were ascribed to their expectations or trust in the system's capabilities, regardless of whether they had been given instructions about its limitations or experienced a critical event before. Drivers were ostensibly paying attention to the road ahead and were ready to take over, but they simply thought the automation would deal with more situations than it could actually handle. Given that we used the same automation failure event (ACC) in both conditions, it seems unlikely that these explanations would account for the observed effects just because an ancillary system (LC) was also switched on. Moreover, if expectations were influencing participants' responses, this does not explain the differences in failure-primed performance observed across workload conditions for learner drivers in our study.

Similarly, there is evidence that operators of highly reliable automation tend to take advantage of it by redirecting their attention to secondary tasks (Merat et al., 2014), with consequent effects on performance (Rudin-Brown & Parker, 2004). Then, the problems with resuming control may be more about distraction than underload (cf. Lee et al., 2020; Victor et al., 2018; see also Endsley & Kaber, 1999; Large et al., 2018). Our experimental design deliberately did not include any secondary tasks for that very reason; there was nothing else for participants to do other than monitor the automation. Nevertheless, there remains an open question under MART as to what happens to the shrunken resources – why does it shrink and where does that lost capacity go? Indeed, has it really been lost or merely allocated elsewhere (internally or externally), in which case are we just talking about another form of distraction?

Implications: automation and driver skill

In addition to the well-known problems of skill degradation with automation (e.g., Parasuraman, 2000), the present experiment has demonstrated that drivers in the early stages of skill development can be adversely affected when using a highly automated vehicle. Fewer opportunities to learn from experience with manual driving will impair the development of adaptive expertise (Ivancic & Hesketh, 2000), potentially leading to performance decrements in novel situations (which will be increasingly plentiful with an automated vehicle). Consequently, driver training and assessment programmes may have to become more thorough in maintaining the manual control skills of the driving population. There is clearly much further research to be done in determining the optimal implementation of vehicle automation and information systems in order to foster and maintain driver skill.

Brake reaction times

It has been suggested that ACC systems can reduce traffic congestion, increase road capacity and improve safety by eliminating irregular human driving styles and allowing for safe driving at higher speeds and shorter following distances (Chira-Chavala & Yoo, 1994; Gilling, 1997). However, the human driver's capacity to cope with critical events could actually increase the risk associated with such devices. Most motoring authorities stipulate a minimum time headway of 1 to 2 seconds (Taieb-Maimon & Shinar, 2001), with more conservative criteria being based on worst case scenarios of driver reaction times. Sohn & Stepleman (1998) recommended using 85th or 99th percentile data to calculate these values, and from a meta-analysis determined that a headway of 1.75 seconds would be more appropriate. Despite the fact that these numbers represent realistically achievable reaction times, the majority of drivers choose actual headways of less than 1 second (Shinar, 2000; Taieb-Maimon & Shinar, 2001). Moreover, since some ACC systems are set with a *maximum* time headway of 2 seconds, the question may reasonably be asked as to whether the driver can intervene in a timely fashion if they need to.

The present study (along with those of Rudin-Brown & Parker, 2004, and Mueller et al., 2021) demonstrated increased reaction times when resuming control from automated systems. When comparing our data to those gathered during manual driving from previous literature (Tables 7.1 vs 7.2), there was a striking increase in reaction times for the automated conditions used here. Total braking time when driving with automation was around three times longer than equivalent data gathered under manual driving conditions in other studies. Mean brake reaction times in our study were around 2.4 seconds, again a substantial increase over the 0.4 seconds average for manual driving observed by Liebermann et al. (1995). Although the results of van der Hulst et al. (1999) were apparently higher still, it was noted earlier that the design of that study was somewhat different to those of other researchers, in that the deceleration rate was relatively slow. Nonetheless, the results of the present experiment are more in line with textbook values of response times for unprimed drivers, which can be in the region of 2 to 4 seconds (Sanders & McCormick, 1993; Wickens et al., 1998). Perhaps, then, this indicates that drivers using automation are simply less anticipative of having to make an emergency response than they would be when driving manually. However, even primed experienced drivers, who reacted more quickly than when they were naïve to the automation failure (conditions which are analogous to the aware/unaware conditions in the studies on reaction time we reviewed earlier in this chapter), took nearly 3 seconds on average to press the brake after the failure occurred. This result is consistent with previous research which found total braking time is generally slower when the driver is unaware of the hazard (Sohn & Stepleman, 1998). Nevertheless, the learners in our study who were aware of the possibility of automation failure still demonstrated slightly worse performance (in terms of a shorter time until the collision) in the ACC+LC condition.

In practical terms, many researchers favour the use of statistical upper fences (rather than means) as the basis upon which to make recommendations (e.g., Eriksson & Stanton, 2017b). The maximum total braking time value for primed experienced drivers here was 3.5 seconds. In previous studies, the highest latencies were under 2 seconds, whether the braking was expected or otherwise. Thus it seems that level 1/level 2 automation can slow drivers' braking responses by around 1 to 1.5 seconds. For planned transitions, research shows an average lead time of around 6 seconds but a maximum of 30 seconds (Eriksson & Stanton, 2017b).

Since ACC and other longitudinal control devices are primarily aimed at reducing headway in order to increase road capacity, it seems ironic that the evidence suggests drivers actually need more time to react in emergency situations. Designers of ACC systems face a dilemma in trading off safe headway in terms of the vehicle's capabilities against the driver's reaction times (cf. Goodrich & Boer, 2003; Taieb-Maimon & Shinar, 2001). Clearly, the emphasis so far has been on the vehicle's limitations, with typical systems providing headways of between 1 and 2 seconds – far below the drivers' reaction times in the present study. The problem becomes even more critical when drivers need to resume manual control from the automation. In planned takeovers, the system typically gives the driver a few seconds' warning to engage their attention, but the time for drivers to react, step back into the control loop and for their performance to stabilise can take anywhere between 5 and 40 seconds (Eriksson & Stanton, 2017b; Merat et al., 2014; Seppelt & Victor, 2016). A lot can happen in that time when travelling at highway speeds, raising the question of whether this is safe at all (Emmenegger & Norman, 2019) and whether the automation should somehow deal with the failure when the situation is time-critical (cf. Sheridan & Parasuraman, 2000).

CONCLUSIONS

This study tested learner and experienced drivers' responses to automation failure under two levels of mental workload. What set this study apart from many others in the field is the fact that the nature of the automated failure (i.e., ACC losing its lead vehicle target) was the same in each condition – workload was instead manipulated by using an additional automated system (LC) to effectively compare level 1 versus level 2 automation. The results largely supported MART and also extended the theory to encompass automaticity. There was an interactive relationship between automaticity and automation to the extent that, even when prepared for an automation failure, learner drivers who were underloaded could not respond at any better than chance levels. Only half of these participants responded to the failure event, compared to most in the normal workload condition. This suggested that the attentional capacity of this group had diminished as a result of the lower demands and reduced arousal levels. Meanwhile, the performance of experienced drivers was unrelated to task demands, supporting the idea that these drivers were processing information in an automatic manner, free from the constraints of (shrunken) attentional capacity.

Whilst the study design helped us to support MART over alternative explanations such as situation awareness or the out-of-the-loop performance problem, an analysis of the subjective MWL data suggested that the classic vigilance problem may have influenced the results (even though the nature of the task should not have incurred a vigilance decrement). Moreover, heart rate data revealed that physiological arousal played a key role in the underload effect that was observed. Although this latter finding detracts from the unique proposition of MART (in relating attentional capacity directly to mental underload), we argued that in practical terms this may actually prove useful, for purposes such as physiological monitoring of underload states (e.g., Brookhuis, 1993; Fairclough, 1993).

In sum, the findings of Young & Stanton (2002b) coupled with those presented in this study allowed us to refine MART as follows. The size of attentional resource pools can vary according to the level of task demands imposed on the operator. This mechanism may be associated with physiological arousal, and can be used to explain the detrimental effects of mental underload on performance. However, these effects can be mitigated by automaticity. Although the skilled operator does suffer from capacity fluctuations with task demands, processes which are essentially resource-free do not show performance decrements in the same way as controlled, resource-dependent processes.

What we have shown from this series of studies is that attention shrinks in response to underload with automation, and that this is probably responsible (at least in part) for performance problems when needing to resume manual control as the increase in demand exceeds the reduced capacity of the operator. In practical terms, we can expect these problems to be worse with level 3 automation as drivers are even less involved and might have diverted their attention to non-driving tasks (Seppelt & Victor, 2016). We also know that the sudden workload transition of an automation failure causes problems (cf. Young et al., 2015), and there will certainly be a lag in the cognitive response to the transition (see Hancock, 2021, for an exposition of this process), which may be related to the change in arousal having to recruit attentional resources (Huey & Wickens, 1993). Our data presented in Chapter 4 tentatively imply that both reduction and recovery of resources happen within one minute; this would be consistent with other research suggesting reactions to takeover are impaired for anything up to 40 seconds (Eriksson & Stanton, 2017b; Merat et al., 2014). This all suggests that any handover, with its associated increases in demand, would have to be gradual in order to facilitate performance. These studies make the 10-second transition time anticipated for automated lane keeping systems (ALKS; CCAV, 2020) seem rather short, leading some (e.g., Thatcham Research, 2019) to recommend takeover request lead times of up to 60 seconds, to allow time to alert the driver, raise their engagement with the task, and stabilise performance. From a human-centred design perspective, takeover timing should arguably be paced by the driver (Stanton et al., 2021). But there is a conflict in all this, because the longer the transition, the further the car will travel in a potentially unsafe state – we are trading off the consequences of an automated system that is becoming unable to cope against a human who is unready to take over. We might question, then, whether it is appropriate or even possible to rely on a driver as a fallback for automation in the timeframes of a speeding vehicle (Emmenegger & Norman, 2019; Victor et al., 2018).

Of course, it is all too easy to pick on the negatives in anything; much harder to try and accentuate and exploit the positives. But that is where we turn in the next section of this book before moving to close with a discussion of how to get the best out of automation so that we can address all of these problems.

KEY POINTS

- Concerns for the impact of mental underload on performance are typically realised when the human operator must suddenly resume manual control, as the rapid increase in demand outweighs their shrunken capacity to respond.
- Such events may or may not be due to technical failures of the automation; they may simply be scenarios that are beyond the operational design domain of the system.
- Several studies have shown that when using automation, fewer drivers respond and reaction times are slower for these critical events as compared to an equivalent scenario under manual driving; performance can be impaired for anything up to 40 seconds.
- Our research demonstrated that driver skill plays a crucial role, as automaticity may confer some immunity to the shrinkage of attentional resources with underload – meaning that less skilled drivers are especially vulnerable when having to resume control from automation.
- Malleable attentional resources theory helped to explain these results, albeit moderated by physiological arousal.

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Stage 3

Human-centred automation

Chapter 8

What can automation do for us?

OVERVIEW

On this final stage of our journey, we turn to consider how automation could (or should) be best exploited to improve safety, efficiency, and performance on our roads. For the first leg, this chapter considers impairments of human performance as a means of identifying areas where automation can usefully assist. Such impairments are divided into transient and permanent, and the chapter offers a detailed literature review in each of these areas. Transient impairments are largely associated with workload or distraction, the sources of which may be internal to the vehicle (e.g., mobile phones, satnavs) or external (e.g., roadside advertising). Even automation itself can be a distraction – or, more likely, facilitate a driver's distraction (or 'inattention') through engaging in non-driving tasks. Longer term impairments may be associated with perception (e.g., eyesight) or cognition (e.g., ageing). Through understanding these impairments in more detail, the chapter closes by identifying specific applications of driving automation that may be able to compensate. Whilst we are cautious not to advocate the (ab)use of these systems as an excuse to drive when not fit to do so, we also feel there is room to exploit the technology with the aim of making the road system as safe as possible.

INTRODUCTION

So far in this book, the focus has been on largely negative aspects of automation in its relationship with the human operator. This may make us seem rather technophobic in our outlook, but in actual fact that is not the case. We recognise and, indeed, advocate the use of technology and automation to improve safety, performance, and satisfaction where it is appropriate to do so – but it must be designed and integrated in the right way. In these last few chapters, we discuss what 'the right way' means.

Firstly, then, we will look at circumstances where automation may make up for shortfalls in human performance. In the previous chapter, we considered failures of automation and the ability of the human driver to step in and save

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the day (or otherwise, as the case may be). Now, we start to switch that perspective around, and consider limitations of the human condition for which automation may be able to support or compensate. Such impairments may be transient, such as workload or distractions associated with the driving task, or they could be longer-term – even permanent – associated with degradations in perceptual or cognitive ability. In these latter categories, the most pertinent aspects of concern for driving are eyesight and age (and, of course, these two factors are not mutually exclusive either).

In this chapter, we first review research on the effects of each type of impairment – transient, perceptual, and cognitive – on driving performance. Then we take a rounded look at how automation might make a positive impact in mitigating these effects to improve safety. We would heavily preface all of this with the caveat that we are not endorsing the abuse of these systems in encouraging people to drive when impaired in any way, in the hope that the automation will save them. Nevertheless, knowingly or otherwise, drivers do get distracted, drive with substandard eyesight, or suffer cognitive impairments. As we will argue in due course, the case for automation to maintain safe, independent mobility is compelling. Therefore, it is worth considering the role of automation in helping to improve safety and mobility in some or all of these cases. Ultimately, this is about embracing the technology in the right way and exploiting automation for what it should be used – helping drivers to do what they do best.

TRANSIENT IMPAIRMENT: DISTRACTION

The importance of attention (and visual attention, at that) in driving cannot be overstated. Driving is widely accepted as being a predominantly visual task (Kramer & Rohr, 1982; Spence & Ho, 2009), with 87% of driving information coming through the visual modality (Zhang et al., 2021), and over 80% of that visual attention being allocated to the forward field of view (Robbins et al., 2021). Driver attention is therefore a key predictor of performance (Ranney, 1994). Nevertheless, drivers have to share their attention between the road ahead and other distractors. Stanton & Marsden (1996) argued that dividing attention between the elements of the driving task is cognitively demanding as well as visually demanding (for instance, many drivers find it necessary to pause a conversation with a passenger while negotiating a difficult piece of road). The tasks of maintaining lane position, adapting speed, and reacting to obstacles are processed in parallel, and spare capacity is required to respond to unexpected events (Kramer & Rohr, 1982). That said, as we noted in Chapter 2, drivers have a good deal of spare visual capacity available during routine driving (Hughes & Cole, 1986), implying that some secondary tasks may be able to be conducted with no subsequent increase in crash risk.

Despite this, driver distraction is still a frequently cited causal factor in collisions (Parnell et al., 2019; Regan et al., 2009), with 20–30% of crashes involving some form of distraction or inattention (FIA, 2020). Research completed for the landmark 100-car naturalistic driving study by the US National Highway Traffic Safety Administration (NHTSA) in the US (Dingus et al., 2006; Klauer et al., 2006; Neale et al., 2005) concluded that 78% of all crashes and 65% of near-crashes involved some degree of driver inattention. Distraction is, by definition, taking attention away from the primary task of driving and towards some unrelated secondary task; such attention may be visual, cognitive, or both.

One of the original (and classic) studies on driver visual attention used an occlusion technique on a live highway[1] to show that, as drivers look away from the road, uncertainty about their progress accumulates until they need to look back at the road (Senders et al., 1967). Over the years since, research on driver visual distractions has determined that 1.6 seconds is the maximum time that experienced drivers will accept looking away from the road (see Horrey, 2009, for a review). Meanwhile, novices will be more likely to glance away from the road for more than 3 seconds, and spending this amount of time looking away from the road has been associated with extreme steering errors (Wikman et al., 1998). Based on research showing that glances longer than 2 seconds away from the roadway are associated with higher crash risk (see Perez et al., 2012), NHTSA recommended[2] that in-car devices should not require glances away from the roadway longer than this threshold.

Meanwhile, as we already know by now, cognitive overload from a distractor task can adversely affect performance, particularly if workload is already high (e.g., in urban driving; Liu & Lee, 2006; at junctions or in the face of unexpected events; Angell et al., 2006) or if the driver has a lower capacity to respond (e.g., if the driver has less skill or experience, as we have seen in the last section; or, as we shall discuss later in this chapter, in the elderly; May et al., 2005; Sixsmith & Sixsmith, 1993). Such factors can impair the reactions of a distracted driver since their spare attentional capacity has been absorbed by the secondary task.

Studies have also shown the overlap between cognitive and visual distraction. While conducting a cognitive secondary task, drivers spend less time looking at areas in the peripheries (such as mirrors and instruments) and instead focus on looking centrally ahead (Harbluk et al., 2007). Even though time looking outside of the vehicle remained unchanged, these results suggested a change in drivers' allocation of attention associated with the higher workload.

Competition for visual attention is a crucial factor in driving performance (e.g., Antin, 1993). Since the sources of these visual and cognitive distractors can be either inside or outside the vehicle, let us focus our attention on these areas in turn.

In-car distractors

In the NHTSA 100-car naturalistic driving study, drivers distracted by an in-car secondary task contributed to over 22% of all crashes and near-crashes (Klauer et al., 2006). Investigations of the sources of these distractions have to a large extent focused on the myriad and increasing interfaces and nomadic devices available in the modern automobile. Perhaps one of the most familiar is the satellite navigation (satnav) system (Parnell et al., 2018). Many functions of satnavs take considerably longer to complete and place higher demand on visual attention than conventional controls and displays (Antin, 1993; Dingus et al., 1989; Wierwille et al., 1991), with tasks such as destination entry being worse even than entering a mobile phone number (Nowakowski et al., 2000; Tijerina et al., 1998). Nevertheless, other research suggests that the associated glance durations and eyes-off-road times for this task are still within the guidelines for safe operation (Chiang et al., 2004).

Of course, nowadays many users rely on their mobile phone for navigation rather than a bespoke device – and mobile phones are often cited as the test case for distraction, with many countries specifically banning the use of handheld phones while driving. In an observational study (Stutts et al., 2005), just over a third of drivers used a mobile phone. But research consistently shows that using a mobile phone while driving is associated with increased workload, worse reactions and increased crash risk, with the effects being at least as bad as drunk driving (e.g., Alm & Nilsson, 1995; Haigney et al., 2000; Redelmeier & Tibshirani, 1997; Strayer et al., 2003). Moreover, whilst some suggest that using a hand-held phone can affect steering ability (Haigney et al., 2000), on the whole the evidence does little to distinguish between hand-held or hands-free phones, with each having similar effects on reaction times (Consiglio et al., 2003; Lamble et al., 1999), lateral position and driver mental workload (MWL) (Törnros & Bolling, 2005; 2006). These findings imply that the effects are due to cognitive competition for attentional resources (Spence & Read, 2003), rather than the simple physical interference from holding a handset, pointing towards little advantage for hands-free phones (cf. Haigney & Westerman, 2001).

Other in-car distractors have been benchmarked against mobile phone use: talking to a passenger increased brake reaction times just as much as using a hand-held or hands-free phone, while listening to the radio did not have such an effect (Consiglio et al., 2003). There are risks from even more mundane in-car activities such as eating and drinking, map-reading, grooming, etc. (cf. White et al., 2004). Observational (Stutts et al., 2005) and survey (NHTSA, 2003) research showed that eating and drinking are among the most common in-car activities by drivers, second only to operating the radio and talking to passengers. About one-sixth of drivers reported having a coffee or a soft drink to fight fatigue (NHTSA, 2003), consistent with research which suggests that sugary snacks or drinks can indeed help stave off sleepiness and improve lane-keeping performance (Horne & Baulk, 2004; Parkes et al., 2001; Smith & Rich, 1998). However, analyses of crash databases suggest that eating or drinking is implicated in at least a similar proportion of collisions as mobile phone use (Stutts et al., 2005), while all of these activities increase crash risk, with drinking at the wheel nearly doubling the likelihood (Violanti & Marshall, 1996).

A simulator study into the effects of eating on driving performance (Jenness et al., 2002) demonstrated that eating a cheeseburger disrupted performance (in terms of lane-keeping errors and speeding violations) and attention (eyes-off-road time) compared to baseline, but not as badly as using a CD player, reading directions, or operating a voice-activated phone. Similarly, the observational study of Stutts et al. (2005) noted that eating/drinking increased the amount of time drivers had their hands off the wheel and their eyes off the road; preparing to eat and drink also resulted in more lane excursions.

In a similar study, we tested driver performance and subjective MWL when eating or drinking in critical situations using the Brunel University Driving Simulator (Box 8.1; see Young et al., 2008, for more details). Participants drove in an urban scenario with a speed limit of 50 mph (80 km/h), either driving normally or while taking food or drink (a sealed packet of sweets or bottle of water). At a designated point on the drive (timed to coincide with eating/drinking in the experimental condition), a critical incident was simulated by a pedestrian walking in front of the car, programmed such that the car and the pedestrian would collide unless the driver intervened by braking and/or steering.

Whilst driving performance (longitudinal and lateral control) was relatively unaffected by eating and drinking, perceived driver workload was significantly higher and there was a trend towards more crashes in the critical incident when compared to driving normally. The data suggested that eating might have a greater effect than drinking on crash frequency, although the sample size meant that this was not statistically significant. Conversely, Violanti & Marshall (1996) found that drinking at the wheel was associated with higher levels of crash involvement.

Meanwhile, analysis of the subjective workload scales by Young et al. (2008) suggested that the physical demands of eating and drinking while driving made a more substantial contribution to MWL than the cognitive competition for attentional resources that is attributed in the mobile phone debate (cf. Haigney & Westerman, 2001). This is consistent with observations that these activities result in more time with the hands off the wheel and the eyes off the road (Stutts et al., 2005).

