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HUMAN FACTORS IN AUTOMATED VEHICLES
A Bibliographic Study on Enhancing Trust and Situation Awareness in Human-Machine Interface

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SUMMARY

Automated vehicle technology represents a revolutionary advancement in the field of transportation, bringing limitless possibilities to our modes of travel and future transportation systems. As automated vehicles gradually become a part of everyday traffic on the roads, human factors and the associated issues of trust and situation awareness has become particularly important. The thesis aims to explore these critical topics, with the goal of gaining a deeper understanding of how to ensure smoother, more efficient, and safer interactions between automated vehicles and human drivers and passengers.

The novel concept of automated vehicles has piqued the interest of countless researchers, engineers, and policymakers who see it as an effective means to reduce road accidents, alleviate traffic congestion, and enhance travel efficiency. However, to achieve these goals, we must overcome various technological, legal, and societal challenges. Among these, human factors are widely recognized as a key determinant of the acceptance and successful deployment of automated vehicles.

The thesis is organized into three main parts. The first part, Chapter 1: Automated Vehicles, delves into the technological development of automated vehicles. It explores various levels of automation, from advanced driver assistance systems to fully autonomous vehicles. The chapter investigates the historical evolution of automated driving systems, their technological architecture, and key features, laying the foundation for subsequent discussions.

The second part consists of Chapter 2: Situation Awareness and Chapter 3: Trust. This part delves into the concept of situation awareness, examining how humans perceive

and understand their surroundings during the driving process and how this can be maintained in the context of automated driving. This part emphasizes the interaction between situation awareness and automated driving technology to enhance vehicle safety and efficiency. It also places significant emphasis on the critical role of "trust" in automated vehicles. We explore how trust influences driving decisions, a sense of safety, and user acceptance. Furthermore, we discuss strategies for establishing and maintaining user trust in automated driving systems.

The third part, Chapter 4: Optimize HMI Design, focuses on optimizing "human-machine interface design" to ensure effective interaction between humans and automated driving systems. We discuss optimization efforts in interface design, improvements in user experience, and enhancements in system performance.

Through these three parts, the thesis comprehensively addresses "human factors in automated vehicles," highlighting the significance of "trust" and "situation awareness" in the design of human-machine interfaces. The objective is to provide valuable insights that contribute to the ongoing development and improvement of automated driving technology, ultimately leading to safer, more efficient, and user-friendly future transportation systems.

CHAPTER1. AUTOMATED VEHICLES

1.1 Levels of Automation

Driving is currently experiencing an unprecedented transformation, with a growing infusion of information technology into vehicles. These advancements manifest through information and entertainment systems, connected vehicle communication, and driver assistance technologies (Regan et al., 2009). While these innovations, especially in the context of automated vehicles, are lauded for offering improved, safer, and more user-friendly personal transportation experiences, discussions regarding the evaluation, feasibility, and regulation of both existing and forthcoming vehicle automation technologies should take center stage. This is particularly pertinent during the transitional phase of shifting control from partial automation to partial self-driving, where human drivers continue to play a diminished yet crucial role in overseeing vehicle operations. Notably, five key issues affecting the safety of automated vehicles have been identified (see Figure.1): (i) driver mobility, (ii) technological acceptance, (iii) failure management, (iv) third-party safety testing, and (v) government involvement and regulation.

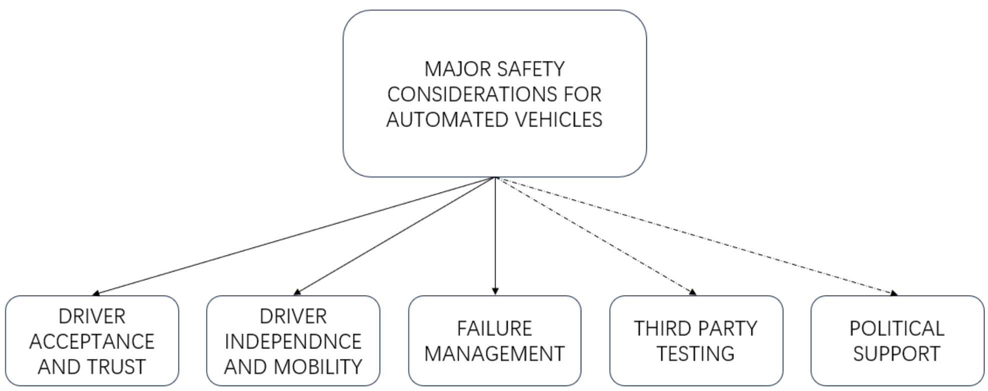

Figure.1 Driver (solid line) and regulatory (dashed line) safety-related considerations for automated vehicles.