Although not statistically significant, a visual inspection of the data suggested that drivers became more cautious when eating and drinking, implying that drivers may be able to adapt to the circumstances and task to a certain extent. This echoes previous research into mobile phone use while driving, which suggests that the increased workload of mobile phone use can lead to compensatory behaviours such as slowing down or increasing headway (Haigney et al., 2000; Strayer et al., 2003; Tornros & Bolling, 2005; 2006). Since drivers see eating and drinking as a relatively low-risk activity (White et al., 2004), they choose not to modify their behaviours by only eating when stopped, as they would for other, higher-risk activities (Stutts et al., 2005), and rely on adapting their driving instead (cf. Haigney et al., 2000). Whilst

BOX 8.1 THE BRUNEL UNIVERSITY DRIVING SIMULATOR

If we can beg the reader's indulgence for a short interlude, as it will not escape your attention that several of the studies reviewed in this and the next chapter are, of course, from our own laboratory. By this time, though, that laboratory had moved to Brunel University and the driving simulator had been upgraded. Since the simulator features a number of times over the following pages, it is worth briefly describing it here.

The Brunel University Driving Simulator was a fixed-base simulator based on a 2006 Jaguar S-Type full vehicle body (Figure 8.1). The simulation software (STISim Build 2.08.04) ran on a PC equipped with high-specification processor, graphics, and sound cards. Forward images are projected onto three 2.4 × 2.0 metre screens at a resolution of 1280 × 1084 pixels, giving the central scene plus the left and right peripheral scenes for a total field of view of 150° horizontal and 45° vertical. Simulated images of the dashboard instrumentation as well as rear view and side mirrors are projected onto the viewing screens. Audio was reproduced in Dolby Pro Logic, with a low-frequency subwoofer under the car to suggest vibration. Driver inputs and haptic feedback were made via a games console steering wheel, gear lever and pedal block, integrated into the car's original controls and fitted as a UK-standard right-hand drive vehicle. The simulator was capable of capturing data at rates up to 30 Hz.

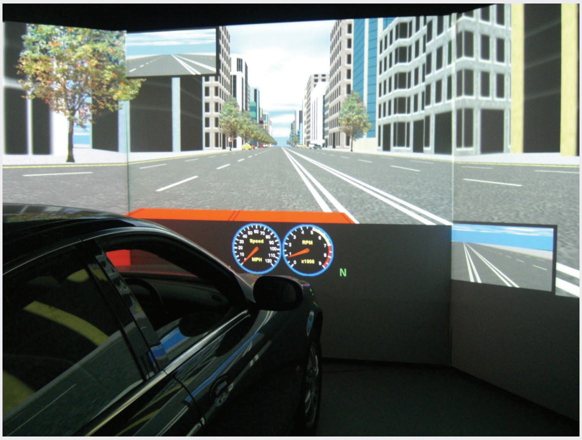

Figure 8.1 The Brunel University Driving Simulator.

this may appear to be inconsequential during normal driving (Jenness et al., 2002), it can break down during abnormal or emergency situations as drivers are less able to cope with the sudden peak in demands, resulting in a greater risk of crashing (Violanti & Marshall, 1996). This is supported by our findings relating to performance in the critical incident scenario, and parallels the issue we discussed in the previous chapter about reclaiming manual control from automation.

External distractors

Whilst there has been a wealth of research investigating in-car distractions (e.g., Antin et al., 1990; Goodman et al., 1999; Jamson et al., 2004), less is known about distraction from objects outside the car (cf. Young et al., 2003). Of these external objects, roadside advertising billboards are designed by their very nature to attract attention. There has long been concern that roadside advertising presents a real risk to driving safety, with conservative estimates putting external distractors responsible for up to 10% of all road traffic collisions (Wallace, 2003). Crucially, though, the related potential threat to road safety is generally not acknowledged by the industry (Crundall et al., 2006).

There is a substantial body of evidence demonstrating the impact of roadside advertising on drivers' visual attention. A study of drivers' eye movements by Beijer et al. (2004) showed that 88 per cent of drivers were distracted by adverts, with 20 per cent glancing away from the road for more than that crucial 2 seconds. Similarly, Perez et al. (2012) found that both standard and electronic billboards reduced drivers' gaze towards the road ahead with, again, some examples of dwell times over 2 seconds.

Once a driver's attention has been captured, there are attentional resource costs associated with assessing and disregarding any task-irrelevant stimuli (cf. Smith, 1989). Horberry et al. (2004) cited evidence that drivers' visual attention is often attracted by adverts or other irrelevant objects. If this should occur when the driver's visual workload is already high (such as at a complex junction), the driver could fail to detect more relevant signage, hazards, or potentially lose proper control of their vehicle (cf. Engström et al., 2005). Crundall et al. (2006) also found that participants watching a video of a drive spent more time looking at street-level advertisements (e.g., bus shelters) when they were supposed to be monitoring for hazards. The implication from such studies is that roadside adverts can not only disrupt the identification of more relevant road signs (Castro et al., 2004), but also potentially affect hazard perception and, consequently, crash risk.

Early field studies investigating the relationship between collision rates and presence or absence of roadside billboards were conflicting and equivocal (e.g., Ady, 1967; Blanche, 1965; Rusch, 1951), possibly due to the conspicuity and location of the billboards (Ady, 1967). A review of six studies conducted by Wachtel & Netherton (1980) suggested that roadside advertising particularly at such visually demanding locations can affect collision rates. A later field study by Lee et al. (2003) showed that billboards had no effect on driver performance (in terms of speed or lane-keeping) or eye movements – although, in their case, the drivers were familiar with the test route.

Thus we can be relatively sure that roadside advertising affects drivers' attention, but less so about the impact on performance and safety. Given this quandary, Young et al. (2009) reported a study in the Brunel University

Driving Simulator quantifying the effects of billboards on driver visual attention (using an eye-tracking system), MWL and performance in Urban, Rural and Highway environments. Subjective MWL was consistently higher in the presence of billboards, while in terms of visual attention, the presence of billboards resulted in a shift towards more frequent but shorter glances, suggesting an increase in visual demand (cf. Chapman & Underwood, 1998; Crundall & Underwood, 1998; Wierwille, 1993). Moreover, recall of billboards was better than road signs in the Rural and Highway conditions, implying that drivers paid more attention to billboards at the expense of road signs (cf. Castro et al., 2004). It has been suggested that novel stimuli (such as billboards) might attract attention more when the driving task itself is relatively monotonous, such as on a highway (Wallace, 2003). Finally, although longitudinal performance was unaffected by the presence of billboards, lane-keeping was worse in the conditions with adverts. Whilst these data contradict the field results of Lee et al. (2003), they do concur with the series of studies by Engström et al. (2005) and Östlund et al. (2006), who found that higher visual demands do increase lateral variation. Moreover, Young et al. (2009) tentatively suggested that more crashes occurred when billboards were present, although this was not borne out statistically.

Automation-related distractors

We have already hinted at how the kinds of distractions discussed above might be exacerbated under automated driving conditions. We mentioned in the previous chapter how drivers of automated vehicles take advantage of the released attention by engaging in non-driving secondary tasks (Merat et al., 2014). Where the task does not provide it, people will seek out novelty and stimulation (what Hancock, 2021, calls ‘infostasis’). Given free rein, the majority of drivers have been shown to engage in non-driving tasks (80% on their smartphones, 25% reading books or papers) while the automation was in control (Burnett et al., 2019). But these distractions can have an adverse impact on driver performance when reclaiming manual control from automation, whether in a planned transition or as the result of an automation failure, resulting in poorer lateral and longitudinal control in the 10 seconds after takeover (Burnett et al., 2019). Similarly, drivers who were reading a newspaper took some 1.5 seconds longer over the transition than those who were focused on monitoring the system (Eriksson & Stanton, 2017b). Whilst non-driving secondary tasks might be the main concern, the automation interface itself can also cause a distraction as it tries to attract the driver’s attention during takeover requests – one simulator study suggested that drivers rely more on the interface than the real world for such handovers (Large et al., 2018). This is a matter of interface design, which we discuss in the next chapter.

It is, of course, the allocation of attention to the non-driving task that affects the driver’s ability to respond (Huey & Wickens, 1993). Since operators who are engaged in a secondary task are poor at monitoring automation

(Molloy & Parasuraman, 1996), the distraction can impair their ability to detect the need to take over (Mueller et al., 2020). These effects on attention are more pronounced with higher levels of automation (Seppelt & Victor, 2016), especially when both lateral and longitudinal control are automated (Pampel et al., 2020). As a consequence, response times in resuming manual control are slower (Mueller et al., 2020) as drivers are unprepared to take over (Shaw et al., 2020). Indeed, adverse visual attention patterns (such as not paying suitable attention to the road ahead) can predict crash involvement in critical scenarios with automation (Tivesten et al., 2019). Interestingly, it has been suggested that these problems are because drivers are focusing on resuming control at the operational level, and neglecting tactical control until after they have taken over (Burnett et al., 2019; Shaw et al., 2020). Some drivers persist with a secondary task even after a takeover request (Large et al., 2018). Providing drivers with a 60-second notification to prepare for the takeover did not help much, only cueing them to disengage from the secondary task, rather than preparing for driving (Burnett et al., 2019).

It is perfectly understandable that drivers use the attention that has been released by automation on other tasks – there is little point in having automation and then continuing to attend and respond to the same task that the system does (Larsson et al., 2014). With this in mind, and as we discussed in Chapter 3, it has been argued (CIEHF, 2020b) that we should not consider such behaviour to be distraction at all, since it is a voluntary reallocation of attention; rather, we should consider the driver to be 'inattentive' to the driving task.

PERCEPTUAL IMPAIRMENT: EYESIGHT

We have already touched on the importance of vision for driving performance, with most of the information that drivers use arriving through the visual modality (e.g., Evans, 2004; Hole, 2007; Kramer & Rohr, 1982). Consequently, visual function (in terms of visual acuity, visual field, contrast sensitivity etc.) is also crucial for driving safety (Molina et al., 2021). No wonder, then, that most driver licensing regimes worldwide involve an element of eyesight testing, usually a test of static visual acuity (Higgins et al., 1998; Owsley & McGwin, 2010). But the effects of acuity (or, indeed, other visual impairments) are – pardon the pun – not exactly clear.

In one study, Molina et al. (2021) imposed a loss or deterioration of binocular vision (by monocular occlusion or monocular blur respectively) in a simulated driving task. Their results showed that the reduction in visual function adversely affected driving performance (in terms of time spent out of lane and harsher braking) and increased driver MWL, particularly in complex traffic environments.

We investigated the effects of static visual acuity on a wide range of driving performance variables in the Brunel University Driving Simulator (see Young et al., 2012). We manipulated acuity using blurring spectacles at two levels of blur (Snellen equivalents of 6/12 and 6/18) and compared performance against a control condition at standard acuity (6/6). Nineteen younger participants (aged 25–45, all with normal or corrected-to-normal vision) were required to follow a (simulated) car at a set speed on an inter-urban single-carriageway route. To explore hazard detection and response, participants were faced with two scripted critical events in the mould of our earlier study on automation failure: lead car braking, and either a pedestrian walking out into the road or a car pulling out from a driveway, all of which necessitated a response from the driver in order to avoid a collision. They also had to negotiate three cyclists on the route, to see if safety margin would be affected by acuity. Finally, participants were asked to recall six road signs on the route, shortly after passing them.

The results were mixed as many of the driving performance variables did not show a clear relationship with acuity. But, among the notable findings, the study showed that reduced acuity (at either level) resulted in drivers straying off the road more often. Curiously, brake reaction time to the lead car braking event was significantly slower in the weak blur condition, but the strong blur condition was not statistically different from the control condition. There were also no differences in crashes between the conditions. On the whole, these results were consistent with previous research which suggests static visual acuity has little effect on either crash risk (e.g., Charman, 1997) or driving performance (e.g., Brooks et al., 2005). In particular, Brooks et al. (2005) found no effect of blur on steering performance but, as in this study, they did report that drivers strayed out of their lane more with reduced acuity.

Meanwhile, with each reduction in acuity, drivers more or less doubled the amount of room that they gave to cyclists, probably due to compensatory behaviour. Similar behavioural adaptations have been observed elsewhere, as drivers attempt to increase their safety margins in response to a loss of visual function (Molina et al., 2021). However, such compensation came at a price in our study, with perceived MWL increasing linearly in response to reduced acuity. In other words, drivers experiencing blurred vision had to concentrate harder on the road ahead. Whilst this may be sustainable in the short-term, on a longer drive this could increase the chances of acute fatigue – and hence increase crash risk as drivers struggle to maintain performance (cf. Arnedt et al., 2001).

In terms of sign reading ability, recall performance was at ceiling in the normal condition, but both levels of reduced acuity resulted in fewer road signs being recalled than in the control condition. Thus, anything other than normal visual acuity has a significant impact on drivers' ability to recall road signs. These findings seem to accord with the suggestion that road signs are designed on the basis of much better levels of acuity (e.g., Higgins & Wood, 2005; Owsley & McGwin, 2010). Focal vision is an important aspect in sign reading ability, and is in turn dependent on static visual acuity (Wood et al., 2009). Previous research has found that sign recognition is affected at higher levels of degradation (6/30 acuity – Higgins & Wood, 2005; Higgins et al., 1998). Signs are an important source of information when driving, and missing such information can adversely affect drivers' situation awareness for hazards, as well as potentially causing them not to comply with instructions (such as posted speed limits) – all of which can increase risk on the roads.

But while acuity may be important for reading road signs, many argue that visual acuity alone is not related to various measures of driving performance and safety, such as steering, lanekeeping, or gap acceptance (Brooks et al., 2005; Charman, 1997; Currie et al., 2000; Evans, 2004; Higgins & Wood, 2005; Higgins et al., 1998; Hole, 2007; Owens & Tyrrell, 1999; Owsley & McGwin, 2010; Taylor, 2010; Wood et al., 2009). Some (e.g., Hole, 2007) suggest that detection is more important than identification (i.e., merely being able to see something is the minimum requirement; it is not necessary to know what that object is), the latter only being crucial for reading road signs (cf. Higgins & Wood, 2005; Higgins et al., 1998). But it is one thing to be able to see an object on the road; it is quite another to then do something about it (Taylor, 2010). In any case, visual acuity must be sufficient to allow time for the driver to detect and react to hazards when driving at the posted speed limits (Taylor, 2010). This may explain why some studies do show that acuity is a determinant of hazard detection and avoidance (Brooks et al., 2005; Higgins & Wood, 2005; Higgins et al., 1998).

Moreover, visual acuity is only one aspect of vision. We have so far implicitly been discussing static visual acuity, but there is evidence that dynamic acuity is more closely associated with crash risk (Burg, 1971; Charman, 1997). Besides, there are many other internal and external factors related to vision that also affect performance and safety, such as fog (Owens et al., 2010), darkness, contrast sensitivity and retinal adaptation (Wood & Owens, 2005), glare sensitivity and clinical conditions (such as cataracts; Wood & Troutbeck, 1994; 1995), or – as we have already discussed in this chapter – distractions and eyes-off-road time (Liang et al., 2012; Young, 2012). Finally, field-of-view is often cited as a critical factor in vehicle control, since contrast and movement are better detected in peripheral vision (e.g., Schieber et al., 2009).

There is an argument that peripheral vision plays more of a role in immediate steering corrections (cf. Schieber et al., 2009), whereas longitudinal control might be more dependent on central vision (e.g., Coeckelbergh et al., 2002). This helps to explain why research finds that visual acuity (central vision) affects speed but not lanekeeping performance, while related studies investigating restricted fields of view (i.e., peripheral vision) do show a relationship with steering (e.g., Brooks et al., 2005; Owens & Tyrrell, 1999). In particular, experienced drivers make efficient use of information in the periphery to maintain lane position (Underwood & Everatt, 1996). Wood & Troutbeck (1992) found that a restricted field-of-view had a significant impact on speed, lateral position, reading road signs, hazard detection and gap manoeuvring. Although some of these tasks are arguably dependent on central vision (e.g., reading road signs, hazard detection), interestingly speed estimation – traditionally thought to be served by ambient vision (cf. Schieber et al., 2009) – was not affected by visual field loss.

Field-of-view particularly stands out in the literature as being associated with crash risk, with the consensus of opinion being that field-of-view affects both safety and performance (Brooks et al., 2005; Evans, 2004), with visual field impairments apparently doubling crash risk (CIECA, 1999; Johnson & Keltner, 1983). Typically, it is degradation of the ambient or peripheral visual field (Rogé et al., 2004; Schieber et al., 2009) which predicts driving performance and crash risk (e.g., Ball et al., 2006; Owsley et al., 1998). Others have argued for more refined metrics of field-of-view, such as 'useful field-of-view' (UFOV; e.g., Burridge et al., 2020; Owsley et al., 1998) or peripheral motion detection (Henderson et al., 2010). However, there is a significant body of evidence to show that visual acuity and the UFOV test do not predict all aspects of driving performance (e.g., Owsley et al., 1998; Roenker et al., 2003), and that central cognitive processing plays more of a key role alongside visual perception and decision-making (Ball, 1997; Hole, 2007; Lees & Lee, 2009; Verhaegen, 1995).

Nevertheless, where correlations (albeit weak ones) have been observed between acuity and crashes, they have tended to be based on older drivers (e.g., Burg, 1968; Charman, 1997; Hole, 2007; Owens & Tyrrell, 1999; Owsley et al., 1998). Older drivers are undoubtedly affected by reduced visual acuity (Classen & Alvarez, 2020; Jones & Holden, 2020), peripheral detection (Burridge et al., 2020; Classen & Alvarez, 2020; Costa et al., 2018), contrast sensitivity (Classen & Alvarez, 2020) and visual search at junctions (e.g., DfT, 2009; Schieber et al., 2009). As older drivers are affected by both perceptual and cognitive impairments, we now turn to consider their cognitive performance in more detail.

COGNITIVE IMPAIRMENT: AGEING

If the future of driving is automated, it is also about older drivers. The population is undoubtedly ageing and, with it, people are continuing to drive later in life: the proportion of those over 70 years of age holding UK driving licences increased by about two-thirds in the first couple of decades of the 21st century (Jones & Holden, 2020). It has been established for some time (e.g., IAM, 2010) that the relative and absolute number of drivers over the age of 70 is on a steep upward curve, with expectations that we will soon see 90% of men and 80% of women in that age group holding a driving licence, up from three-quarters of men and only 31% of women in 2010. In absolute terms, the number of drivers over 70 is set to hit 10 million by 2050 (IAM, 2010). Moreover, as the older driving population grows and becomes more mobile, it is anticipated that their mileages will also increase (DfT, 2001).

Before we go any further, though, we should be clear that age affects driving performance at both ends of the scale. It has been repeatedly found (e.g., Evans, 2004; Kim et al., 1998) that younger drivers, especially young males, are involved in more crashes than other driver groups. There is a more modest increase in crash involvement for very old drivers, but the curve is certainly at its steepest during the youngest driving ages. Part of the reason for this is undoubtedly the level of driver skill, although a significant proportion is probably due to differences in behaviour and attitude. Young drivers have been shown to underrate dangerous elements in traffic scenes (Groeger & Chapman, 1996), and are probably motivated to take more risks (Evans, 2004). Very often, driving performance and driving behaviour are two different things, which could explain why crash involvement reaches a plateau around the age of 40. Optimal perceptual-motor performance occurs much earlier than this, but higher-level information processing improves over a number of years. It is therefore easy to speculate that two competing processes – the degradation of perceptual-motor abilities and the development of driving ability – combine to produce the distorted U-shaped curve of crash involvement against age.

Nevertheless, with more older drivers, driving more miles, and for more years (PACTS, 2007), the potential impact on road safety in future is significant. Although there is some debate over the prevalence of older drivers in road collision statistics, it is widely agreed that, on a mile-for-mile basis, drivers over 70 are at increased risk of fatal crashes (e.g., McGwin & Brown, 1999; Pampel et al., 2019) and at-fault collisions – with the data being comparable to those for the under-25 age group (e.g., DfT, 2009; Evans, 2004; Groeger, 2000; Hole, 2007; Lees & Lee, 2009; McGwin & Brown, 1999; McGwin et al., 1998). Casualty rates per mile driven increase with age after 70–75 years (Eberhard, 2008), and the risk increases exponentially for drivers in their 80s (DfT, 2009; Evans, 2004; Hole, 2007).

When the types of collisions are analysed, though, it is clear that older drivers differ from younger groups in that their collisions are less about taking risks, but more about errors of perception or judgement (DfT, 2009; Evans, 2004; Hole, 2007; McGwin & Brown, 1999). Rather than single-vehicle collisions involving speed, alcohol or fatigue, older drivers have multiple-vehicle collisions at junctions involving giving way, or when turning or changing lanes. In terms of driving tasks, negotiating junctions and merging traffic are both known to cause particular difficulties. These difficulties tend to be due to deficits in 'bottom-up' visual and cognitive processing, as opposed to 'top-down' failures of experience or expertise (Lees & Lee, 2009), factors which are consistent with the notion of age-related declines in cognitive functioning (Verhaegen, 1995), '…such as attention, anticipation, executive functioning and information processing [which mean] that older drivers tend to have difficulty in dealing with complex traffic situations and reduced capacity to respond quickly and flexibly to changing traffic situations' (PACTS, 2007; p. 45). There is a wide body of scientific evidence to suggest that these declines can be a source of increased crash risk on the roads (e.g., Brouwer et al., 1991; Lundberg, 2003; Verhaegen, 1995).

The literature on driving performance and cognitive functioning typically finds that decrements begin around the ages of 60–65 years (Brouwer et al., 1991; Evans, 2004; Reid & Green, 1999; Stelmach & Nahom, 1992; Verwey, 2000). Whilst this is slightly earlier than the apparent 70-year-old threshold for crash risk in the research reviewed above, it may be that some of this decline is offset by experience (Evans, 2004; Stamatiadis & Deacon, 1995) or automaticity in cognitive processing, which is believed to be resilient to the effects of ageing (Conway & Engle, 1994; Rogers & Fisk, 1991). Nevertheless, as age increases beyond 65 years, cognitive fitness to drive becomes more important in determining driving competence (Brouwer & Ponds, 1994).