Despite the immense advantages promised by automation, there remains significant work to be done before a fully functional system can be realized. New human-machine interfaces (HMI) must be developed to handle unforeseen situations where individuals may need to take control of the vehicle temporarily and to adapt to the evolving role of the driver as automation levels (LOAs) increase. In this context, we emphasize several critical human factors issues in the safe implementation of automation, including trust in automation, acceptance of automation, and how the driver/user responds to technological failures.

Automated driving technology has the potential to fundamentally change road transportation and improve the quality of life. It is anticipated that automated vehicles (AVs) will reduce the number of accidents caused by human errors, enhance traffic flow efficiency, increase driver comfort by allowing them to perform other tasks, and ensure mobility for everyone, including the elderly and individuals with physical impairments.

AVs can be categorized based on their technological capabilities and the level of human involvement, ranging from manual driving, where human drivers perform all driving tasks, to full automation, where there is no human intervention.

Specifically, as AV technology advances from Level 0 to Level 5, there will be systematic changes in the roles and tasks of humans and vehicles.

Monitoring of driving environment	Level of automation	Description
Human driver	0: Driver only	The human driver performs all aspects of the dynamic driving task
	1: Assisted automation	A driver assistance system performs either steering or acceleration/deceleration, while the human driver is expected to carry out the remaining aspects of the dynamic driving task
	2: Partial automation	One or more driver assistance systems perform both steering and acceleration/deceleration, while the human driver is expected to carry out all remaining aspects of the dynamic driving task
Automated driving system	3: Conditional automation	An automated driving system performs all aspects of the dynamic driving task (in conditions for which it was designed), but the human driver is expected to respond appropriately to a request to intervene
	4: High automation	An automated driving system performs all aspects of the dynamic driving task (in conditions for which it was designed), even if the human driver does not respond appropriately to a request to intervene
	5: Full automation	An automated driving system performs all aspects of the dynamic driving task under all roadway and environmental conditions

Table1. Levels of automation as defined by the SAE

At lower Levels of Automation (LOAs), the human directly operates the vehicle's control systems, albeit using drive-by-wire connections. Traditional control interfaces like steering wheels, gear shifts, and foot pedals continue to play a central role, much like they have throughout the history of driving.

As LOAs increase to higher levels, the vehicle gradually assumes more of the driver's responsibilities. The vehicle takes charge of both its longitudinal and lateral positioning, as well as making emergency avoidance maneuvers when potential collisions are detected. In this scenario, the human's role becomes that of a supervisor, providing strategic instructions related to destinations, infotainment, environmental settings, and so on.

Another consideration is whether to entrust the final decision to the human or to pursue an "optimal" solution that may not align with the preferences of the human controller. An example of potential conflict between human and automation arises in navigation, where the system suggests an "optimal" route that the driver may choose to disregard in favor of an alternative, preferred route – one that feels more familiar, safer, or more attractive, for instance.

1.2 Current and Future Directions of Vehicle Automation

1.2.1 Available Technological Solutions

Currently, L1 automation technology can be applied to some new light-duty vehicles (but not all). L2 technology is beginning to be adopted across different manufacturers, according to a report by NHTSA (National Highway Traffic Safety Administration, 2013). L1 automation technology aims to partially take over primary control tasks, such as adaptive cruise control.

L2 technology allows the driver to physically disengage from driving tasks but requires ongoing monitoring of the road and vehicle performance. Some L2 technologies, like adaptive cruise control and lane centering features, are also gradually appearing in new light-duty vehicles.

L3 technology enables the driver to hand over monitoring and control of the entire driving task to the automation system under specific conditions but requires readiness to take back control when necessary. An example is the use of L3 technology in traffic congestion pilots, allowing drivers to relax their monitoring of the road. Unlike L2 technology, L3 technology allows the driver to fully relinquish control of the driving task. While L3 technology is in various stages of development, there are currently very limited models available on the market.