Age thus brings with it a range of declining cognitive abilities that can have a detrimental effect on driving performance and MWL, including memory, spatial cognition, alertness, information processing speed, decision-making, reaction time, selective and divided attention, and executive function (see e.g., Adrian et al., 2019; Brouwer et al., 1991; Burridge et al., 2020; Classen & Alvarez, 2020; Evans, 2004; Groeger, 2000; Jones & Holden, 2020; Lundberg, 2003; Owsley et al., 1998; Pampel et al., 2019; Ranney, 1994; Schlegel, 1993; Verhaegen, 1995; Wright et al., 2018; Young & Stanton, 2007a).

From our earlier foundation work to establish malleable attentional resources theory (MART; see Chapter 3 and Young & Stanton, 2002a), we know that age affects attentional capacity. Attention and executive function have both been implicated as predictors of driving performance (Adrian et al., 2019; Brouwer et al., 1991; Owsley et al., 1998), with older drivers being more susceptible to errors under conditions of high MWL (Groeger, 2000; Hole, 2007). Various studies (e.g., Bunce et al., 2012; Tsimhoni & Green, 1999) have demonstrated that older drivers experience higher MWL associated with driving in a range of scenarios. This is consistent with the attentional resource models we have discussed throughout this book so far (e.g., Kahneman, 1973), which suggest that attentional capacity declines with age, impairing the ability to deal with unexpected events on the road. For older drivers in particular, then, highly demanding driving situations can reduce spare capacity and lead to competition for attentional resources. In turn, resource competition can result in performance degradation and errors. This has been shown to affect older drivers, who are less able than their younger counterparts to integrate their responses on a dual task competing for the same attentional resources (Brouwer et al., 1991).

To examine reaction times as another example, there is good evidence that it is actually an increased variability, or inconsistency, of reaction times that is particularly associated with older age, rather than accuracy or mean reaction time, which are less sensitive measures (e.g., Bunce et al., 2012; Young & Bunce, 2011). These have parallels with the metrics of consistency for driving performance (Bloomfield & Carroll, 1996) successfully adopted in our laboratory (see Young & Stanton, 2002b; 2007c; and the chapters in Stage 2 of this book), which can distinguish good from poor drivers (Young & Stanton, 2007c). We have previously argued that such variables are more appropriate indicators of driving performance than measures of mean or standard deviation, in line with best practice for safe driving which suggests that smoothness and consistency is key (Young, Birrell & Stanton, 2011). Indeed, pilot studies in the Brunel University Driving Simulator indicated that, in comparison to a younger group, older adults exhibited higher inconsistency on a neuropsychological test battery as well as higher inconsistency on these driving performance metrics (Young & Bunce, 2011).

Bunce et al. (2012) explored this notion by assessing age differences in driving inconsistency in younger (mean age 21 years) and older (mean age 71 years) drivers alongside their responses to a standardised cognitive test battery. Participants drove the Brunel University Driving Simulator in Residential, Urban and Highway conditions. For both longitudinal (headway) and lateral control, older drivers exhibited significantly greater performance inconsistency, particularly in the Highway condition. Meanwhile, their performance was also more variable on the cognitive tasks, and many of the cognitive variability measures were significantly associated with the simulator variables, suggesting that similar cognitive processes may support the respective tasks. Their analyses suggested that some of the variability in driving performance is accounted for by variability in cognitive performance, and they attributed the greater variability in both cognitive and driving measures to age-related increases in attentional and executive control fluctuations. In other words, the cognitive changes associated with normal ageing could, in part, be responsible for greater inconsistency in driving performance which, in turn, may compromise safe driving (cf. Young, Birrell & Stanton, 2011).

Currently, we rely on self-regulation (cf. Evans, 2004) to control these risks – either expecting older drivers to declare for themselves when they are unfit to drive, or alternatively many choose to adapt their behaviours to cope by restricting themselves to roads on which they feel safe and comfortable (Groeger, 2000; Haddad & Musselwhite, 2007; Hole, 2007; Pampel et al., 2019). Anecdotally, drivers report taking less complex routes (even if this means driving further), avoiding difficult road junctions and avoiding night-time driving. But the evidence suggests this does not always work – many drivers are not aware of (or do not recognise) their own limitations (Groeger, 2000; Hole, 2007), and either do not cease driving early enough, or conversely, cease driving too soon (Berry, 2011). 'Because of [a] lack of information, feedback, and insight, elderly drivers are not, I believe, in a good position to determine for themselves when they should reduce or cease driving' (Groeger, 2000; p. 171).

Nevertheless, in an enlightened society, we have a responsibility to meet the mobility needs of older adults (Ball, 1997). It is no good to say that they should simply restrict their driving habits or even stop driving altogether, for this curtails their freedom, with a huge impact on their mental wellbeing. Wellbeing in older people depends to a large extent on their ability to successfully engage with various practical and recreational activities in daily life (Menec & Chipperfield, 1997). In turn, many of these activities are dependent on being able to drive. Independent mobility is therefore a significant marker of quality of life in ageing – driving enables older adults to 'keep on living' independently and maintain their quality of life (Box et al., 2010; Gilhooly et al., 2002).

Thus, the rise in the ageing driver population presents society with a significant challenge – how to maintain safety *and* mobility on the roads. The aim is to prolong independence, rather than try to remove older drivers from their cars. This so-called 'older driver problem' (cf. Evans, 2004) requires a solution which not only supports older drivers, but also balances their needs with road safety targets to continue reducing the number of killed and seriously injured on the roads.

One such solution would be to compensate for the cognitive limitations of older drivers by making '…changes to the driving environment to make driving safer for the older person, both inside the car in terms of design factors, and perhaps advanced driving information systems, but also outside in terms of traffic system design' (DfT, 2001; p. 5). Both academic (e.g., Haddad & Musselwhite, 2007; Lees & Lee, 2009) and policy reports (e.g., Box et al., 2010; DfT, 2001; IAM, 2010; PACTS, 2007) have suggested that this should exploit vehicle design and safety technology innovations inside the car, underpinned by a sound understanding of the older driver's cognitive abilities and information requirements. 'There is a very clear need for such research addressing appropriate technology to aid safe car driving behaviour amongst the older driver population' (Haddad & Musselwhite, 2007). In that respect, we can turn to current and near future automation, which might have the potential to compensate not just for the specific cognitive decrements associated with ageing, but also the other transient and perceptual impairments related to driving that we have discussed in this chapter.

AUTOMATION LENDS A HAND

With a better understanding of the nature of these impairments, then, we can start to think about whether, how and which driving automation systems might compensate for such. Candidate systems include speed limit displays, vision enhancement, parking assist, blind spot monitoring, adaptive cruise control (ACC), lane centring (LC), forward collision warning, or automatic emergency braking (AEB). For the avoidance of doubt, we repeat the caveat that this is not about justifying impaired driving on the basis that automation provides a fallback. But there will always inevitably be times when drivers suffer from one of these impairments, so we should be aiming to make the system as safe as possible. If automation can play a part in that, then we should absolutely seek to exploit it (Stanton & Salmon, 2009).

Following the order in which the research was reviewed above, let us start by thinking about distractions. On the whole, the research we reviewed found some overlap but also some differences in the effects of in-car versus external distractors. In-car distractors primarily affected responses in critical situations, while the main effects of external distractors were on visual attention patterns, steering performance, and road sign recall. Meanwhile, both types of distractor increased driver MWL.

We will treat these effects together with respect to the role of automation in mitigating the impact of distractions on driving, and there are two elements to consider: detecting and warning about the distraction, or intervening to prevent it becoming a problem. For the former, and given the effects of external distractors on visual attention found in our study (Young et al., 2009), there is a good case for head or eye tracking systems to monitor whether drivers might be distracted. Such driver attention monitoring systems are becoming increasingly popular and, whilst the focus of many of these is primarily on fatigue, they can equally provide alerts for a driver whose attention might not be entirely on the driving task. With the appropriate algorithms, an eye-tracking system could make a reasonable guess at the driver's attention patterns, knowing where they are looking and, perhaps, what they are attending to. It could then provide visual, auditory, or haptic warnings if the driver's gaze is diverted from the primary attention zone for too long (more than 2 seconds, going by the NHTSA criterion).

Indeed, some studies have tested automation interfaces that provide prompts or warnings based on eye-tracking in an effort to maintain the driver's attention on the driving task (e.g., Victor et al., 2018). Based on the findings that responses to critical situations were impaired when distracted, an obvious role for automation in this case would be a form of collision detection or avoidance, such as pedestrian detection, forward collision warning, or AEB. Putting these two ideas together, Smith et al. (2009) described an adaptive collision warning system that monitors the driver's head position and adapts its warnings depending on whether the driver is watching the road or not. In other words, if it detects the driver is distracted, it could try to attract their attention by either presenting the collision warning earlier, in a different location, or through a different modality. On the other hand, for an attentive driver, the system would attenuate its warnings so as not to cause annoyance or frustration (or, worse, an additional distraction).

Taking this a step further, driver attention state monitoring could be fed into an adaptive interface in order to manage workload and distractions on the driver. Discussed further in Chapter 9, adaptive automation adjusts the level of automated support or information provided to maintain driver MWL at optimal levels and prevent them from becoming overloaded. As well as eye-tracking, workload might be derived from driver behaviour (steering, acceleration, and braking inputs) or environmental context (such as satnav data). Such systems have shown promise in the driving domain (e.g., Donmez et al., 2007; Piechulla et al., 2003), with systems that can postpone or suppress low-priority messages or telephone calls if driver workload is deemed to be too high (e.g., Broström et al., 2006).

To address the observed effects of distraction on steering and MWL, there is an argument for just automating lateral support through lane-keeping assist or lane centring systems. Our research (Chapter 4; see also Young & Stanton, 2002b) has shown that such systems can both reduce driver workload while (in the simulator, at least) offering more consistent performance than the human. However, any automated support to mitigate in-car distractions must be tempered with the caution that things might not go so well if and when the driver has to take over control. We know from Chapter 7 that automation can have adverse effects on drivers' responses in critical situations. We also know from the research reviewed in this chapter that similar problems arise with distracted drivers, even if they are trying to adapt their driving to cope. And we know that drivers using automation are likely to engage in non-driving (distractor) tasks. So offering up automation to offset the effects of distraction might, instead, create a perfect storm in the event of an emergency.

A more moderate approach picks up on one of the specific concerns with external distractors, that of recalling road signs. Many cars are now fitted with road sign recognition cameras that show a repeater of the sign in the instrument cluster or on a head-up display. These could help to maintain situation awareness, especially as road signs are transient by their nature – once the driver has gone past them, their information is lost. Moreover, such displays would also serve drivers with foveal acuity issues, as well as relieving the visual accommodation problems particularly faced by older adults.

Other systems that can compensate for low acuity or similar visual impairments include parking aids, lane departure warning systems and vision enhancement (Classen & Alvarez, 2020). Again, though, we must caution about potential behavioural adaptation with vision enhancement systems, as drivers have been shown to drive at higher speeds when using them (see Stanton & Pinto, 2001). With these kinds of perceptual enhancement systems in mind, the particular visual demands of driving call for the exploitation of other sensory modalities and even multimodal displays, which can offer enhanced feedback whilst avoiding distraction or overload for the older driver (cf. Spence & Ho, 2009). At an even more fundamental level, if – as some have been calling for – driver eyesight testing is made more stringent, then we might see more people being restricted from driving and, hence, a greater need for driving automation so that they may maintain their independent mobility. This echoes the 'older driver problem'.

Before we turn the focus towards automation for older drivers, though, it is worth pointing out that it is not just the older age bracket or those with overt disabilities who may benefit from automated driving systems. Classen & Alvarez (2020) discussed the cognitive difficulties faced by younger drivers on the autistic spectrum, such as errors in steering or braking associated with difficulties in problem-solving or focused attention. Systems such as lane centring or intelligent speed adaptation (which helps drivers comply with speed limits) may help with these difficulties. Automation can certainly help to improve the situation awareness of those with low spatial ability to bring them on a par with others of high spatial ability (Wright et al., 2018).

Similarly, Lees & Lee (2009) suggested that emerging vehicle technologies can be exploited to enhance the safety of older and younger drivers, by tailoring such systems to support bottom-up or top-down processing respectively (i.e., to compensate for the perceptual or cognitive limitations associated with older age, as opposed to the lack of experience in younger drivers). Previous research on younger drivers supports this, indicating that automated driving systems can bring some improvements to driving performance (Nilsson, 1995; Young & Stanton, 2004), while European projects such as PReVENT and EDDIT (Oxley & Mitchell, 1995) have explored the potential for extending these findings for the specific needs of older drivers.

But it is in later life where we really feel that driving automation can have a positive impact. Automated driving and other driver assistance systems can potentially compensate for the decline in cognitive abilities with ageing (Burridge et al., 2020; Classen & Alvarez, 2020; Haddad & Musselwhite, 2007; Jones & Holden, 2020; PACTS, 2007) with multiple benefits for those older drivers whose driving is affected by cognitive impairment. As well as improving road safety for older drivers, automation can support their independent mobility needs (Classen & Alvarez, 2020; Hancock et al., 2019; Young & Bunce, 2011). We discussed earlier how older drivers tend to restrict their driving to familiar roads by way of compensating for their abilities (Groeger, 2000; Haddad & Musselwhite, 2007; Hole, 2007; Pampel et al., 2019); automation could therefore help this group to re-extend their mobility to areas that they were otherwise less comfortable with (cf. Burridge et al., 2020; Hartwich et al., 2018). Moreover, since older people are less likely to use public transport for non-urgent travel, such independent mobility provides access to leisure, activity and social connection that is crucial in underpinning wellbeing, quality of life and even mortality (Burridge et al., 2020; Hartwich et al., 2018; Jones & Holden, 2020). As impairment increases, so too could the level of automation to compensate (Gaspar, 2020). In doing so, the very highest levels of automation (level 4 or level 5) may mean that these groups can still travel independently without needing to hold a driving licence (Grier, 2020). This does bring a potential issue, though, if automation becomes a condition for older people to retain a driving licence, since the capability of automation itself may be limited on the less uniform rural roads frequented by older drivers (Jones & Holden, 2020).

So how can automation help older drivers? We have seen how reaction times and associated metrics of driving performance become less consistent with ageing (Bunce et al., 2012; Young & Bunce, 2011). Systems such as adaptive cruise control or lane centring could actually help to maintain consistency in vehicle control – in our studies reported in earlier chapters of this book, we hardly ever examined differences in performance data between manual and automated control, because the automation was invariably more consistent than the human. However, age-related impairments associated with reaction times (Bunce et al., 2012; Evans, 2004; Groeger, 2000; Jones & Holden, 2020; Pampel et al., 2019; Young & Bunce, 2011; Young & Stanton, 2007a) may make older drivers especially susceptible to the key problem of resuming manual control (cf. Classen & Alvarez, 2020). Nevertheless, one study found no differences in takeover times between younger and older age groups (see de Winter et al., 2014).

Picking up on the core theme of this book, the same systems could help to manage the MWL of older drivers. Whereas throughout this book and our research (e.g., Young & Stanton, 2007c) we have been concerned with the effects of mental underload thanks to the reduction in workload brought about by automation, if we think about the inverted-U curve of workload against performance (refer back to Figure 3.2), such a reduction could be advantageous for older drivers if their starting point is higher up on the curve, in the overload region (as observed in the study by Bunce et al., 2012). Whilst older drivers have more driving experience, they also have less spare attentional capacity (cf. Kahneman, 1973). This gives rise to concerns about information overload, with the implication that older drivers would benefit more from automated driving systems that assume some elements of vehicle control, rather than in-vehicle information systems which provide feedback and warnings. For example, one study (Pampel et al., 2019) found that a head-up navigation display improved performance for older drivers to put them more on a par with a younger group, albeit at the expense of increased MWL. As we have seen, adaptive cruise control and especially lane centring could help to reduce the demands of challenging driving situations. Early work in the DRIVAGE project (e.g., Fraser et al., 1994; Harvey et al., 1995) set out to evaluate the driving abilities of older people, and to examine the potential benefits and distractions of providing additional information to the driver. Meanwhile, adaptive automation could equally (if not more so) apply to older drivers, perhaps with some tweaks to the workload algorithm in order to account for differences in attentional capacity (cf. Kahneman, 1973).

There is clearly great potential for automation to support the independent mobility of older drivers. Nevertheless, it is probably fair to say that few – if any – of these systems have been designed with older drivers in mind, being very much a result of technology ‘push’ rather than user ‘pull’, so their benefits may be limited. Participatory research has highlighted that the theoretical opportunity for technology to assist with the specific limitations of older drivers could not always be accessed by the older driver group for a variety of reasons, including poor user interface design and technology immaturity (Keith et al., 2007). Some of the extant issues with automation that we have discussed earlier in this book may especially affect older drivers, whose requirements need to be taken into account with respect to issues such as trust, acceptability, perceived utility and concerns over complexity or distraction (see Burridge et al., 2020; Hartwich et al., 2018). More research is necessary to develop technologies and interfaces which are acceptable and accessible to the older driver population (see Stanton et al., 2021, for an example of the ‘design for all’ approach). The design of automated driving systems should therefore be matched not only to the cognitive abilities of older drivers, but also to their needs and wants (Bunce et al., 2012).

One project explored this very issue, and reported that most new in-car technologies have so far ignored older drivers' needs (Haddad & Musselwhite, 2007). Again using participatory methods, older drivers identified systems that provided enhanced feedback as having potential to assist their driving. Interestingly, another study (Hartwich et al., 2018) showed that older drivers wanted automated driving systems to exhibit faster driving styles than they themselves used, by way of regaining some of the freedom that they had lost, in contrast to younger drivers who preferred the automation driving style to be more consistent with their own. However, these approaches could exacerbate problems of high MWL with older drivers (Groeger, 2000; Hole, 2007). In particular, the diminished capacities of older drivers could render them more susceptible to overload with poorly designed assistance (cf. Harvey et al., 1995; Lundberg, 2003), although Horberry et al. (2006) found that older drivers were no more susceptible to distraction from in-car systems than younger drivers.

To resolve these issues, a user-centred approach to designing automated driving interfaces is needed. As a general rule, in-vehicle interfaces should be designed to minimise distraction and information overload, and thus must be sensitive to individual differences in drivers as well as different driving contexts. A UK government report (PACTS, 2007) noted that whilst in-car systems could help older drivers, their interface design and the limitations of divided attention might cancel out such benefits. Research suggests (e.g., Keith et al., 2007) that technological assistance inside the car will only be of benefit if it has been designed from a user-centred perspective. As Waller (1996) noted, the extent to which '…new technology could assist [older drivers] is not known. Nevertheless, if new technology is designed, taking into account the abilities and limitations of older users, it holds promise of extending the self-sufficiency of many elderly drivers' (p. 24). In the next chapter, then, we consider user-centred design of automated driving interfaces in depth.

KEY POINTS

- Limitations in human performance can have an adverse impact on driving under various circumstances, from short-term distractions to longer-term impairments in perceptual and cognitive ability.
- Research in our laboratory and elsewhere has explored these limitations, showing detrimental effects on driving performance associated with mobile phones, eating, and drinking, roadside advertising, reduced visual acuity and ageing.
- Automation offers the potential to compensate for many of these limitations, extending independent mobility and improving quality of life for many people.

- However, we need to be cautious not to abuse the technology and encourage people to deliberately drive while impaired, relying on the automation to protect them.
- Moreover, automation itself can cause (or encourage) distractions, either from its own interface design or through people taking advantage of the reduced demands to engage in other, non-driving tasks.

NOTES

1. It really is worth taking a moment to view the footage of Professor John Senders demonstrating this research at https://www.youtube.com/watch?v=kOguslSPpqo (accessed 4 February 2022).
2. https://www.federalregister.gov/documents/2013/04/26/2013-09883/visual-manual-nhtsa-driver-distraction-guidelines-for-in-vehicle-electronic-devices (accessed 4 February 2022).

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Chapter 9

How do we get along?

OVERVIEW

Having considered in the previous chapter some areas where driving automation can help compensate for human performance, we now focus on how it might best achieve that. The interface between human and automation is crucial to ensure the benefits are maximised while avoiding any negative impacts for driver workload or distraction, and we argue a user-centred approach to interface design is essential. In some respects, the design principles for a driver-automation interface reflect those for any other interface, but there are also some particular considerations specific to automation. This chapter reviews generic design principles before focusing on the ecological interface design approach via a detailed case study about the development of an eco-driving interface. From there, we consider how such interfaces might be adaptive to the situation, typically in response to the mental workload being faced by the driver. That takes us into a discussion of adaptive automation in its own right, followed by a brief summary of related developments in driver monitoring technologies that might feed the adaptation algorithms. The chapter concludes with some views on how these issues might fit in with the near- and long-term future of driving automation.

INTRODUCTION

In Chapter 8, we examined the role of automation in managing, among other impairments, the various distractions that drivers face. These, of course, include the potential distraction from information and assistance systems inside the car, with the interface to any automation being no exception. Notwithstanding the claim (which we have cited elsewhere in this book) that drivers might have up to 50% spare attentional capacity when driving (Hughes & Cole, 1986), the proliferation of technology in the modern automobile (whether part of the original equipment or nomadic devices imported by the driver) could very quickly consume that capacity if not properly managed (Parnell et al., 2018). Indeed, as we already noted in Chapter 2, the complexity of technology in the

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modern automobile has been used as a justification for automation to support human operators in dealing with it (Cuevas et al., 2007).

So, although we have spent a good portion of this book addressing the effects of automation on underload, many authors have also expressed their concerns about the other end of the spectrum, with potential adverse effects of distraction or overload arising from the need to deal with myriad additional information sources in the car (Donmez et al., 2007; Harbluk et al., 2007; Horberry et al., 2006; Regan et al., 2009).

Legislation (such as the banning of mobile phones) may help to tackle the symptoms of the problem, but to treat the cause, in-car devices should be designed according to robust ergonomics principles to ensure positive benefits are gained while negative impacts on workload or distraction are avoided. Indeed, codes of practice for the design and development of such systems are available (e.g., Amditis et al., 2010; Cotter et al., 2006; van Driel et al., 2002). We concluded Chapter 8 with a call for a user-centred design approach particularly with older drivers in mind, but the approach would doubtless benefit all drivers. In this chapter, then, we consider what that might look like by first reviewing good human factors practice in interface design, focusing on one particularly promising approach to user-centred displays. Towards the end of the chapter, we also consider the literal human-machine interface (i.e., the boundary between the driver and the automation) in discussing aspects of adaptive interfaces and driver monitoring.