As for L4 and L5 technology, they are expected to require only the input of a destination from the driver, with the system responsible for monitoring the road and performing all critical safety functions. However, except for some advanced research concepts, these technologies have not yet been truly realized. L4 systems are subject to certain limitations in specific areas, while L5 systems can operate without any restrictions.

1.2.2 Driver's Responsibilities

As vehicle automation advances, the responsibilities of drivers in the driving task have undergone changes. In manual driving (L0 or L1 automation), drivers are actively engaged in the driving task, taking full responsibility for vehicle control and road monitoring to ensure the safe operation of the vehicle. However, as the level of automation increases, some tasks are taken over by the automated systems, leading to less active involvement by drivers under normal operating conditions and a more passive role. For example, in L1 automation, drivers may still need to steer, but when using adaptive cruise control, they don't have to actively maintain a safe following distance from the vehicle in front. In L2 automation, which includes features like adaptive cruise control and lane centering, drivers need to monitor vehicle performance, but the system can manage the following distance and lane position for extended periods without intervention.

With the increasing level of automation and the transition to a monitoring role, drivers may face less demanding tasks. Research suggests that an increase in the time spent on monitoring tasks, as seen in fields like autonomous vehicles and control systems, can lead to a decline in performance (Cummings, Mastracchio, Thornburg, and Mkrtchyan, 2013). However, it is currently unclear whether this situation applies to driving tasks. As automation technology continues to improve and develop, it is essential to continuously assess and reevaluate the role of drivers in the driving task.

1.2.3 Automation Transitions

As higher levels of automation advance in research, design, testing, and eventual implementation, additional design factors need to be considered. One of the primary concerns with current and future levels of automation is the planned and unplanned transitions between different automation levels and the impact of these transitions on the timing and manner in which information is conveyed to the driver. This includes the lead time for notifications before a transition, notification modes (e.g., auditory cues, visual icons), and specific information (e.g., the functions being automated or transitioning from L3 to L1). To ensure that drivers can maintain optimal readiness to quickly take back manual control of the vehicle, when necessary, questions need to be addressed: What information should drivers receive during automation level transitions? When should drivers be alerted to pay attention to transitions between automation levels? How best to inform drivers of changes in automation levels? This topic is especially important because transitions between automation levels within current vehicles (such as L2 and L3) may occur frequently in a short span of time, meaning there is a short time frame from enabling automation to returning to manual mode.

Short cycles of automation have also been observed in the aviation field. For example, in a study by Parasuraman, Hilburn, Molloy, and Singh (1991), participants monitored three flight-related functions that could be executed either automatically or manually, with transitions from manual to automatic occurring every 10 minutes during a 30-minute training session. When these functions were automated, participants needed to perform supervisory control tasks of the automation. The results of the study showed a performance advantage for all three flight functions, with no evidence of performance degradation as these functions were automated. Furthermore, the results suggested that dynamic transitions between automation levels were advantageous for the performance of flight-related tasks, with no evidence of performance degradation when reverting to manual control. While these findings provide valuable insights into short-cycle automation, further research is needed to ensure their applicability to ground vehicles.

1.2.4 Maintenance of Driving Skills for Drivers

Introducing higher levels of automation (L2 and L3) presents another challenge, which is the potential degradation of driving skills as reliance on automation increases and opportunities for manual driving decrease. While this may not seem like a significant issue at current levels of automation, it may become more pronounced as automation levels advance. Skill degradation has been a recognized issue in the aviation industry, prompting even the Federal Aviation Administration (FAA) in the United States to issue a safety alert advising pilots to engage in regular manual flight practice rather than relying entirely on automated systems (FAA, 2013). Skill degradation encompasses not only basic driving operational skills but also decision-making skills (Miller and Parasuraman, 2007). Given that the reliability of automation systems is not yet flawless, maintaining proficiency in driving skills is crucial. Drivers may need to take back manual control of the vehicle at some point, so keeping these skills sharp is essential.

1.2.5 Drivers' Familiarity with the System

Until L4/L5 technology is fully realized, it is anticipated that drivers will only need to provide a destination input, and the vehicle will assume all safety-critical functions, including road monitoring. However, at lower levels of automation, the driving task will still be shared to some extent with the vehicle. To ensure safety, the design of automated vehicles should help drivers to fully understand the capabilities and limitations of the automation system and be aware of the current automation status. If the automation system fails or encounters issues, drivers need to be able to accurately ascertain the automation status and the overall state of the driving task to reduce the risk of accidents. This awareness and understanding of the automation system's functioning are critical for the safe operation of partially automated vehicles.

1.3 Human Factors and the Automated Driving System

In order to achieve their objectives, automated vehicles will need to consistently engage with individuals performing various roles. The specific roster of roles that automated vehicles will interact with will depend on factors such as the business model, application, and operational design domain of the technology. The roles of humans will also adapt depending on the level of automation, ranging from Level 3 vehicles to Level 5 vehicles. However, individuals who are likely to interact with Automated Driving Systems (ADSs) encompass:

1. Individuals within the vehicles:
   • Vehicle passengers
   • Vehicle operators, who may either delegate or regain control from the ADS, effectively becoming a passenger or a ready backup user
   • Ready backup users, a role defined for Level 3 (Conditional) automation, who possess the capability to operate the vehicle and must be responsive to ADS requests for intervention and preparedness for system failures (SAE International, 2018).
2. Individuals external to the vehicle who exert influence over its control and movements:
   • Those requesting or directing the vehicle
   • Remote operators
   • System operational supervisors who oversee and manage the day-to-day operations of the vehicles.

3. Other individuals with whom the ADS may come into contact or interact with on public roadways:

   • Drivers of other vehicles, including freight and passenger vehicles, as well as motorcycles

   • Pedestrians

   • Cyclists

   • Law enforcement officers, such as police personnel

   • Emergency services personnel, including ambulance workers, police officers, and firefighters

   • Individuals responsible for directing traffic in public or private areas (including roadwork site employees and individuals in private parking facilities)

   • Roadside workers.

In brief, it can be concluded that interactions with Automated Driving Systems (ADS) will differ significantly among a diverse group of users. These users will possess varying levels of experience and knowledge regarding how the technology functions and its constraints. A significant portion, if not the majority, will have received no specialized training in understanding how the technology operates but will have previous experience with conventional human-driven vehicles. The associated risks are substantial; making an interaction mistake can lead to injury or even loss of life. Serious design flaws could potentially result in numerous fatalities.

1.4 Certain Human-Related Factors that Might Affect Safety.

Part1.

Human factor-related safety concerns for individuals inside the vehicles: Vehicles will feature interfaces for occupants, including traditional vehicle controls and screen-based interfaces on the dashboard or provided through devices. Safety risks encompass:

•Vehicle passengers may unintentionally or intentionally interfere with the system.

•Fallback ready users must remain awake, alert, sober, licensed, and prepared to assume control, each of which introduces risks and potential monitoring needs. Will the fallback ready user be ready to take over the driving task when required?

•At Level 3, risks may arise during the handover back to a fully prepared fallback ready user, especially if the user fails to comprehend the ADS's request or the specific risk the vehicle is addressing.

•At Level 4, safety risks could also emerge during the transition from the ADS to the human driver.

•Is there a risk of skill deterioration, and if so, is there a requirement to amend regulations for existing drivers? Will there be a decline in performance when the human driver regains control or during the transition to taking control?

•How will drivers be educated about the technology's risks and limitations?

Part2.

People outside the vehicle affecting vehicle control and movement:

• Is there a possibility for these individuals to direct a vehicle to an unsafe location? Conversely, could the vehicle place a passenger in a precarious situation, such as malfunctioning on a busy highway with a young child as the sole passenger?

• What are the specific risks for remote operators, considering their significant detachment from the road environment? Are there potential risks affecting their ability to monitor multiple vehicles? How should they be trained and licensed, and what skills are necessary? Will they have sufficient information to comprehend the operating environment of the vehicle from a remote standpoint?

• What are the potential risks for system operational managers overseeing a network of vehicles? Will they respond appropriately to risks, resembling the roles of air traffic controllers or operators of complex facilities like power stations?

Part3.