IN-VEHICLE INTERFACE DESIGN

In-vehicle interfaces should be designed to support the driver's situation awareness, their mental models of system operation, their attention allocation and, of course, their performance (Endsley, 2017; Kaber et al., 2001; Seong & Bisantz, 2008; Seppelt & Victor, 2016). However, any such interface inevitably faces a trade-off between providing a richness of information to achieve that, while not overloading or distracting the driver. It must, therefore, be designed for ease of perception (Franke et al., 2016) with the primary (driving) task in mind so as to support and, above all, preserve driving performance. Since driving is a predominantly visual task (Kramer & Rohr, 1982), any competition for the limited visual resources of driving could cause distraction (e.g., Donmez et al., 2007). The interface should therefore be designed to reduce visual demand by improving the availability of information, compatible with the short glances used by drivers (cf. Dingus et al., 1989). The NHTSA guidance[1] referred to in Chapter 8 not only recommends that devices be designed such that drivers do not have to glance away from the road for more than 2 seconds at a time, but also that the total eyes-off-road time for completing a task (to be clear, that is the total across multiple glances) should not exceed 12 seconds. Even the positioning of the interface matters – that is, whether it is in the driver's central or peripheral visual field

(Franke et al., 2016) – as the further it is away from the primary field-of-view, the more it will affect the driver's ability to detect trouble on the road ahead (Costa et al., 2018). This is where head-up displays have a big advantage, particularly for older drivers (Pampel et al., 2019).

As an alternative to competing for the intensively-used visual attention channel, it may be worth considering multimodal displays (cf. Spence & Ho, 2009) to exploit the untapped resources of auditory or haptic attention (see Campbell et al., 2020, for a discussion of the relative merits). Under the multiple attentional resources model that (seeing as you have got this far in the book) we know so well now (Wickens, 2002), presenting information via other sensory modalities may reduce any excess demands on visual resources (Van Erp, 2001), leaving more for the primary task of driving and, thereby, theoretically improving performance (McIlroy & Stanton, 2015). Moreover, multimodal feedback is better for capturing attention and leads to faster responses (Mueller et al., 2020; Ulahannan et al., 2020), especially if the visual channel is overloaded (Lee & Seppelt, 2012).

The auditory modality is the most obvious choice for delivering warnings when visual workload is high, particularly when speed of response is critical as in driving (cf. Edworthy & Stanton, 1995; Wickens, 1984). These may take the form of auditory icons, earcons, or speech warnings. Auditory icons have been defined as naturally occurring sounds that can convey information about system events by analogy with everyday events (Gaver, 1986; 1989). In the driving domain these may include sounds such as sirens, horns, engine noise, or rumble strips. Since they convey familiar meaning to drivers, auditory icons should be easier to learn (Gaver, 1986). Earcons, on the other hand, are abstract tones that designate a particular meaning through a learned association (e.g., Brewster et al., 1993; Graham, 1999), such as the email alert on phones or computers. Earcons are the most common type of auditory warning used by vehicle manufacturers. Finally, speech messages do not need to be learned due to their verbal nature, and no inference is required. Whilst response accuracy to speech messages may therefore be greater than non-speech warnings, reaction times can be slower in emergency situations (Graham, 1999). This is because speech signals, even when only one or two words in length, take a relatively long time to present and interpret, as the user has to wait for most of the message to be delivered (Graham, 1999; Patterson, 1982). Thus a key benefit of auditory over speech icons is that their information can be processed more effectively, especially at times of high workload (Bliss & Kilpatrick, 2000). Graham (1999) assessed the use of auditory icons against more conventional warnings for a vehicle collision avoidance system, and found that the auditory icon warning produced significantly faster brake reaction times. So although users generally prefer speech icons over earcons and auditory icons, we cannot design systems just on users' preferences (e.g., Jones & Furner, 1989; Lucas, 1994) and need to consider the effects on performance. Meanwhile, there is considerable evidence that haptic interfaces impose significantly fewer demands than visual or auditory displays – and, indeed, that haptic feedback can to some extent be automatically processed (Gustafson-Pearce, 2007; Sklar & Sarter, 1999; Van Erp & Van Veen, 2004).

When we talk about multimodal interfaces, though, we generally mean the presentation of redundant information simultaneously via multiple channels, rather than considering them as alternatives. But this does not mean just using multimodal feedback for the sake of it; if the visual display is already effective, then additional auditory information can just be distracting noise (Dunn et al., 2020). The point is to make the most of the relative advantages of each modality. Where a visual interface can display persistent status information, auditory or haptic warnings are more effective for conveying a change in status (Mueller et al., 2020). It may therefore be better to use non-visual feedback to signal mode changes when the visual channel is already overloaded (Sarter & Woods, 1995). Moreover, research has shown that supplementing visual information with an auditory alert improves performance in a high workload takeover situation with automated vehicles (Dunn et al., 2020). Clearly, then, there is particular potential for visual distraction during automation takeover, since any alert will require some attention on it rather than the road during the handover (Large et al., 2018).

When it comes to automated driving interfaces, though, many have criticised the lack of guidance (Campbell et al., 2020; Large et al., 2018) and testing (Mueller et al., 2020). Current good practice and standards in interface design are largely focused on manual driving, but it has been argued that these are not applicable to interfaces for automated driving and so need to be extended to consider such (CIEHF, 2020b; Ulahannan et al., 2020). Clearly, some of the high-level principles would stand: the interface needs to support mental models and situation awareness of the automation mode and states, especially in takeover situations (Kaber et al., 2001; Seppelt & Victor, 2016), while not presenting so much information that it cognitively overloads the driver (Ulahannan et al., 2020).

Take adaptive cruise control (ACC) or lane centring (LC) as examples, seeing as we have focused on these systems a lot in this book. Drivers need to know how they function, the limits of their sensors and control, otherwise safety could be compromised (Seppelt & Lee, 2007). Yet these are precisely the nuances that people struggle to understand, such as when ACC loses a target vehicle ahead (Mueller et al., 2020). This may be a simple matter of paucity of feedback, one of the classic problems of automation we discussed in Chapter 2; we have heard anecdotal evidence of current level 2 systems being very prompt in chastising the driver for not playing their part (such as keeping their hands on the steering wheel as required), but being decidedly less forthcoming if the system itself is struggling (such as the sensors losing detection of lane markings). A visual display providing continuous information about the ACC functionality can improve situation awareness (de Winter et al., 2014).

For automation in particular, then, the interface needs to support the driver's understanding of the system's behaviour as well as its operational limits (Kaber et al., 2001; Ulahannan et al., 2020). Automation interfaces should integrate the presentation of information to support direct perception of the performance of the automation (Cuevas et al., 2007). It is therefore important to design interfaces that convey the state and the intentions of vehicle, making it easier to understand and more acceptable (Pampel et al., 2020). Where this does not occur and the interface is opaque, it has led to problems with mode awareness (Sarter & Woods, 1995). On the other hand, many have called for transparency in interface design to facilitate mental models, understandability and situation awareness – essentially offering a window on the inner workings of system (CIEHF, 2020b; Kaber et al., 2001). Transparent interfaces convey the system's limits (Banks & Stanton, 2016) and also influence appropriate trust in the automation (Gustavsson et al., 2018; Lee & See, 2004).

ECOLOGICAL INTERFACE DESIGN

One way of achieving this transparency would be to apply principles of ecological interface design (EID; Burns & Hajdukiewicz, 2004; McIlroy & Stanton, 2015; Vicente, 2002), which is in turn based on the foundation of cognitive work analysis (CWA; Vicente, 1999). CWA is a structured framework for considering the driver's information requirements, taking account of the environment within which the task takes place and the effects of constraints imposed on the system's ability to perform its purpose (Stanton, Salmon, Walker & Jenkins et al., 2017). By representing these constraints in a graphical format for direct perception, performance is improved and workload is reduced over conventional displays which require the user to integrate information in their heads (Davidsson et al., 2009; Hajdukiewicz & Vicente, 2004; Hoff, 2004; Sanderson et al., 2003). Instead, an EID display integrates the information for the user (Lee & Seppelt, 2012; Metzger & Parasuraman, 2005), therefore potentially improving performance at no cost to workload.

EID is based on the ecological psychology paradigm (cf. Gibson, 1979), exploiting the precept that we directly perceive invariants in the world, rather than indirectly through mental representations – meaning that, for interface design, we must study what is actually in the world (Hoff, 2004). It was developed to reflect the complexity of automated process control systems in an organised way, so that operators could visualise that complexity, make associations and meaningfully chunk the information, thus reducing processing demands and facilitating skill development (Borst et al., 2015). As such, EID does not oversimplify the system nor is it necessarily about intuitive displays, but what it does do is show the boundaries of the system so that operators can exploit its performance without crossing its safety limits (Borst et al., 2015). For automated driving systems, EID could keep drivers in the loop (Seppelt & Victor, 2016) and improve performance even at high levels of automation, by providing more transparency on what the system is 'seeing' and who is in control (Li & Burns, 2017).

Within the scientific literature a number of studies have used EID for driving automation; for instance, a lateral collision warning system (Jenkins et al., 2007), lane change manoeuvres (Lee et al., 2006; Stoner et al., 2003), intelligent transport systems (Salmon et al., 2007) and ACC (Seppelt & Lee, 2007). Seppelt & Lee (2007) used EID to visually and dynamically represent the behaviour and limits of ACC. Key variables to be shown on the display were derived from the CWA: headway, time-to-contact and relative velocity, making explicit the subtle cues of lead vehicle braking to provide drivers with better mental models and ensure their appropriate response when the braking limits were exceeded. Their simulator study showed EID resulted in better understanding of the ACC's capabilities, leading to more appropriate reliance on the ACC in failure situations, with better braking responses, longer time headways and fewer collisions. The EID even helped drivers' awareness of headway and car following behaviour in manual driving. Seppelt & Lee (2007) concluded that the continuous display of automation state was better than just providing warnings when it fails, especially as ACC failures tend to be subtle, and at no costs to workload or distraction, as the EID reduced the demands of monitoring the lead vehicle.

In our own laboratory, Young & Birrell (2012) described the development of an EID display for 'Foot-LITE', a driver performance monitoring system which provides feedback on driving style to encourage both safe and eco-driving. We will detail that system shortly, but first, in order to set the context, a brief foray into what we mean by eco-driving.

EID FOR ECO-DRIVING

Until relatively recently, the key focus of human factors research in transportation has – quite properly – been to enhance road safety. However, road transport is also a significant environmental concern, producing nearly one-quarter of the UK's total greenhouse gas emissions in 2019 (DfT, 2021). While there is a welcome trend towards low-emission vehicles (i.e., electric or hybrid cars), there will still be petrol or diesel cars – not to mention commercial and heavy goods vehicles – on the road for several years yet (even after the UK bans the sale of internal combustion engine cars and vans in 2030, there will remain many extant petrol and diesel vehicles on the roads). In the meantime, drivers can turn to eco-driving practices to both save fuel and help save the planet (McIlroy & Stanton, 2017).

Eco-driving describes a driving style which results in an increase in fuel economy, such as keeping engine speeds down, anticipating traffic flows to avoid stopping, adopting more moderate and consistent speeds, and avoiding harsh acceleration or braking (cf. Ericsson, 2001; Johansson et al., 2003; Pampel et al., 2015; Pampel et al., 2018; Pampel et al., 2020). Although the effects of eco-driving are relatively small when compared to longer-term strategies such as infrastructure or technological change, studies suggest that it can reduce fuel consumption by up to 15% (af Wåhlberg, 2002; 2007; Pampel et al., 2015; van der Voort et al., 2001; Waters & Laker, 1980). Broadly speaking, the techniques and behaviours that contribute to eco-driving also contribute to safe driving (af Wåhlberg, 2006; Haworth & Symmons, 2001; Hedges & Moss, 1996); a driving style that balances these priorities has been termed 'smart' driving (Young, Birrell & Stanton, 2011).

Encouraging smart driving techniques is easier said than done, though. People do seem to have an instinctive idea of how to drive economically (Pampel et al., 2017), so simply telling them to drive more economically can lead to some small reductions in fuel use (Pampel et al., 2015; Pampel et al., 2018). Training may have a positive effect (e.g., Haworth & Symmons, 2001), but maintaining an eco-driving style can be demanding if it is not habitual for the driver so, without ongoing feedback, the effects are often short-lived (af Wåhlberg, 2007; Johansson et al., 2003; Pampel et al., 2018). Using in-vehicle support systems to provide that real-time feedback can not only help sustain these changes in behaviour, but also enhance the reductions in fuel use (McIlroy et al., 2017; Pampel et al., 2014; Pampel et al., 2015; Pampel et al., 2018; van der Voort et al., 2001; Young, Birrell & Stanton, 2011). Various studies have shown that providing in-vehicle advice and feedback to help drivers anticipate traffic flows and adjust their speeds accordingly can lead to significant reductions in fuel use (e.g., Brookhuis et al., 2009; van der Voort et al., 2001; van Driel et al., 2007; Widodo et al., 2000). A system such as Foot-LITE could, therefore, provide real-time smart driving feedback to improve both safety and efficiency (Young & Birrell, 2011).

A number of vehicle manufacturers have already offered interfaces which provide eco-driving feedback to the driver, while a variety of smartphone apps and satnav options for eco-driving assistance have also emerged (e.g., Ericsson et al., 2006; van der Voort et al., 2001; van Driel et al., 2007). Such support tools hold great potential to positively influence driver behaviour (Gonder et al., 2011). However, they also present their own challenges, as providing the driver with more information in the vehicle may increase workload and cause distraction (e.g., Haworth & Symmons, 2001). The driver's task and information needs must be taken into account when designing such a system in order to ensure that the positive benefits are gained while avoiding any negative impacts on safety (cf. Harbluk et al., 2007). This was the objective of the Foot-LITE project.

Development of the Foot-LITE EID

Young & Birrell (2012) argued that an ecological interface design for Foot-LITE would achieve the objective of encouraging the desired smart driving behaviours while minimising the potential for distraction. So, following the EID process, a CWA for safe and eco-driving was developed (Birrell et al., 2012). As per the eco-driving techniques outlined above, the CWA pointed towards factors such as conserving momentum, accelerating and braking smoothly, planning ahead and gear selection being important for smart driving.

The CWA also suggested that only skill-based (cf. Rasmussen, 1983) – or, in vehicle control terms (Ranney, 1994), operational level – elements of driving should be represented on the in-car interface. This seemed appropriate, given the assertion that operational control is a critical factor in eco-driving (Franke et al., 2016), coupled with concerns about knowledge-based processing being attention-demanding (Rasmussen, 1983). Moreover, the Foot-LITE EID aimed to make explicit the contextual cues that are automatically processed by skilled drivers (such as engine note, kinaesthetic feedback or advance visual information), of which most average drivers are likely to process only a small proportion (cf. Hoff, 2004). Thus, the CWA highlighted several aspects of operational driving feedback to be shown on the display, such as headway, lane deviation, and cornering speed for safety, complemented by engine speeds and acceleration forces for eco-driving.

The Foot-LITE EID sought to dynamically reflect the driving environment and integrate this complex information onto a single, direct perception display. Figure 9.1 shows a prototype of the EID interface that was developed for the Foot-LITE project. The principal aspects of the interface are based on the ecological notion of the 'field of safe travel', which was noted as '…a spatial field but it is not fixed in physical space. The car is moving and the field moves with the car through space' (Gibson & Crooks, 1938; p. 456). On the EID display, the inner oval, which represents mainly safety parameters, directly illustrates the driver's field of safe travel in the real world, as the representation of the car moves within the shape and warnings are given for reductions in headway or for lane departures. Thus the boundaries of

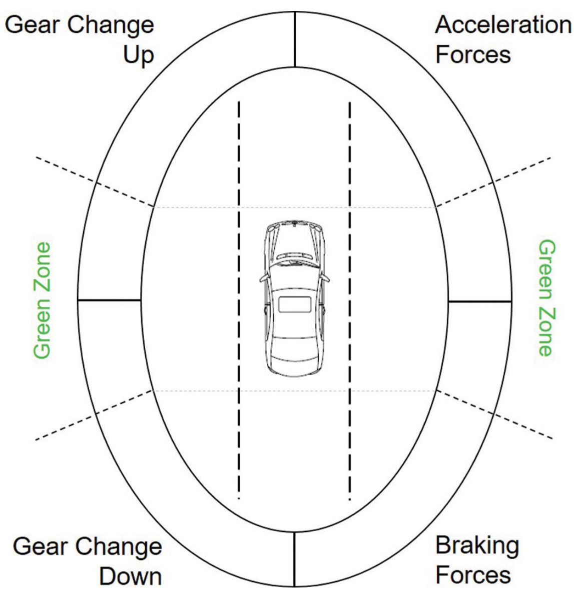

Figure 9.1 Prototype EID interface.

the oval represent the limits of the field of safe travel. The outer ring presents the dynamic parameters associated with eco-driving performance; these are essentially bars moving up or down with engine speed and acceleration (respectively), with the optimum level in the middle of the bar. In both safety and eco-driving cases, the driver's goal is to maintain the car within a 'green zone' of performance (in the middle of the display), to optimise each set of parameters. The grouping of both safety and eco-driving elements around this green zone clearly identifies the constraints on desired performance, and suggests to drivers which actions ought to be taken to maintain such. Any behaviours which exceed set tolerances in the system result in amber or red indicators on the relevant aspect of the display, providing the driver with direct feedback about how their driving affects each parameter.

A key feature of the Foot-LITE EID was the integration of complex information from two priorities (eco-driving and safe driving) onto a single direct perception display, in order to facilitate behaviour change while not distracting the driver or causing an unacceptable increase in workload. For instance, the ecological representation of headway, showing an image of the car moving closer to a forward boundary, did not require any additional interpretation on the part of the driver (as, for example, a numerical distance readout would).

As an alternative to the EID concept, a more conventional dashboard-type interface (DB) was also developed according to best practice interface design guidelines in the human factors literature (such as the European Statement of Principles on Human Machine Interface for in-vehicle information and communication systems; EC, 2008). Based on a vehicle instrument panel layout, the DB interface consisted of bar charts, warning icons (derived from ISO 2575: 2004), pop-ups and textual information (see Figure 9.2). The basic principles of the design were that driving information is grouped (as with the EID), with the eco-driving parameters all presented in the left-hand circle, while

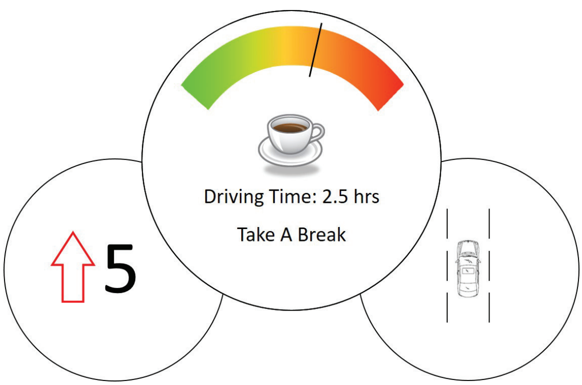

Figure 9.2 Example prototype DB interface, in this case showing gear change advice in the left circle, lane departure warnings in the right circle, and general driving tips along with a smart driving meter in the centre circle.

safety-related information was shown in the circle on the right. The main centre circle has a smart driving meter situated at its crest, with additional driving related information or predefined smart driving tips presented underneath. The DB design was intended to offer familiarity to drivers, being akin to standard instrument binnacles available in most vehicles. The DB display was purposefully designed to impart exactly the same information as the EID to provide an opportunity to empirically evaluate them against each other.

Alongside development of the visual displays, similar work was undertaken to develop auditory and haptic interfaces for Foot-LITE as well (see Birrell et al., 2013; Young & Birrell, 2012). Auditory feedback is particularly suited to skill-based, operational elements of driving (i.e., those displayed on the Foot-LITE interface), since the auditory modality is limited in terms of the amount and complexity of data it can transmit. For each driving parameter (acceleration, headway etc.), three audio options were created: auditory icons, earcons, and speech icons.

From our perspective, auditory icons are the closest to an ecological interface, as they convey information which should be familiar to the driver for a specific event. The auditory icons created for the Foot-LITE interface included a sound of rumble strips for lane deviation, a 'sonar Doppler' for headway (similar to that used for parking sensors), an over-revving engine for gear change, and the skidding of tyres for excessive braking. For earcons, a range of beeps were used to signify compromised headway and lane deviation (with increasing frequency to denote urgency for these safety-critical messages; cf. Hellier et al., 1993), two-tone chimes for gear change (mid-high for change up; mid-low for change down), and a set of three high or low pitched chimes for excessive acceleration or braking respectively. Finally, speech icons in our case comprised a synthetic voice verbalising a maximum of two units of information (or three words) relating to the specific driving parameter presented: 'too close' (for headway), 'out of lane' (for lane deviation), 'change up' or 'change down' (for gear change), and 'heavy braking' and 'excessive acceleration'.

Haptic feedback to facilitate eco-driving was provided through a vibrating accelerator pedal, which activated when the throttle was depressed past a 50% threshold, in accordance with guidelines to optimise fuel efficiency. This reflected similar work elsewhere on congestion assistants that provide warnings of traffic jams ahead (Brookhuis et al., 2009; van Driel et al., 2007), which found a haptic pedal reduced mean speeds on the approach to the congestion. However, the haptic pedal was not well accepted by drivers in their study, a finding in common with research suggesting that systems which restrict drivers' control are less likely to be accepted (van der Laan et al., 1997).

Evaluation

To refine the detail format of presentation on the display, the Foot-LITE EID and DB concepts went through user evaluation in an early human factors analysis phase (Young & Birrell, 2012). This phase comprised two studies.