Other individuals that automated vehicles will encounter or interact with on public roads:

- Will pedestrians alter their behavior if they perceive automated vehicles as safer? Will they, for instance, step directly into the street, akin to how people wave their hands in front of closing elevator doors, assuming they will open for them?
- Will other human drivers become more aggressive in their driving habits?
- Will other road users attempt to interfere with or manipulate automated vehicles in some way?
- Are there road user behaviors or interactions between road users that currently lack regulation, such as making eye contact with human drivers before crossing, which could pose safety risks?
- How will automated vehicles and other road users negotiate right of way in situations similar to those today? Will automated vehicles adopt the practice of nudging into traffic to signal intent, as human drivers often do?
- Automated vehicles are expected to adopt a more cautious approach than many current vehicles in terms of speed, following distances, merging, and other aspects. Could this cautious behavior lead to specific safety concerns?
- How will travel patterns change with the new opportunities offered by automated vehicles?

In addition to these questions, it's important to consider the human factors pertaining to automated vehicle manufacturers and technology providers. The safety landscape is significantly influenced by the creators of the technology, so it's essential to comprehend the human factors at play in their decision-making processes. What motivates them? How will they determine what is considered safe? What role will senior executives play, and how might they shape outcomes? It's important to note that within each of these roles, different individuals may face varying risks based on factors such as age, experience, training, impairments, and their understanding of the technology.

CHAPTER2. SITUATION AWARENESS

2.1 Introduction

Situation awareness (SA) refers to a driver's comprehensive understanding of what is happening in the driving environment, and it is crucial for successful driving. Poor situation awareness is a significant factor contributing to vehicle collisions.

Building upon this, we can discuss the impact of autonomous and semi-autonomous vehicle technologies on driver situation awareness. These technologies offer opportunities to enhance situation awareness, but they also introduce certain risks that are unique to automated vehicle features.

Situation awareness (SA) serves as the fundamental cognitive mechanism by which drivers comprehend the state of their vehicle and the environment, laying the groundwork for continuous decision-making in the rapidly changing world of road traffic.

It has been established that SA is the cornerstone of successful driving. Poor situation awareness is recognized as a significant contributor to vehicle accidents, with inadequate monitoring and inattention being two prominent examples. Distraction and recognition errors (where drivers 'look but fail to see') also stand out as major causes of vehicle collisions that point to problems with SA.

2.2 SA Requirements for Driving

1. SA is defined as the perception of elements in the environment within a specific spatial and temporal range, understanding their significance, and predicting their future status.

2. Specific perceptual (SA Level 1), comprehension (SA Level 2), and projection (SA Level 3) requirements are demanded. This is typically achieved through Goal-Directed Task Analysis (GDTA), offering a systematic approach to understanding the cognitive demands associated with any job or task, encompassing performance under both normal and abnormal conditions.

3. The overarching objective is to transport the vehicle from the point of origin to the destination safely, legally, and in a timely manner. Numerous related primary objectives include (1) ensuring the safe operation of the vehicle, (2) selecting the optimal route to reach the destination, (3) executing the chosen route safely, legally, and on time, and (4) minimizing the impact of exceptional circumstances to the greatest extent possible. Additionally, each objective can be further subdivided as needed.