The first was a questionnaire to determine user requirements. The questionnaire also sought users' rankings of icons to represent different aspects of eco- and safe driving (headway, fuel economy, lane deviation, acceleration, and braking forces, inappropriate cornering speed, gear shift indicators, approaching hazard warning, and a driver alertness warning). These icons were derived from reviewing other standardised icons which are already present in existing vehicles (i.e., ACC, gear shift indicators etc.), following International Standards Organisation guidelines for in-vehicle icons (e.g., ISO 15008:2003; ISO 11429: 1996), and other icons generated specifically for the project. The questionnaire study was followed by a static desktop rapid prototyping study to gather objective and subjective data on the efficacy of the two designs. A minimum of 10 participants was needed for the desktop study in accordance with SAE Recommended Practice J2364, which suggests that for early development phases when using a mock-up or computer simulation, static task time averaged over 10 participants should be less than 15 seconds (Green, 1999).

The study revealed that despite the novelty of the EID, once participants had got over the initial learning curve the EID was at least as understandable as the comparable dashboard-style interface. Average response times for both interfaces were well within the 15 second rule, thus implying safe use of either while driving. There were no significant differences in subjective usability between the two displays; results suggested that participants rated EID as being more complex but more consistent compared to the DB design. Participants also made clearer links between their driving style and fuel economy with the EID interface, ratifying the integrated and direct perception nature of this design and suggesting that it can support effective action as well as users' understanding of how these actions move them toward their goals (cf. Davidsson et al., 2009). This represents a significant achievement for the EID in helping drivers to understand key factors in eco-driving and linking these to positive changes in their driving behaviour. That said, participants tended to prefer the DB display over the EID, echoing the findings of others (e.g., Jamieson et al., 2003) who have found initial resistance to EID displays when compared to traditional interfaces. However, it is interesting to note that those who preferred the DB design still performed better with EID, generally responding faster to each driving scenario and correctly identifying more EID scenarios when compared to DB information. Thus, it may just have been unfamiliarity with the EID which was holding it back; with extended use the advantages of EID may become even more apparent (e.g., Christoffersen et al., 1998).

A separate desktop rapid prototyping study was conducted to evaluate the different audio options. In general, users preferred auditory icons for safe driving feedback, but speech for eco-driving advice. Given that auditory icons best align with the principles of EID, we concluded that these would be most suited to the ecological visual display for safety-related driving parameters.

The next phase of the research was take the refined EID and DB visual interfaces forward to more rigorous dynamic testing in the Brunel University Driving Simulator (Birrell & Young, 2011). A working prototype of each interface was developed and installed in the simulator. Participants drove two simulated routes (urban and extra-urban), receiving real-time feedback from either the EID or DB interfaces. A baseline, no-interface condition was included as a control, in which participants were asked to drive according to the same principles of eco-driving but without the feedback. Measures were taken of driver attention and workload, as well as driving performance as recorded by the simulator software.

The results of the simulator study demonstrated that both designs had the desired effects on safe and eco-driving behaviour (in terms of reduced speed and acceleration) while avoiding negative impacts of increased workload or driver distraction (using a peripheral detection task). However, the EID performed better in terms of its perceived demand on driver attention (a 17% reduction over the dashboard-type interface), and was also preferred by participants in the study. The haptic pedal was also tested in the driving simulator. Driving performance and workload measures suggested that it had many beneficial effects on acceleration and throttle parameters associated with safe and eco-driving, and reduced driver mental workload (MWL) when compared with the control condition.

Apparently, then, additional in-vehicle information need not increase workload and distraction if the interface is designed appropriately – and the EID seems to fit that bill. Positive and helpful information, such as that given to the driver by Foot-LITE, may actually improve driving performance while minimising additional workload and distraction. But driving is a dynamic task and its demands are constantly changing (Foy & Chapman, 2018), yet it remains crucial to maintain sufficient spare capacity throughout to deal with unexpected or emergency situations. This makes it difficult to propose a single, static interface design suitable for all driving situations. Instead, we might consider adaptive interfaces.

ADAPTIVE INTERFACES

Based on the now well-established premise of optimising MWL (e.g., Wilson & Rajan, 1995; Young et al., 2015), the potential for adaptive interfaces has been perennially studied (e.g., Byrne & Parasuraman, 1996; Hancock & Verwey, 1997; Parasuraman & Hancock, 2001). Adaptive systems infer the level of MWL on the operator by monitoring the task and/or the driver, and then regulate the level of information or assistance accordingly (cf. Verwey, 1993). This is how Piechulla et al. (2003) developed their prototype adaptive interface for driver workload, which used complex task-based modelling of situational factors (such as road type, physical features etc.) to detect mental overload, and during overload periods it would route incoming phone calls to voicemail. Their adaptive interface showed promising results in terms of managing driver MWL. Similar systems have also been offered in cars from some major manufacturers, which estimate workload from driver inputs (steering, acceleration, braking) in order to reschedule emails and phone calls (Engström & Victor, 2009).

The point of adaptive interfaces is to maintain a consistent, optimal state for the operator (Byrne & Parasuraman, 1996) while avoiding peaks and troughs of overload and underload which may degrade performance (Hancock & Parasuraman, 1992; Hancock & Verwey, 1997; Parasuraman, 1987). This approach is the technological complement to behavioural adaptation in response to workload – when faced with increases in task demands, drivers seek to balance that demand by slowing down, changing their priorities or abandoning a secondary in-car activity (Cnossen et al., 2004). Having the system adapt, rather than the driver, should (theoretically) improve not just performance, but could also mitigate negative behavioural adaptation (such as overreliance), because the system context is not static.

Adaptive systems have been applied in the driving context (e.g., Donmez et al., 2007; Piechulla et al., 2003), and such systems have shown benefits in terms of operator behaviour and performance (Hoc & Lemoine, 1998). Young & Birrell (2011) proposed an adaptive framework for the Foot-LITE in-car interface, based on a rudimentary task-based workload model. Whilst the interface was carefully designed to minimise distraction, the adaptive element had several levels of filtering for elements of the visual and auditory display, based primarily on characteristics of the road environment. These characteristics are picked up by the Foot-LITE sensor array, which includes GPS position monitoring, a forward-looking camera with object recognition, and numerous parameters from the vehicle's on-board diagnostics. The interface then dynamically provides appropriate levels of feedback in different driving situations, to manage the driver's mental workload.

So what characteristics would the adaptive algorithm be based on? Previous research suggests that different driving manoeuvres demand different levels of visual attention (Groeger, 2000), and the literature on driver MWL offers several task-related indicators of workload (see e.g., Dingus et al., 1989; Hancock et al., 1990; Schlegel, 1993). Factors of the environment, such as traffic and road situation, as well as different elements of the driving task (e.g., vehicle control and guidance, navigation) can influence MWL. For instance, steering appears to be a significant source of workload in vehicle control (Young & Stanton, 2004), while tuning a car radio or using a navigation system are amongst the most demanding of the conventional in-car tasks (Dingus et al., 1989). In terms of driving manoeuvres, workload increases during a turn (Hancock et al., 1990), particularly when emerging from a junction when the driver has to cross a lane of traffic. Mental workload also increases in towns and cities when compared to highway or rural driving, due to the unpredictable nature of the former (Harms, 1991; Zeitlin, 1995). These high workload situations are also associated with collision involvement. This has led to the idea of constructing mental load maps of towns, in order to predict collision rates and so design appropriate interventions (Wildervanck et al., 1978).

Such characteristics were taken into account along with pragmatic considerations about what parameters could be measured, as well as other factors such as driving standards, to propose a set of rules for the adaptive interface. In the Foot-LITE model, driver mental workload had three levels:

- *High* – mental workload is deemed high when driving on urban roads with a high density of junctions (i.e., in a city or town centre). Speed limits of these roads may be between 20 and 40 mph (32 to 64 km/h), but actual speeds will probably be around 0 to 25 mph (40 km/h). The drive is characterised by numerous stop/starts, frequent turns, or highly inconsistent speed profiles.
- *Medium* – medium mental workload situations may still be in an urban or inter-urban setting but in the absence of many junctions, and with fewer stops and turns. Speed limits are likely to be 30 or 40 mph (48 or 64 km/h), with probable speed ranges of 20 to 40 mph (32 to 64 km/h). The drive is characterised by lower mean driving speeds but more consistency in speed profiles.
- *Low* – on roads with speed limits of 50 mph (80 km/h) or over, with relatively consistent actual speeds of approximately 45 mph (72 km/h) and over, low junction density and low numbers of turns. This category also incorporates any extra-urban highway.

With the rules for mental workload levels derived, the next step was to determine how these affected the adaptive nature of the display. Recall that the EID had several components – the inner oval for safety related information (headway, lane departures) and the outer oval for eco-driving feedback (acceleration, gear changing). Furthermore, within the oval, the status of the eco-driving and safety parameters can be either green, amber or red. Each of these elements can be independently enabled or disabled on the display, providing various combinations of levels of information available to the driver.

The principle was established within the Foot-LITE project that, in the event of any conflicts in advice from safety or eco-driving perspectives, the safety-related information should always take precedence. With that in mind, it was determined that the feedback provided at each level of workload should be as follows:

- *High* – only ‘red’ safety warnings to be given; audio and eco-driving feedback are disabled
- *Medium* – all safety warnings active (red and amber), only red eco-driving feedback is given, audio is active
- *Low* – all information active

The prioritisation rules for the display were ultimately founded on the skill-rule-knowledge elements of driving derived from the CWA, and the adaptive interface merely elaborates these in a dynamic fashion. Thus, by limiting feedback during high workload only to skill-based, safety-critical tasks, the intention was to optimise both the beneficial effects on driving performance as well as mitigating any consequences of distraction.

As an alternative to real-time adaptation to workload, Young, Birrell & Davidsson (2011) offered a kind of 'temporal adaptation', which they termed 'pre-loading', as a means to smooth out longer-term peaks and troughs in workload, thus reducing problems of overload and underload and improving performance (Hancock, 2017b; Huey & Wickens, 1993; Young & Stanton, 2007b). Based on resource theories of underload such as malleable attentional resources theory (MART; Young & Stanton, 2002a), pre-loading gives the operator an additional task to stimulate their attention during low workload periods to avoid underload and improve performance, which is then traded off against reduced demands during later workload peaks in the drive. The premise is that drivers have spare capacity during low workload periods of driving (e.g., highway cruising; cf. Hughes & Cole, 1986) which could usefully be occupied by presenting advance information about task-relevant activities in the near future. Huey & Wickens (1993) explicitly supported this kind of idea, suggesting that when the task is familiar and predictable, completing some of it ahead of time and developing contingencies during periods of low workload can alleviate later peaks in demand and so improve performance. A skilled operator can predict these peaks and so adapt their effort accordingly (Hancock & Chignell, 1988).

There is some evidence that additional tasks could improve driving performance during conditions of underload. Specifically in level 3 driving automation, Gold et al. (2018) reported evidence that non-driving secondary tasks can improve performance in a takeover scenario. Elsewhere, Gershon et al. (2009) showed that an interactive cognitive task can suppress fatigue symptoms caused by underload in driving, while Nowosielski et al. (2018) similarly found that for drivers on a simple (i.e., underloading) route, hazard response times were improved by listening to an audiobook. It has even been suggested (Liu, 2003) that making a mobile phone call could improve performance for drivers facing low workload (e.g., a monotonous highway journey), an effect which has been interpreted in terms of MART (Zeeb et al., 2016). But such a strategy is controversial when it comes to safety-critical performance domains such as driving and does not sit well with road safety advice, or the significant ergonomics and human factors evidence base on the increased crash risk associated with phoning and driving (see e.g., Collet et al., 2010). Problems will inevitably arise when primary (driving) task workload increases, causing conflict and overload. Rather, we prefer the notion that drivers engage in a task-related activity, so that if workload does increase, their attention is at least directed towards the driving task.

Instead, then, with task pre-loading the additional task is specifically designed as preparatory activity for a later, anticipated peak in demand. For example, one of the ironies with current satnav devices is that they provide the driver with additional assistance at precisely the moment when driving task workload has increased – i.e., at a junction. One implementation of the pre-loading concept might then be a satnav system which provides information about a forthcoming junction much further in advance than typical devices do, at a time when workload is lower. This has the additional advantage of priming the driver for the forthcoming hazard, giving them plenty of opportunity to plan how they deal with it. There is precedent for this in parallel human activity: Antrobus et al. (2017) highlighted how passengers naturally gave such preview information in their navigation instructions to drivers during periods of inactivity, taking account of the driver's context and workload.

Young, Birrell & Davidsson (2011) conducted a study in the Brunel University Driving Simulator to evaluate this concept with a view to designing adaptive systems around a pre-loading activity. Participants drove in a simulator under low and normal workload conditions, with and without pre-loading. The pre-loading task consisted of a hazard identification task, intended to increase drivers' attention to the driving task. In addition, at the mid-point of the run, a critical event occurred which required drivers to react in order to avoid a collision. The results showed that participants were clearly sensitive to the pre-loading task, reporting increased subjective MWL when using it. However, there was no effect on either objective metrics of attention or performance, suggesting that the pre-loading task does not have the anticipated effects in terms of compensating for underload – at least for the conditions in their experiment. Young, Birrell & Davidsson (2011) discussed potential reasons for this relating to the experimental design, or even the possibility that the underload 'problem' might be automation-specific, rather than relating to other low workload scenarios (a notion also posited by Young & Clynick, 2005; see Chapter 4). That is, the underload effect may actually be a qualitatively different phenomenon from very low workload, and may then not be so distinct from automation-related explanations such as out-of-the-loop performance (e.g., Endsley & Kiris, 1995; see also Young, 2021). Although the results did not prove the hypotheses, then, the pre-loading task was clearly noticeable to participants and it may yet have some potential for cancelling out subjective peaks and troughs as anticipated.

ADAPTIVE AUTOMATION

Although we have above been discussing adaptiveness in the context of driving assistance interfaces, these principles equally apply to adaptive automation. Like adaptive interfaces, automation is adaptive when the allocation of control changes in response to either aspects of the physical environment or the human (Sheridan, 2011), and is often based on workload (Hancock & Chignell, 1988; Schlegel, 1993; Sheridan, 2011; Verwey, 1993). This approach, also known as dynamic task allocation, offers an alternative to blanket use of a high level of automation (Li & Burns, 2017). The relative merits of human and machine will change across tasks as well as during a task, making dynamic allocation preferable to static function allocation in order to avoid extremes of underload and overload (Lee & Seppelt, 2012).

The aim of adaptive automation, of course, is to improve performance and workload (Hancock & Chignell, 1988; Kaber & Endsley, 2004). Studies show that adaptive automation can improve situation awareness and MWL (Bailey et al., 2006; Charles & Nixon, 2019; Parasuraman et al., 2008; Sheridan, 2011). Adaptive automation could also cater for user preferences for more or less information during automated or manual control (Ulahannan et al., 2020). Some even suggest that adaptive automation could mitigate against automation-related complacency (Bailey et al., 2006) while improving acceptability (Parasuraman & Wickens, 2008).

The idea that adaptive systems would be more acceptable was tested in a study of a forward collision warning system conducted in a driving simulator (Jamson et al., 2008). Drivers experienced two versions of the system: one that used fixed warning thresholds based on a constant reaction time to a forward event, and an adaptive version that was trained on the basis of a driver's observed reaction time. For non-aggressive drivers – defined as long followers and low sensation seekers – there was little difference in acceptance between the non-adaptive and the adaptive systems. However, for the more aggressive drivers – those who generally engaged in close following and who scored higher on sensation-seeking – acceptance of the adaptive system was substantially higher than acceptance of the non-adaptive system. In terms of objective safety, defined as the capability to avoid a crash, the two systems performed with roughly equal effectiveness. Thus, the adaptive system resulted in higher overall acceptance with no diminution of objective safety performance.

The benefits of adaptive automation result from maintaining meaningful operator involvement in active control while managing workload (Kaber & Endsley, 2004). However, some of these benefits may vary depending on the type of task (Kaber & Endsley, 2004) and type of cognitive processing, leading some to suggest that adaptive automation should take account of multiple attentional resources and be matched to the type of demand (Hancock & Chignell, 1988; Matthews et al., 2015; Taylor et al., 2013). Other studies have shown that performance with automation can be improved by occasionally interspersing periods of manual control, since it serves as a kind of rehearsal to offset skill degradation (see e.g., Endsley & Kaber, 1999; Kaber & Endsley, 2004; Kaber et al., 2001; Parasuraman et al., 1996a). Although this is not truly adaptive automation, it does demonstrate another of its potential benefits.

It is worth distinguishing between adaptable (where the change in allocation is invoked by the human user) and adaptive (when the change is invoked by the automation; Scerbo, 2001; 2007). Both have pros and cons (see Scerbo, 2007) – adaptive in terms of potential conflicts, distrust or automation surprises (i.e., how does the human know what the automation is doing and who has control?); adaptable in terms of increasing the driver's workload burden as it draws attention away from the task itself (Bailey et al., 2006; Inagaki

& Sheridan, 2019). Indeed, an adaptive system has been shown to result in better situation awareness, MWL and performance than an adaptable system (Bailey et al., 2006).

Whilst the principles of adaptive systems are sound in terms of managing the traditional problems of workload and situation awareness that are associated with static function allocation, their dynamic nature also brings its own design challenges. For one thing, there is the question of managing feedback for the driver so they know which level of the system is operating – otherwise it could lead to inconsistency and unpredictability. Indeed, Smith et al. (2009) warned that an inconsistent system could adversely affect user acceptance of it, if drivers cannot understand it. Furthermore, adaptive automation can increase the complexity of the task as the operator has to keep track of how their behaviour affects not just the task itself, but also how that impacts on the behaviour of the automation (cf. Cuevas et al., 2007; Kaber et al., 2001). There is also an inherent problem in constantly switching between human and machine control. When the automated system takes over, the task may stabilise quickly, resulting in reallocation to the human. Taking control back, though, might impose high MWL for the operator, and if workload is the basis for allocation decisions, this means the task would immediately come under computer control again. This can lead to rapid cycling of automation, which can lead to better performance, but higher subjective MWL (Scallen et al., 1995), even though physical workload may not change (Hilburn, 1997). Moreover, there is the important question of authority over the transition – that is, who (human or machine) decides when and how control transfers from one to the other (see Inagaki, 2003, for a discussion). Adaptive automation requires a part of the system (either human or machine) to act as the allocation agent, distinct from the automation controlling the function itself (Sheridan, 2011). The allocation algorithm that determines how, when and why to switch control, though, is one of the trickiest aspects of adaptive automation (Bailey et al., 2006; Kaber et al., 2001; Tsang & Vidulich, 2006).

Perhaps because of these challenges, actual examples demonstrating the value of adaptive automation in practice are scarce (Gustavsson et al., 2018). As much as anything, adaptive systems depend on the ability to define and monitor threshold limits of workload (Hancock & Chignell, 1988), something which has long proved notoriously difficult (Young et al., 2015). But advances in driver state monitoring offer promise for evaluating not just workload, but also distraction and fatigue. Such monitoring is now recognised as a central safety measure in next generation automated driving (Lenné et al., 2020).

DRIVER MONITORING

Adaptive interfaces typically work by inferring the driver's MWL based on some metric of the task context, observable task performance or the driver themselves. Early investigations of systems for real-time driver monitoring pursued physiological metrics (Byrne & Parasuraman, 1996; Fairclough, 1993; Kramer et al., 1996), which proved more effective than either performance measures (Brookhuis, 1993) or subjective measures (Lindh & Gårder, 1993). As we have demonstrated in our own research (see Chapter 7), there seems to be an inextricable link between workload and physiological arousal, which may be exploited to detect situations of underload or overload (see also Brookhuis, 1993; Fairclough, 1993; Wildervanck et al., 1978). Interest in physiological measures has persisted since (e.g., Charles & Nixon, 2019; Inagaki, 2003; Kaber & Endsley, 2004; Parasuraman & Wickens, 2008; Scerbo, 2007), with more advanced brain-based physiological metrics (i.e., electroencephalogram or near infra-red spectroscopy) showing promising results (e.g., Bailey et al., 2006; Matthews et al., 2010; Scerbo, 2007).

Nevertheless, developments in technology and sensors meant that later systems moved away from physiological measurement in favour of more overt behavioural indices of driving style or stored models of the driver (e.g., Donmez et al., 2007). In the European AIDE project (Adaptive Integrated Driver-vehicle interfacE; see e.g., Amditis et al., 2010; Engström & Victor, 2009), sensors monitored the driver-vehicle-environment system, using eye and head tracking, on-board diagnostics, and satnav data respectively. These data were compared against a stored model of driver workload for a range of scenarios, as defined by experts and empirical testing (e.g., Tango et al., 2010).

As driving becomes more automated, though, there are fewer behavioural indicators to monitor (Lenné et al., 2020). But there is still a need to monitor the driver's attention to ensure they are ready to reclaim control when the system needs to hand it over, so it knows whether they are 'available and attentive' (CCAV, 2020) or 'fallback-ready' (SAE, 2018). Current systems are therefore moving towards using infra-red camera-based approaches to monitor the driver's eyes, head or face (Lenné et al., 2020), which are increasingly capable and are thus rapidly becoming the preferred solution. For instance, Tivesten et al. (2019) suggested that eye-tracking could be used to detect behavioural patterns associated with higher crash risk when reclaiming control from automation. Alternatively, other manufacturers check for physical (i.e., hands-on) contact with the steering wheel to determine whether the driver is 'fallback-ready' (Bishop, 2020).

While these systems have their place in automated driving, they can equally be applied to monitor fitness to drive in manual driving (Lenné et al., 2020). Eye- or head-tracking can be used to detect whether the driver is distracted and, if so, provide them with a warning (see e.g., de Winter et al., 2014). Some of these systems are designed to alert the driver purely to their own distraction, in an effort to 'train' the driver to be aware of potential distractions and thus adapt their behaviour (e.g., Donmez et al., 2007; Engström & Victor, 2009). Similar systems have been developed as a countermeasure for fatigue, monitoring for predetermined patterns of behaviour or vehicle control that have been associated with tired drivers. When it detects a threshold level of these behaviours, the driver is given a warning message in the instrument cluster suggesting that they take a break. As we touched on in Chapter 8, other systems are available that use eye-tracking cameras embedded in the dashboard, in order to detect signs of fatigue through eye movements, blink rate or eye closure.

Some of this technology could also be used to provide the basis for adaptive interfaces. For instance, Smith et al. (2009) described a collision warning system developed under the European SAVE-IT programme (SAfety VEhicles using adaptive Interface Technology) that monitors the driver's head position and adapts its warnings depending on whether the driver is watching the road or not. If the driver is distracted, the system could present its warning earlier, in a different location, or through a different modality; alternatively, if the driver is detected as being attentive, then the warning could be attenuated so as not to annoy them. In a similar way, driver monitoring can be used to prime the driver before resuming manual control from automation (Large et al., 2018) or to provide more takeover time for distracted drivers (cf. Eriksson & Stanton, 2017b).

Whilst such attention reminders can ostensibly improve visual attention patterns, this does not necessarily translate into drivers' takeover performance, which is as much based on higher-level cognitive expectations as it is on actually looking at the road ahead (Victor et al., 2018). Consistent with this, some evidence suggests that adaptive systems based on this kind of monitoring are not necessarily beneficial. A simulator study by Merat et al. (2014) examined how drivers resumed control from level 2 automation depending on whether control was handed over at regular intervals (i.e., a static allocation policy) or if it was based on drivers' eye movement patterns (whether they were looking away from the road for more than 10 seconds). It turned out that the adaptive version resulted in worse driving performance and more erratic attention patterns. Bringing us full circle in this chapter, some of these issues may very well be down to how carefully the interface has been designed (cf. Ljung Aust, 2020; Stanton et al., 2021).

CONCLUSIONS

Whilst this chapter has taken us briefly outside the specific realm of automated driving, it was with good intent: to see how interfaces could be designed not just to minimise distraction and overload arising from the new technology in the automobile, but to go further and optimise the driver-automation interaction. The design of any in-vehicle interface, including those for automated driving, must be user-centred, taking into account (and supporting) the primary information needs, capabilities, and limitations of the driver. Techniques such as ecological interface design and adaptive automation offer promising ways of achieving that for the benefit of safety, efficiency, and performance.

Nevertheless, we have also highlighted some of the practical challenges in implementing these solutions, particularly with adaptive automation which, in turn, depends on some form of driver monitoring. These challenges will be brought into sharp relief as we move towards level 3 automation. The automated lane keeping system (ALKS) being advocated for UK roads depends on a driver being 'attentive' and 'available' to resume control if needs be; such availability is determined every 30 seconds by a driver monitoring system which effectively checks whether the driver's eyes are on the road and hands are on the wheel (CCAV, 2020). While this rather defeats the object of level 3 systems allowing the driver to engage in non-driving tasks, it also very much depends on the assumption that in doing so, the driver is indeed 'attentive' (Ljung Aust, 2020) – which may or may not necessarily be true. The implicit recognition that drivers may have an impaired ability to respond due to the reduced demands on attention also speaks to the central concern of this book around mental underload – remembering that this is exactly the sort of task that Hancock (2019) said humans are 'magnificently disqualified' for.

In our human-centred 'autopian' future, then, we need human and machine to work in harmony, with the technology adapting to the driver rather than the other way around. Probably, this will mean a more sophisticated level of driver monitoring, such as brain-computer interfaces. Haufe et al. (2011) took a neuroergonomics approach to emergency braking in a driving simulator study, and managed to detect the driver's intention to brake via muscle and brain activity fractions of a second earlier than via actual pedal movements. If the appropriate sensors could feasibly be installed in cars, this could be a prime source of data for the technology to know what the driver is thinking – to sense their intent, and to match its actions accordingly. More broadly, future systems may draw on a suite of internal and external sensors to create an integrated picture of what is going on with the driver and the environment so that the automation can act in response, such as increasing headway if it senses the driver is distracted (e.g., Veoneer, 2018).

This kind of technology may have sounded like the stuff of science fiction even only a few years ago, but the possibilities are very real. And, if we are to truly achieve human-centred automation, both human and machine need to have a very good understanding of what is going on in the other's head (Stanton, Salmon & Walker, 2017). Cutting-edge interface design and driver monitoring are therefore essential to two-way communications, fostering collaboration and cooperation. These bring us to philosophical elements of human-centred automation, which we turn to in our final chapter.

KEY POINTS

- The increased complexity in modern automobiles (including, of course, from automation) presents a risk of overloading the driver; user-centred design should play a key role in managing this issue.
- Guidance suggests that in-car interfaces should be designed such that drivers do not have to glance away from the road for more than 2 seconds

at a time, or for more than 12 seconds in total (across multiple glances) to complete a task; however, good practice and standards in interface design for manual driving might not be applicable to automated driving.

- Multimodal displays offer a useful alternative to the overused visual channel when designing driving interfaces.
- Interfaces should present a transparent and integrated view of the system; ecological interface design (EID) principles have been shown to offer promise in doing so, managing complexity without causing an unacceptable increase in workload.
- Adaptive interfaces (and adaptive automation) take this further by monitoring aspects of the task and/or the driver, and changing the nature of information presentation or automated support to suit, but the evidence for the effectiveness of these systems has so far been mixed.

NOTE

1. https://www.federalregister.gov/documents/2013/04/26/2013-09883/visual-manual-nhtsa-driver-distraction-guidelines-for-in-vehicle-electronic-devices (accessed 29 April 2022).

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Stage 4

Letting George do it

Chapter 10

An autopian future?

OVERVIEW

So we finally reach our destination, and the last leg of our journey revisits the story so far, summarising the 'promises and problems' of automated driving, before going on to consider in detail what we have learned for the design of such systems from a human-centred perspective. More discussion is had on adaptive systems and interface design principles, but the bulk of the chapter is given over to advocating a number of high-level design philosophies for driving automation. We recap the dichotomies reviewed in earlier chapters about vehicle versus driving automation and hard versus soft automation; we argue that automation should be problem-driven rather than implemented for its own sake (and provide some examples to illustrate this point); we propose a 'cliff-edge' approach to implementing automation, whereby the full capabilities of the technology are constrained until it can truly take over all aspects of the task without any need for human supervision; and, finally, we detail the considerable human factors literature on human-automation teaming, applying principles of teamwork to the design and implementation of automated systems. Before closing, we also consider some implications for driver training with automation, but the book concludes by reiterating the point that driving automation has to be a team player if we are to realise the 'autopian' ideal in future.

INTRODUCTION

We have spent a good deal of this book highlighting the various potential human factors problems with automation in general, and driving automation in particular. But we are neither Luddites nor technophobes; whilst we cannot deny the satisfaction that many (including ourselves) gain from driving manually, the last couple of chapters have shown us that it is equally impossible to ignore the potential for automated driving to improve safety, mobility, and the environment. Automated driving systems are coming, and to some extent are already here. If not already, many of us will soon experience driving

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automation, whether as a driver or a passenger (or both at the same time!). As we approach the end of our journey with this book, then, it is worth reflecting on what we have encountered so far, such that we can try to get the best out of automotive automation in future.

WHAT WAS THE PROBLEM WITH AUTOMATION AGAIN?

In the interests of balance, it seems only fair to start off by revisiting the benefits of automation. Automated driving systems have long been seen as having the potential to improve safety and traffic flow on future roads (Biesterbos & Zijderhand, 1995; Hancock & Parasuraman, 1992), as well as offering independent mobility for older drivers (see Chapter 8). Indeed, there is an argument[1] that, even though current automation cannot yet cope with all the complexities of driving in the way a human driver can, it is still safer than a distracted driver, so we should embrace the technology as soon as possible. This is particularly true given that the proliferation of other technology in vehicles has been increasing the propensity for drivers to be distracted[2] (Landau, 2002). The argument continues that whilst accidents of automation will happen, there will not be as many as those caused by (distracted) human drivers.

Leaving aside the sticky issue of how society accepts (or otherwise) collisions caused by automated vehicles (e.g., Krügel & Uhl, 2022), what this argument reminds us of is the spectre of mental workload (MWL) hanging over automation. Previous authors have suggested that in-vehicle technologies have the potential to overload and confuse the driver if they are not designed appropriately (Revell et al., 2020; Verwey, 1993). Meanwhile, justifying automation by recourse to the additional demands introduced by other technology in the car betrays the presumption that automation will reduce mental workload. Yes, that reduction may be beneficial during peaks in workload that may otherwise cause problems for the driver (e.g., Liu, 2003). But, as several chapters in this book have expounded, under most normal driving circumstances, workload is actually manageable, so any reduction risks tipping the driver into underload.

But underload in and of itself might not necessarily be the problem; all the time things are working well, performance might even improve with reduced MWL (cf. Ma & Kaber, 2005). Rather, many of the 'problems' of automation are actually about reclaiming manual control, either in a scheduled takeover scenario (Eriksson & Stanton, 2017a; 2017b) or in an abnormal or emergency situation (Stanton et al., 1997). In these circumstances, the overwhelming evidence in human factors research is that people struggle to cope, and performance suffers as a consequence. Explanations for this have ranged from effort (Desmond et al., 1998; Matthews et al., 1996), through situation awareness (Endsley & Kiris, 1995; Kaber & Endsley, 1997) and trust (Lee & Moray, 1994; Parasuraman & Riley, 1997), to vigilance (Molloy

& Parasuraman, 1996; Parasuraman et al., 1996b). Whilst we do not disregard these other explanations (they are all, in many ways, compatible with each other), in our work and throughout this book, we have focused on the common thread of MWL, having shown that underload with automation has a clear impact on takeover performance through a shrinkage of attentional resources (Young & Stanton, 2001b; 2002a; 2002b). Like the proverbial frog in the boiling pot of water, unexpected and sudden peaks in MWL are more disruptive to performance than a gradual increase in difficulty (Huey & Wickens, 1993). Under malleable attentional resources theory (MART), this is because capacity has been reduced below the level which the takeover situation demands, and the sudden increase in MWL outstrips the speed at which resources can be replenished. The general consensus – which is consistent with the MART model – is that MWL optimisation is crucial to maintaining effective task performance.

Determining the right level of automation for a task can help to optimise driver workload as well as situation awareness, performance, and satisfaction. Rather than just blanket automation (Endsley, 1987), though, automation should be targeted where it is needed, so as to reduce overload and, indeed, compensate for underload (cf. Mueller et al., 2021). This is different to piecemeal automation, where subtasks are automated according to technical feasibility as much as anything (or even just for the sake of it; cf. Endsley, 2019; Endsley & Kaber, 1999; Hancock, 2014), and which leaves the operator with an incoherent set of tasks that remain unautomated. But even traditional levels-of-automation approaches have been criticised for being engineering-centred rather than human- or collaboration-centred (see also Wiener, 1989). All of the problems of automation that we have been warned about by the likes of Bainbridge (1983), Norman (1990) and Reason (1990) largely arise from a technology-centred approach to automation, which focuses on the limitations of human performance and justifying automation as a means to eliminate human error. But what this fails to recognise is that people bring a range of strengths to complex dynamic systems and, in most cases, make a positive contribution in creating safety (cf. Hollnagel, 2014; Reason, 2008).

This human contribution has proved time and time again to be pivotal in emergency situations. Learning more lessons from aviation, take the example of United Airlines Flight 232, which crash landed at Sioux City, Iowa, on 20 July 1989 (see Faith, 1996; Huey & Wickens, 1993; Reason, 2008). The DC-10 aircraft had suffered an explosive failure of its number two engine[3], which in the process had destroyed the hydraulics to the control surfaces. Unable to fly the aircraft by conventional means, the three flight crew enlisted the help of an off-duty pilot who was a passenger on the flight, and they managed to fly to Sioux City airport purely by using differential thrust on the two remaining engines. The approach was going well considering such improvisation, but an unfortunate windshear on landing caused a catastrophic impact with the loss of 112 lives. That is of course a tragedy, but the fact that there were 184 survivors can be put down to the ingenuity and skill of the flight crew. In a similar vein is the much-celebrated US Airways flight 1549 in 2009, ditched on the Hudson River in New York by Captain Chesley Sullenberger and First Officer Jeffrey Skiles, in which all 155 on board survived thanks in no small part to the teamworking of the crew (see Borst et al., 2015; Reason, 2016). In the driving context, human drivers travel over 490,000 miles between collisions and over 95 million miles between fatal collisions; according to Endsley (2019), this compared to 5,600 miles per manual intervention (i.e., a human having to take over in a situation that the automation cannot cope with) for the best automated vehicles of the time.

Despite the problem of automation being about manual takeover, it is also in out-of-course situations such as these that the value of human input is realised (another irony!). More than fifty years before writing this book, another Young (1969) presciently noted that the role of human operators of automated systems will be to bring 'versatility, adaptability and reliability … to observe the environment … monitor instruments … control in parallel with the automatic system and take over in the event of a failure' (p. 672). Tellingly, all of those observations – particularly the latter one about taking over in the event of failure – remain relevant today, especially given the presumption that it will (almost?) never be possible to design an automated system capable of dealing with all possible situations (Borst et al., 2015). In fact, it is in the abnormal situations where humans can adapt and shine (Mallam et al., 2020). But that does not mean that we should continue to rely on people to mop up for clumsy automation (cf. Sarter & Woods, 1995), as this is just a sticking plaster for all of the other underlying problems with automation (Lee & Seppelt, 2012).

We have known for some time now that simply trying to automate the human out of the loop does not deliver the solutions that engineers crave (e.g., Parasuraman, 1987; Wiener & Curry, 1980). The keepers of future technologies should recognise this and forego efforts to design humans out of systems as an attempt to prevent 'human error' (cf. Bainbridge, 1983). Instead, they should integrate the human fully and nurture their abilities. Under a systems perspective, the user and the technology are not separate entities, but part of a single interactive system, and the goal should be to optimise the performance of that system as a whole (Singleton, 1989). Neither component of the system is infallible, but by capitalising on the strengths of each, the joint sociotechnical system really can be greater than the sum of its parts. The criteria for sharing tasks between human and machine should therefore be based on human performance over automation reliability (Parasuraman et al., 2000). This means exploiting the capabilities of each component of the system and being aware of their limitations. Particularly in the case of driving, we should appreciate that humans are actually very capable of performing the task, and any additional devices should be problem-driven rather than technology for its own sake.

This is not to say that technology should not be used, but that more thought needs to be given to its appropriate implementation and how it impacts on the user's goals (Read et al., 2020). Several luminaries in human factors (e.g., Hancock, 2014; Parasuraman, 1987; Wiener & Curry, 1980) have argued that, when it comes to automation, designers should ask not whether we *can*, but whether we *should* – or, as Hancock (2019) put it, whether we should just because we can. Now, the question of whether we *should* automate remains moot (Parasuraman & Wickens, 2008); in fact, the question is surely *how* we might best go about it (Harris & Smith, 1997; Young & Stanton, 1997), given that automation is coming anyway (cf. Billings, 1991; Hancock et al., 2019). Technology should of course be embraced where appropriate, but it should be seen as a tool to support the unique skills and flexibility of human operators, rather than trying to replace them (cf. Borst et al., 2015; Endsley, 2015; Read et al., 2020; Reason, 2008). While we still retain a human in the loop, we need to consider how the design of the automation fits around the driver.

HOW TO DESIGN AN AUTOMATED DRIVING SYSTEM (FROM A HUMAN FACTORS PERSPECTIVE)

The converse of the technology-centred approach is to adopt a human-centred design philosophy (cf. Billings, 1997; Navarro et al., 2018; Reichart, 1993), and there have long been calls for human-centred design in vehicle systems (Hancock et al., 1996; Hancock & Verwey, 1997; Owens et al., 1993; Reichart, 1993; Rumar, 1993; Stanton & Marsden, 1996). Following the arguments presented above, human-centred automation seeks to optimise overall performance of the human-machine system by designing it around not just what the technology can do but also the capabilities, the limitations and the needs of the human user (Endsley, 1987; Kaber & Endsley, 2004; Navarro et al., 2018).

These high-level principles are all very well, but they are also easier said than done. So let us try to turn them into something more concrete by addressing one of the key themes of this book: mental workload. To unashamedly labour the point, many agree that a key goal is to match task demands and human capacity, thereby optimising workload and avoiding underload or underload (e.g., Bainbridge, 1991; Gopher & Kimchi, 1989; Lovesey, 1995; Neerincx & Griffioen, 1996; Reichart, 1993; Rumar, 1993; Wiener & Curry, 1980). In accordance with MART, this strategy will help to maintain attentional resources too, thereby ensuring spare capacity is available if (and when) it might be needed. But this is not just about providing "make-work" for the sake of it in order to avoid underload; the activity has to be meaningful and directed towards the primary task (Wiener & Curry, 1980), lest it take the driver's attention even further away from driving. And this seems to suit a sizeable proportion of drivers: research has shown us that more than one-third prefer to carry out a low workload task manually, even in the face of perfectly reliable automation (Navarro et al., 2018). Varying workload and ensuring the user interacts with the automation in some way – in other words, making the task more interesting – are also beneficial in counteracting both perceived and actual underload (Hancock, 2017b; 2021).

Some advocate the use of adaptive interfaces as a means of optimising driver mental workload and achieving human-centred automation (e.g., Byrne & Parasuraman, 1996; Hancock & Verwey, 1997; Verwey, 1993). The reader will recall from Chapter 9 that adaptive systems monitor the task, the driver (which we will return to later) or the environment so that they can adjust the level of support offered to the driver in real-time based on the level of workload. Designing and implementing an adaptive system is a challenge to get right, not least because of the problem of managing the handover of activities between human and computer, which can end up with the driver cycling between extremes of overload and underload (Scallen et al., 1995). Nevertheless, if adaptive automation can be properly achieved, it truly fits the system to the user.

Crucially, then, human-centred automation does not cut the user out of the loop, but rather involves them in the task at hand (cf. Wiener & Curry, 1980) for both objective and subjective benefit. We know that it is important for performance to retain an active role for the human operator (Metzger & Parasuraman, 2005). In the Euro NCAP tests mentioned in Chapter 1, the best rated systems struck a balance between easing workload and keeping the driver in the loop without promoting over-reliance.

If there is one consistent message to emerge from all this work, it is the importance of system feedback to support the operator (e.g., Cuevas et al., 2007; Hancock & Verwey, 1997). Quality feedback keeps the operator in the loop rather than out of it, helping to both prevent complacency setting in (Kaber, 2018) and to maintain situation awareness, which are both critical to responding effectively.

This feedback is provided through the system's human-machine interface, so good interface design is fundamental in promoting good coordination and shared situation awareness between human and automation by ensuring that system operation is easily interpretable and understandable (Borst et al., 2015; Endsley, 2017; Johnson et al., 2014; Wiener & Curry, 1980). Since the interface is the 'window' into the system, transparency in interface design is critical (Hancock et al., 2019) to maintain mental models, mode awareness and the ability to keep track of 'what the automation is doing now' (Endsley, 2015; 2017; Hancock, 2019; Kaber et al., 2001; Richards & Stedmon, 2016; Sheridan & Verplank, 1978; Victor et al., 2018). In other words, the automation needs to let the user know clearly what it is doing, what it plans to do, and why (Stanton et al., 2021). For example, Eriksson & Stanton (2016) discussed vehicle displays that show what the car can 'see' through its sensors, thus providing that transparent window into the what the system is thinking and arguably improving the driver's understanding of, and trust in, the system (Young, 2013). Recent innovations in head-up displays have seen at least one manufacturer taking just such an approach with adaptive cruise control (ACC), overlaying a marker on the lead vehicle that the ACC system is following.

Ecological interface design (EID) is one way of achieving this, as it allows the user to better understand the rationale behind the system's behaviour (see Borst et al., 2015; Stanton et al., 2021). We discussed in Chapter 9 the benefits of EID in improving users' understanding of the system while avoiding overload or distraction. Representing information on the display in a way that is more directly compatible with users' mental models, as EID does, can help to manage mental workload since the automation is carrying out the necessary calculations and transformations of data to information (which, of course, is what it is good at), supporting the human and relieving them of this burden (Parasuraman et al., 2000).

However, we can (and probably should) also take a step back from these issues and consider a similar question at more of a macro level, before we even get into the specifics of designing automation. That is, what is our guiding philosophy when implementing automation?

DESIGN PHILOSOPHIES FOR HUMAN-CENTRED AUTOMATION

All of the automation problems that we have been concerned with in this book are based on the presumption that there is still some human involvement in the task. In SAE terms, we are talking about automation up to and including Level 4. We will soon discuss where Level 5 fits into this debate but, as we saw in Chapter 1, it seems unlikely that this will be realised any time soon (Endsley, 2015). Therefore, we need to consider the role that the human plays and, concomitantly, answering the question we posed earlier of how we should implement automation. In this section, we make the case for a selection of higher-level philosophical approaches to human-centred design for automated vehicles.

Hard or soft, vehicle or driving?

One of the fundamental questions concerns which party has ultimate authority over decision-making: human or computer? In Chapter 1, we discussed the aviation philosophies of hard and soft automation, whereby in hard automation the computer has the final say, while in soft automation this is down to the human. The technology-centred approach would favour hard automation, recalling those arguments about accidents being caused by human error, so the human should be automated out of the equation. But there are circumstances in which this level of computer authority can cause problems rather than resolving them. The crash of an Airbus A320 at an air show near Paris in 1988 (described in Chapter 2) was arguably a consequence of hard automation systems taking charge.

We also transposed the hard/soft dichotomy against one of our own (Young et al., 2007): vehicle automation (automation of low-level vehicle control aspects) against driving automation (in which the driver is relieved of more conscious, higher-level tactical or strategic tasks). Being less overtly visible to the driver, there can be advantages to vehicle automation systems that really act as safety nets and only impose their presence when the situation has gone past the point of no return. Systems such as automatic emergency braking and electronic stability control have proven effectiveness in reducing collisions (e.g., Navarro et al., 2011).

Concerns arise, though, when considering driving automation, whether hard or soft. Issues of mental workload have been identified with some soft driving automation systems. In our series of studies reported earlier in this book (see also Young & Stanton, 2002b), the mental underload associated with ACC and (especially) lane centring resulted in performance problems when drivers needed to reclaim control from the system. Hard driving automation, on the other hand, is largely associated with problems of trust, situation awareness, and mental models. If the system is designed to assume control with little input from or feedback to the driver, then the driver may have difficulty in developing an appropriate mental model or situation awareness of its operation in a given scenario. Without knowing exactly how it might behave, the driver could become distrustful of the system (i.e., lack of trust) or even develop misplaced trust (i.e., overtrust or complacency; cf. Parasuraman & Riley, 1997). Then, the driver's situation awareness will be inadequate or inappropriate, resulting in potential performance problems in a critical situation.

In a nod to vehicle automation rather than driving automation, Endsley (2017) suggested that automation should be used for routine tasks rather than higher-level cognitive tasks. Meanwhile, Metzger & Parasuraman (2005) took this a step further and argued that operators should be supported in routine tasks to keep them in the loop, while it is the repetitive, less important tasks that should be given over to automation. Furthermore, Young et al. (2007) suggested that 'strong-but-silent' vehicle automation would have fewer human factors implications than driving automation because it is essentially invisible to the driver during normal operation, and only intervenes in abnormal situations.

From this line of thinking, we could argue that hard automation should be restricted to the vehicle automation category, where it might cause fewer problems. Conversely, the human factors problems may be more significant when implementing hard driving automation. But that does not necessarily mean that soft automation is better for the driving automation category, since we have seen that even soft driving automation can cause problems of underload.

In all likelihood, the answer is to match different elements of the driving task with different philosophies. In a sense, this has already happened, with traditional vehicle automation mostly falling into the hard automation category, while more driving automation systems straddle the boundaries of soft and hard. Rather than an overarching philosophy of soft or hard automation for driving (as has been seen in aviation), a blend throughout the driving sub-tasks may prove most effective.

Problem-driven automation

We have already argued the relative merits of human-centred over technology-centred design for automation. A problem-driven approach takes that a little further, maintaining that whatever solution is offered, it should address a need on the part of the driver. Crucially, though, the message is not to use technology for its own sake, when a more rudimentary solution may be available. This may mean implementing a low-technology solution, or possibly not using the full potential of the automation in favour of optimising human performance (Hancock et al., 1996; Owens et al., 1993).

Take ACC as an example. As we know, the argument for automation is often based on evidence from errors or accidents (e.g., Broughton & Markey, 1996); the case for ACC was in part based on the fact that over a quarter of all road traffic collisions are due to rear-end collisions (Gilling, 1997). If we break this down, it follows that drivers have some difficulty perceiving relative speed in a car-following situation[4]. But do we really need a technological solution for that problem, or would a low-tech approach suffice? Perhaps we should instead build on the success of centre high-mounted brake lights (Farmer, 1996) and improve the perception of vehicle rear-ends?

We said earlier that we are not technophobic, so we could alternatively use the same technology to different ends, providing the driver with information to support the task that they normally do, rather than taking over that task for them (Billings, 1991; Wiener & Curry, 1980). This approach can reduce workload while maintaining situation awareness (Selcon & Taylor, 1991; Selcon et al., 1992) as well as facilitating the acquisition of experiential knowledge (Böhle et al., 1994). Meanwhile, any concerns about resuming control in the event of failure are negated (Wickens et al., 2015), as the driver maintains control of the task and the system simply provides them with extra information. As such, this would avoid many of the problems of automation associated with mental underload, skill degradation and being out of the loop.

Applying this to the ACC example, the system's sensors could be used to provide drivers with advice and/or warnings (on an EID display, of course; cf. Seppelt & Lee, 2007) about the speed (relative or actual) of, or headway from, the lead vehicle. Instead of assuming longitudinal control for them, this would support their judgement of time-to-collision (Stanton & Young, 2005), which is a complex perceptual judgement especially difficult for inexperienced drivers (e.g., Cavallo & Laurent, 1988). Huang (2020) argued that automated multi-sensory systems to support this vulnerable task are a good idea, particularly given the potential for change blindness in situations when distracted, for instance by roadside advertising (as we saw in Chapter 8). In a similar way, Navarro et al. (2011) suggested vision enhancement as an example of perception support, for the 75% of crashes on rural roads that are a result of poor markings of lanes or road edges.

These kinds of solutions are in line with the general consensus towards technological support rather than automated replacement (Young & Stanton, 2002b), fostering human strengths while compensating for their weaknesses (Grote et al., 1995). Much of this can be achieved through the interface display, without necessarily 'automating' in the traditional sense (cf. Endsley, 1987), as improved sensor and display technology have shifted trends in display design from providing data towards supporting problem-solving and decision-making (Borst et al., 2015).

Using technology for information acquisition and analysis – 'information automation', in Parasuraman et al.'s (2000) parlance (see Chapter 1) – exploits the computing power to take care of calculating and integrating information (Seong & Bisantz, 2008), supporting drivers' judgement and thereby adding value to the human-automation relationship. Similarly, Endsley (2017) stated that automation at earlier stages of information processing (i.e., information acquisition) is more beneficial for situation awareness than at action selection or implementation (see also Wickens et al., 2015), arguing that we should automate only where necessary and at the lowest possible level. In other words, it is better to use technology to support users' perception than to replace control or make their decisions for them (Stanton et al., 2001).

'Cliff-edge' automation

The clear message by now is that a fundamental principle of automation – at least, automation that still requires some human involvement – is to support, rather than replace the operator (e.g., Endsley & Kaber, 1999; Hancock, 2014). As we have seen time and time again, humans should play an active part in a task rather than being a passive monitor of a system, so automation that relies on a human driver as a 'fallback' operator needs to retain a meaningful role for that driver. The point is, we cannot just increasingly cut people out of the loop and then expect them to jump right back in again when we need them to (cf. Noy et al., 2018). To be human-centred, then, this may mean restraining the full potential of the automation until its development reaches a point when it is good enough to cope with every conceivable situation in all contexts without any need for monitoring or intervention (that is, SAE level 5 automation). This is what we mean by the cliff-edge: rather than a gradual slide towards full automation, transitioning through the problematic intermediate levels (Young & Stanton, 2006a), we should instead hold back until such a time when we can jump straight to level 5 (see Figure 10.1 for a conceptual illustration).

Notwithstanding the debate earlier in this chapter about whether even partial automation would be safer than human drivers, there is widespread support in human factors for this cliff-edge type of philosophy in limiting the full functionality of automation (e.g., Hancock, 2017a; Kaber & Endsley, 2004; Mueller et al., 2021; Schutte, 1999). Norman (2015) made a convincing

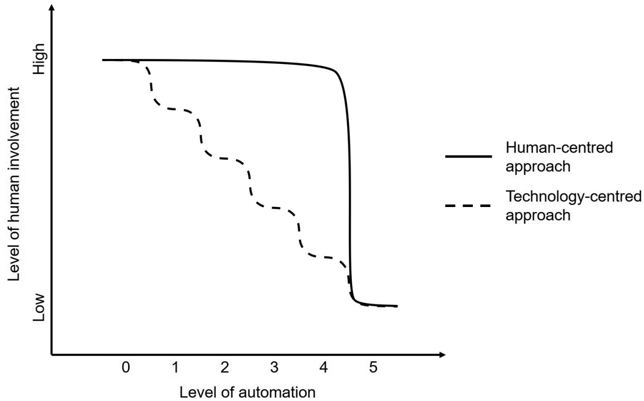

Figure 10.1 Conceptual illustration of the human-centred 'cliff-edge' principle. Rather than implementing each level of automation when it becomes technologically possible, thus reducing human involvement in a stepwise fashion (dotted line), we should maintain human involvement until we can step straight to full automation (solid line).

argument that almost-full automation is most problematic, as drivers come to rely on it and so struggle to take over control when needed (see also Noy et al., 2018). If the system appears to be very able, but is actually imperfect, drivers might overtrust it and think it can do more than it is actually capable of (Banks, Eriksson et al., 2018; Banks, Plant et al., 2018; Ljung Aust, 2020). Lee & See (2004) suggested that, in some circumstances, a simpler but less capable automation may be better than a more complex but less trustable version. Indeed, it was argued a very long time ago that aviation automation had already passed its optimal point (Wiener & Curry, 1980). So full automation in itself is not the problem; the difficulties arise in transitioning through intermediate levels of automation to get there (Norman, 2015) – not to mention concerns about automated vehicles sharing the roads with human drivers during that transition (Brooks, 2017).

We are starting to see shades of this approach in current practice, as some aviation models are indeed predicated on going straight to full autonomy, because this is seen as less complex than transitioning through a human-in-the-loop model (CIEHF, 2020a). Even in the automotive domain, some of the trailblazers of automated vehicles have considered skipping partial automation levels, in which the human might need to intervene, and instead pushing straight on to fully automated vehicles (Noy et al., 2018). Meanwhile, related concerns about the implementation of level 3 automation on UK roads (in the form of automated lane keeping system; ALKS) led one road safety expert to state in the UK media[5] that 'you can't have steps towards automation – either the car is driving or it isn't'. That is to say, we either hand over control fully and completely, or else keep a human in the driving seat – literally and metaphorically (cf. Banks & Stanton, 2016; Stanton et al., 2020).

But what of the technology in the meantime? Again, this is not about shying away from technology, but ensuring it is implemented in the right way. The answer is, of course, becoming all too familiar: support the driver, rather than replace them, in the same way as a human co-driver would (e.g., Hoc et al., 2009; Young et al., 2007). And that brings us to consider the driver and the automation as collaborative partners – in other words, as a team (Norman, 2015).

Human-automation teaming

So if the automation cannot (yet) be engineered so as to be completely independent of the human driver (i.e., level 5 automation), then it should be seen as a teammate to support the driver. Lately, the mood music in the human factors literature has very much shifted towards a teaming approach of cooperation and communication between human and machine (e.g., Dekker, 2004; de Visser et al., 2018; Endsley, 2017; Hoc et al., 2009; Moon et al., 2020; Roberts et al., 2022; Schutte, 1999; Young, 2013; Young et al., 2007), although it is notable that the importance of teaming was even implied in the original levels of automation report by Sheridan & Verplank (1978). There has been a lot of work discussing automation as a team player, moving the focus away from developing more autonomous systems (Klein et al., 2004) and instead following the philosophy of supporting rather than replacing humans (cf. Hoc et al., 2009). To borrow a quote we used in Chapter 1 (Hoc et al., 2009; p. 154): '[t]rue driver support should act as a human co-driver – providing advice when needed, assistance when necessary, but largely remaining in the background and invisible under normal conditions'. A good co-driver does not interfere, but provides assistance when needed. Billings (1991) similarly argued that automation should be restrained under nominal conditions but step up to assist when circumstances get more difficult. In cases where automation does have to intervene, it should communicate its intentions with the driver efficiently and work on the basis of the task context and driver's intentions (Clark et al., 2019). Genuine teaming is about the automation 'picking up the slack' for human capabilities and limitations (Norman, 2015), backfilling tasks if and when the human has had to direct their attention elsewhere in an emergency or abnormal situation[6].

Using cooperation as a principle for automation design is more human-centred than basing it on technological capability (Kaber & Endsley, 2004; Navarro et al., 2018). Contrast this with classical, technology-centred approaches to implementing automation (which, by the way, includes the SAE taxonomy) that have divided tasks piecemeal between human and machine according to fixed rules about which is better at performing them. All this usually achieves is taking away parts of the task that drivers are already good at anyway (cf. Billings, 1991), because these have also been the easiest tasks to automate (cf. Norman, 2015).

Although the pace of technological development is now blurring some of the traditional dividing lines for allocation of function, it also opens the potential to have a more integrated relationship designed around the human (cf. Hancock, 2019). Schutte (1999; 2017) talked about this integrated relationship as 'complemation', while Johnson et al. (2014) called it 'coactive design'. This philosophy flips traditional automation design on its head, by giving a coherent set of tasks to the human and having them make the primary decisions, thus keeping them 'in the loop' and engaged in the task. Meanwhile, the piecemeal tasks left over are allocated to the automation, which monitors human performance (rather than the other way around). Such an approach to human-centred automation fosters human skills for the task while supporting the driver's understanding of its behaviour.

Instead of just thinking about what the machine can do, then, we should take into account the impact on driver behaviour and the requirements for teamwork (Hoc et al., 2009). As Dekker (2004; Dekker & Woods, 2002) put it, rather than designing automation on a quantitative (even competitive) 'who does what' basis, successful automation depends on designers answering the more qualitative question of 'how do we get along?' The driver and the automation are part of a joint sociotechnical system and, as such, should be working together towards a common goal (Christoffersen & Woods, 2002), with the driver playing an active role (Banks & Stanton, 2016). After all, the point of introducing automation should be to improve performance of the overall human-automation system (Hancock & Parasuraman, 1992; Hancock et al., 1996; Johnson et al., 2014).

This very much reflects established wisdom on human-human teams, who also work together dynamically, interdependently and adaptively towards a common goal (Annett & Stanton, 2000; Salas et al., 1995). In that literature, teamwork is defined as 'the ability of team members to work together, communicate effectively, anticipate and meet each other's demands … resulting in a coordinated collective action' (Cannon-Bowers & Salas, 1997). These principles should equally apply regardless of whether any of the team members happen to be machine, rather than human. Accordingly, human-automation teams have been defined as 'the dynamic, interdependent coupling between one or more human operators and one or more automated systems requiring collaboration and coordination to achieve successful task completion' (Cuevas et al., 2007, p. 864). Scerbo (2007) similarly describes human-automation teams in terms based on human-human teams, where it is key to communicate plans and intentions to each other as well as coordinating task allocation.

For human-automation relationships to be human-centred, we need to think about them in the same way as human-human relationships, from a more social or anthropomorphic perspective (Clark et al., 2022; de Visser et al., 2018). People already behave as if they are working with another human when using automation (Lee & See, 2004). Sarter & Woods (1995) noted examples of pilots trying to interact with automation in similar ways as they would have with another human, making assumptions about what it would 'know' based on the inputs they have made. 'In human-human partnerships, communication has always been viewed as a vital aspect of teamwork and collaboration – team members coordinate by anticipating and predicting each other's needs through common understandings of the environment and common expectations of performance' (de Visser et al., 2018; p. 1412).

The common characteristics of good teamworking, whether human-human or human-automation, involve the coordination of resources and skills among team members, having a common understanding of each others' goals and needs, and two-way communication to share information (Cuevas et al., 2007; Endsley, 2017; Gregory & Shanahan, 2017; Salas et al., 1995; Wickens et al., 1998). These aspects are explicitly considered in the human-automation cooperation framework (Hoc, 2001; Hoc & Blosseville, 2003; Hoc & Lemoine, 1998; Hoc et al., 2009; see also Navarro et al., 2011), which we reviewed in Chapter 1. Its central tenet of the 'common frame of reference' (COFOR) reflects the importance of the human and machine understanding each other's goals and how they will work together to achieve them. The COFOR is essentially a complementary representation of the sociotechnical system held by both human and machine, a vital common ground in which information is shared to the extent that both parties understand not just what is going on, but also what the other knows and is doing about it (Cuevas et al., 2007; Eriksson & Stanton, 2016). Under the distributed situation awareness model (Stanton, Salmon & Walker, 2017), for teamworking to be effective both parties have to share their understanding with the other (Salmon et al., 2020).

The key to establishing the shared understanding that is so necessary for effective team performance, then, is communication (Salas et al., 1995; Stanton et al., 2006; Yee et al., 2020). Various researchers agree that, for automation to be a team player, its activities should be observable, directable, and predictable (Christoffersen & Woods, 2002; Dekker & Woods, 2002; Klein et al., 2004). In being observable, information presentation should be as transparent as would the actions of another human team member – which could be achieved using ecological interface design to visually integrate information on the display (for example, see Metzger & Parasuraman, 2005). In being directable, it should be possible to hand over tasks fluently between human and automation. This transfer of control is a scenario which particularly depends on breadth and depth of information communication regarding the current system status as well as when, how, and why the driver needs to take control (Campbell et al., 2020; Clark et al., 2019). Grappling with this most thorny of human-automation cooperation issues, Flemisch et al. (2012) discussed the importance of mutual awareness about who is in control. They suggested using a visual token (i.e., an icon on the display) to show who has control, and for there to be an explicit handover ritual (such as putting hands on the steering wheel) so that each party is clear that control has been transferred. Finally, in being predictable, there should be shared knowledge, beliefs and assumptions about the system's remit and responsibilities in a given situation. Automation needs to be matched to a driver's mental models, to behave like the driver so that they can detect and respond when the automation reaches its limits (Lee & Seppelt, 2012).

Whether you call it COFOR or situation awareness, then, it is critically dependent on information constantly flowing between the agents in the system (cf. Griffin et al., 2015). This reflects earlier points we covered in Chapter 2 about the importance of feedback in automated systems (e.g., Norman, 1990; 1991), since 'perception of the elements in the environment' is the foundation of situation awareness (Endsley, 1995; Jones & Endsley, 1996). The automation must be transparent in making its status and intentions obvious to the user (Endsley, 1987), and this includes its capabilities as much as its limitations. If the system is struggling to deal with a situation – whether due to a malfunction or because the situation is outside its design limitations – it needs to clearly communicate this to the user, so as to maintain appropriate mental models and, hopefully, avoiding problems of complacency (Richards & Stedmon, 2016; Victor et al., 2018).

Poor feedback along these lines has been identified numerous times as an issue in aviation automation (cf. Dekker, 2004). Take Norman's (1990) case study of the Boeing 747 with the loss of engine power (described in Chapter 1). In this example, an autopilot system attempted to compensate for the loss of power by balancing the control surfaces. However, as Norman pointed out, the autopilot did not provide feedback to the flight crew on its actions – so when it could compensate no more, the human team members were faced with a drastically worse situation than if they had been informed earlier. From the teamworking perspective, the absence of communication in this kind of automation drop-out scenario is unacceptable (Eriksson & Stanton, 2016).

In fairness, the UNECE (2018) resolution on automated driving systems recognises the importance of transparency, stating that these systems should communicate their status and intention clearly and enable an appropriate interaction. Christoffersen & Woods (2002) suggested that the higher the level of automation, the more feedback it needs to supply to make its behaviour observable. As an illustration, drawing again on good human-human interactions, Antrobus et al. (2017) showed that navigation instructions given by a passenger were better than those from a satnav, being enriched with contextual and non-verbal information and facilitated by the passenger being able to check if the driver had understood. But caution needs to be exercised here – more information is not always better, as this can lead to overload. Quality is more important than quantity (Kaber et al., 2001); communication needs to be effective, relevant (Stanton & Roberts, 2020), and timely (Yee et al., 2020). In safety-critical industries, the ABC mnemonic is used to encourage communications to be Accurate, Brief, and Clear. Eriksson & Stanton (2016) discussed rules for optimum communication along similar lines, based around the quantity, quality and relevance of the information being communicated. Similarly, Clark et al. (2019; 2022) devised a set of principles based on human-human communication that can inform human-machine dialogue in the transfer of control.

Moreover, information has to flow in both directions between human and machine in order to share goals, intentions, and to develop good mental models of each other (Endsley, 2017). The Airbus A320 crash at the Paris air show was a prime example of how this can go wrong, and one which could have been prevented if both human and machine were more aware of each other's intentions. The automation was unaware of the context of the flight (i.e., a low pass along the runway at an air show as opposed to a landing at an airport) and also the intent of the pilot (i.e., not to land). These kind of automatic mode transitions were one of the principal concerns identified in the implementation of automation on the flight deck (FAA, 1996).

So, as much as the interface must allow for effective monitoring of the system state by the human, the system must also be able to monitor the human for the same (Klein et al., 2004). In order to achieve this, the automation needs to know about the driver – their intent, their current state etc. – and that is where the behavioural models and physiological sensors of adaptive systems come in, which we reviewed in Chapter 9. To pick some of the techniques out, driver monitoring could include eye or head tracking (bearing in mind, though, that eyes-on-road does not necessarily mean mind-on-road; cf. Banks et al., 2014; Ljung Aust, 2020), steering or lane keeping, duration of drive, or reaction times to specific 'attention reminders' (Mueller et al., 2021). Using these kinds of metrics, the system could infer information about driver state and feed that into the interface to help manage the driver's attention. For instance, it could be a real team player by providing alerts or cues to direct attention to relevant information (Campbell et al., 2020; Klein et al., 2004), or re-engaging the driver if it detects their attention is waning (Merat et al., 2014). Physiological monitoring could even be used to automatically take over or hand back tasks in safety-critical situations, depending on the relative state of the driver (Endsley, 2015; Flemisch et al., 2012).

Historically, though, physiological monitoring in the messy environment of the real world has been fraught with difficulty. Physiological metrics tend to be unidimensional, and so may be limited in their ability to monitor the multidimensional nature of interacting with automation across tasks and stages of information processing (cf. Taylor et al., 2013). But the field is constantly developing and opening up new possibilities. In the previous chapter, we touched on the potential of brain-computer interfaces to detect drivers' intentions (e.g., Haufe et al., 2011). Similarly, eye-tracking systems could, with appropriate algorithms, make a reasonable guess at the driver's attention patterns, knowing where they are looking and, perhaps, what they are attending to. We might even envisage future systems that could 'get to know' the driver on a more emotional level, just as a human co-driver would – being sensitive not just to their workload or distraction but also to their particular driving style or priorities on any given day (see e.g., Rudin-Brown, 2010).

Driver state monitoring is now being widely promoted as a vehicle safety technology (Lenné et al., 2020). From the teamworking perspective, it is just the other side of the essential communication coin: the driver monitors the system through a transparent interface, and the system monitors the driver. It has been argued (CIEHF, 2020b) that, if the system is unable to do so, then the loop is incomplete and the system should not operate – in the same way as a driver incapacitated through fatigue or alcohol should not operate a vehicle.

It is therefore crucial that if an automated system is to operate effectively as part of a human-automation team, it should be aware of the task context – both in terms of the environment around the vehicle and of the driver's intentions. This recalls the analogy, as we have already noted, of considering automation in the same way as a human co-driver (e.g., Noy et al., 2018). This is a relationship in which the driver very much leads and shares control (Victor et al., 2018), as a manager of a set of resources which happens to include the automated system (Dekker, 2004). But exactly what this all looks like for automation is still an open question (de Visser et al., 2018; Larsson et al., 2014; Victor et al., 2018).

In aviation and other transport systems, the evolution of crew resource management (CRM; e.g., Helmreich et al., 1999; Kanki et al., 2010; Wiener et al., 1993), and non-technical skills (NTS; e.g., Flin et al., 2008) followed a series of aircraft accidents in the 1970s and 1980s in which teamworking between flight and cabin crew broke down. CRM is about using all the resources at the disposal of the crew – people, information and equipment – to achieve safe and efficient operations (Lauber, 1984; cited in Flin et al., 2008). Core themes of CRM have included communication, cooperation, shared situation awareness, leadership and team decision making (Jensen, 1997) – all those elements of good teamwork we have reviewed above. There is academic (Salas et al., 2006) and practical evidence of the success of such programmes in changing behaviour and improving safety. Indeed, the aircraft accidents at Sioux City and on the Hudson River (reviewed earlier in this chapter) could have been a lot worse, were it not for the CRM skills on the flight deck (see Reason, 2008; 2016). At Sioux City, Reason (2008, p. 228) quotes the DC-10 captain as saying after the accident: 'There were 103 years of flying experience in that cockpit … but not one minute of those 103 years had been spent operating an aircraft in the way we were trying to fly it. If we had not worked together, with everybody coming up with ideas and discussing what we should do next and how we were going to do it, I do not think we would have made it to Sioux City'. Similarly, the official investigation report into the Hudson River accident (NTSB, 2010, p. 91) concluded that the 'professionalism of the flight crew members and their excellent CRM during the accident sequence contributed to their ability to maintain control of the airplane, configure it to the extent possible under the circumstances and fly an approach that increased the survivability of the impact'.

Early in the development of CRM approaches, Wiener (1989) hinted at the importance of considering automation in a CRM context. Since then, in aviation and in maritime, automation has developed to such an extent that it is now seen as a vital non-human member of the team (Cuevas et al., 2007; Endsley, 2015; Kaber et al., 2001; Mallam et al., 2020; Roberts et al., 2022).

The principles of CRM therefore apply equally to machine agents as they do to human colleagues (Wiener, 1989), although this is typically from the perspective of training operators to use the automation as an additional resource (EASA, 2013; Shively et al., 2018; Wiener & Curry, 1980).

Rather than thinking of CRM purely in terms of human-to-human or human-to-automation (cf. Fitzgerald, 1997), though, why not also invoke it for automation-to-human scenarios? In other words, if we are expecting the automation to behave as a team member – coordinating and cooperating with the driver – then we should be thinking in terms of applying CRM principles to the design of automated systems (Schutte, 2017; Shively et al., 2018; Young et al., 2007). As a set of principles for human-human cooperation, it has worked very well – so perhaps it would work equally well as a set of design principles for human-machine cooperation (Clark et al., 2022). After all, good human-centred practice should be about the design of the system, not training the operators (Jensen, 1997).

A CRM-designed automation can be achieved in two ways. Firstly, by erring on the side of 'soft' automation, thus leaving the human in active control and able to delegate tasks as appropriate – in line with the frameworks proposed by Parasuraman et al. (2000) and Hoc (2001). Secondly, as argued earlier in this chapter, the teamworking aspect ultimately comes down to communication in both directions – which means a significant design effort on the control-display interface to optimise the flow of information (cf. Griffin et al., 2010).

Let us illustrate this by again thinking about Norman's (1990) case study of the Boeing 747 with the loss of engine power. If we substitute the automation with a good co-pilot, they might have noticed early on that they were having to compensate for the yaw imbalance, and alerted the captain, rather than staying silent. This could have led them to investigate the problem and solve it without the near-catastrophic consequences that actually did occur.

The idea of CRM-designed automation is not entirely without precedent. Scerbo (2007) described developments in the 1990s in military aviation for the 'crew-automation team', in which the system was designed to function as an assistant or junior crew member, managing information and acting as a cognitive decision aid. One application of this was in the F-16D Ground Collision Avoidance System which, if the aircraft was getting too close to the ground, would first warn the pilot and then, if no action was taken, take control to get the aircraft safely away from the terrain, before handing back to the pilot with a suitable 'you have control' message (Scerbo, 2007). Contrast this with what a lot of current automated vehicle systems do, which discourage shared participation by instantly giving up control the moment the driver dares to make any input (Mueller et al., 2021).

It is worth noting the explicit distinction between the non-technical, teamwork skills (i.e., cooperation, coordination, and communication) which are required to work together effectively, against the technical taskwork skills, which are necessary to actually get the job done (Wickens et al., 1998). Teamworking itself comes with additional demands associated with coordination of resources (cf. Endsley, 2017), and we have to be careful that these do not outweigh the reductions in taskwork and impact on performance (for instance, having to actively seek out information instead of the automation communicating it effectively; Christoffersen & Woods, 2002; Hoc et al., 2009; Parasuraman et al., 2000). We might draw parallels with technology-centred approaches to allocation of function (which are firmly taskwork-based) as opposed to the human-centred, teamwork-based philosophy that we have been advocating here. In designing optimal human-human teams, the aims are to have a balance of skills and good communication and understanding between team members (Roberts et al., 2022). Likewise for human-machine teams, the objective should be to design an automated system with complementary taskwork skills (cf. Schutte, 1999) and good teamworking abilities (cf. Hoc, 2001).

Designing the automation to be a team player is in keeping with the sociotechnical systems perspective, with both human and machine working in harmony towards a common goal. Being able to delegate tasks to an automated co-driver should address the core theme of this book, optimising mental workload by literally sharing the load (cf. Hancock, 2021; Parasuraman, 1987; Parasuraman & Wickens, 2008). Good coordination can even counteract some of the detrimental effects of sudden transitions in workload, such as when taking over control from automation (Huey & Wickens, 1993). Similarly, human-like automation should ameliorate the other problems of automation covered in Chapter 2: mental models, situation awareness, and trust, especially in those all-important takeover situations (Hancock, 2019). It has even been said that human-machine collaboration is actually better than semi- or full automation (Hancock et al., 2019; Hoc et al., 2009).

DRIVER TRAINING

It only seems fair to balance out our focus on designing the automation with some consideration of training needs for drivers of future automated vehicles (Merriman et al., 2021a). To be clear, our position is that design solutions should indeed be the primary focus; we should not be relying on upskilling drivers in order to mask a badly designed system. But training and design are two sides of the same coin and, for all the efforts on design, there is still an important role for training (Victor et al., 2018). As we have noted many times in this book, introducing automation into vehicles qualitatively changes the driving task and so there is an argument for properly integrating it into driver training (Rigner & Dekker, 2000).

Professional bodies in road safety[7] and human factors (CIEHF, 2020b) have called for driver training with automated vehicles to be legislated. The question for driver licensing is therefore whether special training will be required to operate an automated vehicle. As it currently stands, the only level of automation that is treated differently is automatic transmission, but training drivers in the abilities and limitations of automation is being considered at governmental level (CCAV, 2020) as part of the introduction of level 3 automation on UK roads.

To some extent, this training may cover how to use the new technology itself (i.e., taskwork), but it should also focus on utilising automation as a resource, and coordinating its input to the task (i.e., teamwork). That would follow the aviation model of incorporating automation into CRM training (EASA, 2013; FAA, 1996; Wiener & Curry, 1980). Whilst there is some merit in this, as Norman (2015) explained, there are problems in comparing the automotive domain to aviation. Compared to airline pilots, drivers are much less well trained and there is a wider degree of variability in skill amongst the driver population (Stanton et al., 2007). Furthermore, the time available for drivers to react in emergency situations is in the order of seconds, rather than minutes, so expecting even trained drivers to be able to take over from automation is unreasonable (Stanton et al., 1997).

The role of the human driver in these conditions becomes more and more critical as the level of automation approaches – but has not yet reached – level 5 (Noy et al., 2018). As we learned through our series of studies reviewed in Stage 2 of this book, skilled drivers may be able to draw on their overlearned reactions to critical situations to mitigate the effects of underload. Ironically, though, as automation increases, these drivers face their skills being stripped away through a lack of practice with the actual driving task, because the automation is in control (Bainbridge, 1983; Hancock, 2014). Conversely, it is conceivable that – in the not-too-distant future – a newly-qualified driver with basic training could immediately get into a vehicle equipped with more advanced level 2 or 3 (or higher) automation. Again based on our research, we anticipate that this may improve their performance in the short term, but they would be even less able to cope if (when) they have to take over control from the automation. Consequently, increasing levels of automation will perversely result in higher investments in driver (re)training (Parasuraman, 2000) – at least until we reach level 5 and can remove any role for the human completely.

Fortunately, the human factors community has risen to this challenge, with numerous studies addressing driver training for automation (Merriman et al., 2021b). For instance, at least one large-scale project[8] has been exploring the need for training and licensing associated with new levels of automation. Meanwhile, several studies have shown promise that training improves trust (Lee & See, 2004) and situation awareness (Mueller et al., 2020) with automation, even in takeover scenarios (Shaw et al., 2020). Another option would be providing drivers with simulator training of automation failures, to help establish their mental models about the limitations of automation (Sebok & Wickens, 2017) as well as gaining that all-important practice for emergency responses. This kind of technical knowledge about a system has been labelled 'automation awareness', emulating situation awareness (Mohrmann et al., 2015). Taking a slightly different tack, some argue that interactions with future systems will require different skill sets, more akin to operating computers and even serious gaming (cf. Mallam et al., 2020).

Notwithstanding the clear need for training drivers with automation, our stance remains that this should be part of a holistic philosophy in which the first principle should be 'training' the automation through human-centred design. A CRM-type approach is compatible with this, playing as it does to the strengths of each team member (whether human or machine), and can actually serve to develop the skills of the human by keeping them engaged in the task, as they should be.

WHICH WAY NOW?

As we finally reach the end of our journey with this book, it is apposite to review where we have got to and, more importantly, where we are going next.

We started out by reviewing the various taxonomies of automation. As we have seen since, many of these are technology-centred, allocating functions according to what machines can do rather than necessarily what they should do (cf. Hancock, 2014). But these traditional frameworks are rather passé now; apart from anything else, computers are getting better at most tasks and will almost certainly be better than humans in practically all areas at some point this century (Hancock, 2014).

More to the point, the descriptions used in the SAE levels of automation (such as 'fallback-ready user') assume a level of attention and readiness on the part of the user that is not appropriate with highly reliable – but not perfect – automation. With such systems, users are strongly inclined to engage in non-driving tasks (de Winter et al., 2014) and inevitably reduce their monitoring of the automation (Onnasch et al., 2014; Victor et al., 2018). As Hancock (2014) said, humans should not remain in systems purely to watch over the automation in case it goes wrong, a task for which they are 'magnificently disqualified', and then take the blame when it does. If you build systems in which people are rarely required to respond, they will rarely respond when required (Hancock, 2014).

We saw illustrations of how it can all go wrong in Chapter 2, through case studies of automation-related accidents in aviation as well as automotive. One issue we did not confront there was the question of legal and moral accountability (cf. Awad et al., 2018; Hancock et al., 1996): if a system failure results in an accident, who should be held responsible? Many current systems (and their manufacturers) disclaim liability by positioning themselves as 'support' systems (i.e., rather than control systems – despite using names such as 'autopilot'; Teoh, 2020) and by stating in the owner's manuals that the driver always has responsibility for the vehicle. This obfuscation puts the driver legally in control even if they were in all practical senses a mere supervisor, and had no actual control over the subsystem that was automated (cf. Pöllänen et al., 2020). At the turn of the millennium, a mock legal trial

(Noy et al., 2000) put this to the test with a case of a driver making a claim against the manufacturer of an ACC system for inappropriate design that led to a collision, with the underlying issue being the transfer of control from the vehicle to the driver. Whilst the exercise drew no firm conclusions, what it did demonstrate was the need for human factors expertise in these kinds of proceedings.

In any case, the legal landscape may be changing as we transition to level 3 automation, when the driver can genuinely – and legally – detach themselves from the driving task (at least in very defined circumstances). At this point, perceived and actual liability will shift from the human to the car, the manufacturer, even potentially to governments, putting highly automated vehicles more on a par with transport service industries such as rail or aviation and, as such, may need to be regulated accordingly (Brooks, 2017; Pöllänen et al., 2020). Suffice it to say, these questions are being dealt with at governmental level[9] as part of the introduction of ALKS on UK roads (CCAV, 2020). Ultimately, such system-wide factors will need systems-level research and methods in order to properly address them (e.g., Pöllänen et al., 2020; Stanton et al., 2019). It will no longer be acceptable to rely on exhortations of 'driver error' to explain accidents involving automated systems and hope to fix the problem with driver education or enforcement.

These accidents of automation gave us a platform to then start looking at all of the human factors problems with automation, with a focus throughout the next section of the book on the detrimental effects of mental underload – especially when reclaiming control from automation. In short, some levels of automation can underload drivers, resulting in their attentional resources shrinking in response to the reduced demands. Then, when required to resume manual control, the underloaded driver no longer has the requisite capacity to deal with the sudden increase in workload. To some extent, skilled drivers can circumvent these effects, because their responses in emergency situations are automatic and so do not rely on those attentional resources. But, as we have explained, protracted use of automation can see those skills degrade over time.

On reflection, we have since pondered whether the underload effect we have observed stands in and of itself, outside of the automation context (Young, 2021). Given that some of our research (Young & Clynick, 2005; Young, Birrell & Davidsson, 2011) failed to elicit non-automation-related underload, even in spite of ostensibly different levels of demand, there is an argument for suggesting it is automation-specific. Nevertheless, the practical implications for drivers of future automated vehicles cannot be ignored.

In Stage 3, we looked at the positive sides of automation and considered its potential benefits in supporting limitations in driver performance. Such limitations may be intrinsic (e.g., vision, ageing) or situational (e.g., distractions). We described approaches to interface design that promise to maximise these benefits while minimising the negative impacts of the technology. Finally, in this chapter, we took that a step further to set out some design philosophies for human-centred automation, primarily advocating a teamworking approach in which both parties work together for the good of overall system performance.

This means exploiting the capabilities of both human and automation while compensating for each other's weaknesses – not in a Fitts' list-type manner (see Hancock, 2019), but as part of a healthily functioning team. In fact, what we are advocating is almost a reverse Fitts' list, identifying those areas of human performance where technological support is necessary (such as in time-critical situations, when the computer will react more quickly than a human; Sheridan & Parasuraman, 2000), and treating the automation as a co-driver to pick up the slack (cf. Schutte, 2017).

Rather than seeing humans as error-prone and, as such, trying to automate the problem away, we should recognise the fact that they are actually quite good at the task of driving, when you bear in mind all of the variabilities and different ways that it can go wrong. Indeed, one reason that full (level 5) automation is such a long way off (Brooks, 2017) is that only a human can currently deal with the unpredictable environment of the roads, proactively using their experience to anticipate others' behaviour in a way that automation cannot (Endsley, 2019). So we should capitalise on these strengths by integrating the driver into the design of the sociotechnical system in a holistic manner.

This teamworking approach, using the principles of CRM to emphasise coordination, cooperation and communication, can overcome the problems in human-automation interaction and may actually lead to better overall system performance (Hancock et al., 2019; Hoc et al., 2009). We all know that machines can and will go wrong; it is hard to imagine even level 5 automation being 100% reliable. People, on the other hand, bring a level of flexibility and adaptability (CIEHF, 2020a; Johnson et al., 2014) that can – and often does – make a valuable contribution to system safety (cf. Hollnagel, 2014; Reason, 2008). Indeed, the reason many of these systems work well at all is due to the human's resourcefulness in spite of uncooperative automation (Christoffersen & Woods, 2002). But we should design this into the system from first principles, instead of relying on the human as a 'fallback' when things go wrong with the technology.

Given that people will still be involved in the control loop for some time to come[10], they should actually be in control of the vehicle (cf. Billings, 1991). Using the terminology of Young et al. (2007), there is therefore a case for development to focus on vehicle automation, only taking on routine, repetitive tasks (Xu et al., 2019) until driving automation has matured sufficiently (cf. Kyriakidis et al., 2019). But vehicle automation does not represent true human-machine teaming; this occurs more at the mutual control, driving automation level (Navarro et al., 2011). On that basis, and given the arguments we made earlier in this chapter, keeping the driver in control of the vehicle means adopting soft-driving automation. If that means holding off on full automation until the technology is capable enough for true hands- and mind-free driving (cf. Banks, Eriksson et al., 2018), then so be it.

Technology marches on, though; we have long since passed the tipping point with automation (cf. Wiener & Curry, 1980) and we remain in this limbo where it can do a lot of things, but it cannot do everything (cf. Norman, 1990). More to the point, as we write this book, automated driving systems are on the cusp of a particularly challenging stage in their evolution, with the transition to level 3 automation. From a human factors perspective, level 3 presents the most concerns (Kyriakidis et al., 2019), taking the driver out of the loop yet still expecting them to take over control as necessary (Seppelt & Victor, 2016) – which we know is far from ideal (e.g., Kaber & Endsley, 2004). Based on these concerns, researchers and industry experts agree that we should skip level 3 entirely (e.g., Seppelt & Victor, 2016; Williams, 2019).

But, as Seppelt & Victor (2016) also point out, this puts us in a bind where if we automate then human performance gets worse, but if we do not automate then we negate any potential benefits of automation for road safety (cf. Norman, 2015). This argument has some statistical traction, as models suggest that even if automated vehicles are only slightly safer than human performance, hundreds of thousands of lives can be saved over a period of 15–30 years (Kalra & Groves, 2017). There will still be crashes, of course, and there is a moral question about whether society will accept automation-caused accidents (cf. Awad et al., 2018), regardless of how few there may be.

From the human factors perspective, we believe the teamworking approach offers the middle ground to navigate through this dilemma. As automation increases, the need for effective coordination will also increase (Borst et al., 2015). And such cooperation is all-important for system performance, especially in the automation takeover event (Eriksson & Stanton, 2016; Inagaki & Sheridan, 2019). As we have seen, having a strong and silent type for a co-driver can cause all manner of problems (Stanton, 2015). When it comes to human-centred driving automation, communication is key. It is not so much about 'letting George do it', but working together for the greater good. We need to start thinking of George as a co-pilot rather than an autopilot, not there to supplant all the ills of the human condition, but instead to work alongside the human as a team player. That would be the true 'autopia' of the future.

KEY POINTS

- While the debate rages on about acceptance (or acceptability) of driving automation against the potential safety and economic benefits, there is no denying the fact that automation will have (and, indeed, has had) a massive impact on the human in the driving seat, particularly concerning mental workload.
- The technology-centred assumption that automation will eliminate human error is a folly; history is replete with examples in which the flexibility and adaptability of human ingenuity has saved the day.

- A human-centred design approach exploits these human capabilities and puts the driver at the heart of the system, using automation to address a problem rather than implementing the technology for its own sake.
- Given that completely hands- and mind-free driving is a long time coming, we should seek to keep drivers involved in the task for as long as possible, using technology to support rather than replace them, until we can make a 'cliff-edge' transition all at once to full (level 5) automation only when it is available.
- In the meantime, we should think of automation as a co-driver and apply principles of good teamworking to its design – exploiting the strengths of both human and machine while compensating for their respective weaknesses, and engendering the automation with the ability to coordinate, cooperate, and communicate well with its human counterpart.

NOTES

1. Put forward by Professor Don Norman in a 2015 blog post at: https://jnd.org/automatic_cars_or_distracted_drivers_we_need_automation_sooner_not_later/ (accessed 11 May 2022).
2. As we noted in Chapter 2, it is ironic that more technology has led to a greater need for automation to help us deal with the technology!
3. The DC-10 has three engines, one on each wing and one mounted on the tail structure; it was the latter engine which failed.
4. There is a whole literature on driver perception of time-to-collision which is beyond the scope of this book, but see, for instance, Groeger (2000) and Huang (2020).
5. https://www.theguardian.com/uk-news/2020/oct/23/uk-insurers-warn-against-go-ahead-for-self-driving-cars-on-motorways (accessed 29 April 2022).
6. See the excellent webcast by Paul Schutte of NASA Langley Research Center, for the NASA Engineering and Safety Center Academy on 17 March 2016, titled 'How to make the most of your human: Design considerations for single pilot operations'. Available at: https://nescacademy.nasa.gov/video/fdea070f17aa4ceaae5ab03dc8a6c2251d (accessed 22 April 2022).
7. IAM RoadSmart Manifesto 2019. Available at: https://www.iamroadsmart.com/docs/default-source/default-document-library/iam-roadsmart-manifesto-2019.pdf?sfvrsn=6b4a15a6_0 (accessed 19 April 2022).
8. https://www.drive2thefuture.eu/ (accessed 29 April 2022).
9. The UK Automated and Electric Vehicles Act 2018 addresses the liability of insurers in collisions with automated vehicles (see https://www.legislation.gov.uk/ukpga/2018/18/pdfs/ukpga_20180018_en.pdf, accessed 29 April 2022), while the UK Law Commissions report on Automated Vehicles defines the boundaries of self-driving and the legal responsibilities of users, manufacturers and service operators (see https://www.lawcom.gov.uk/project/automated-vehicles/, accessed 29 April 2022).
10. It is worth noting again, given the extensive reliance on lessons from aviation in this field, that the same is true in that industry, where it is thought that humans will play a key role for the foreseeable future (perhaps up to 2050 or beyond), since the equivalent of level 5 automation is very hard to achieve (CIEHF, 2020a).

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