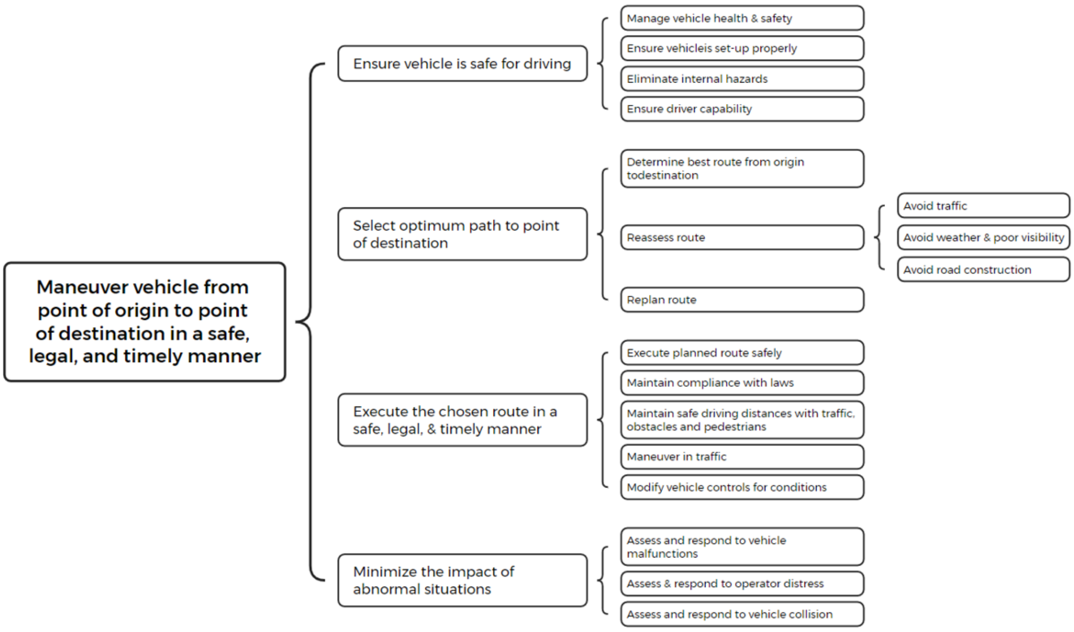

Figure.2 Goal tree for driving in road transportation.

SA Requirements for Driving		
Level 1 SA: Perception	**Level 2 SA: Comprehension**	**Level 3 SA: Projection**
Location of nearby objects (vehicles, pedestrians, cyclists, other objects)	Distance to other objects, vehicles, pedestrians, cyclists	Projected trajectory of own vehicle, other vehicles, objects, pedestrians, cyclists
Relative speed of traffic in adjacent lanes	Preferred lane for traffic avoidance/speed	Projected collision/miss distances
Open areas in adjacent lanes	Vehicle in blind spot	Projected effect of evasive maneuver/braking
Planned route	Compliance with planned route	Projected distance to turns/exits
Planned destination(s) location	Traffic lane needed for route execution	Projected distance & time remaining to destination
Traffic density along route(s) (crashes, construction, major events, time of day, road/exit closures)	Areas of congestion	Projected trip delay time
Emergency vehicles	Alternate routes	Projected time to destination on alternate routes

Emergency personnel	Avoidance of emergency vehicles	Projected traffic stops/slowdowns ahead
Hazardous weather along route (rain, snow, icing, fog, high winds, areas of flooding)	Compliance with safety personnel	Projected changes in weather
Daylight/dusk/night	Impact of weather on vehicle safety, systems, & route time	Projected safety of route(s)
Road conditions along route (road size/paving, construction, frequency of stop signs/lights, security)	Visibility of road and vehicle	Projected time and distance to destination on route(s)
Speed limit	Impact of road conditions on route time	Projected cost/benefit of change in route
Stoplight status	Impact of road conditions on route safety	Projected locations of police
Traffic control measures	Vehicle compliance with laws	Projected time until refueling is needed
Lane markings	Fuel sufficiency & usage	Projected ability of vehicle to make trip
Direction of traffic	Fuel to reach destination	Projected refueling points
Vehicle parameters (speed, gear, fuel level, position in lane, headlights, wipers)	Road worthiness	Projected stop points
Vehicle malfunctions	Vehicle safety	Projected time until stop is needed
Location of fuel stations	Distance to refueling stations	
Location of restaurants	Distance to restaurants	
Parking place(s) (location, size)	Distance to vehicles, curbs	
Driver status (fatigue, injury, hunger, thirst, intoxication)	Need for rest break, assistance, alternate driver	

Table2. SA Requirement for Driving

Michon (1985) has delineated three categories of driving behaviors: (1) strategic, which emphasize high-level decision-making concerning overarching objectives like navigation; (2) tactical, focusing on maneuvering; (3) operational, centering on low-level driving actions - such as steering and braking. When this categorization is juxtaposed with the goal tree in Figure.2, strategic behaviors map primarily to three main objectives: ensuring the safe operation of the vehicle, selecting the optimal route to the destination, and minimizing the impact of exceptional circumstances. Tactical behaviors are mainly mapped to the execution of the chosen route. While operational actions, like steering and braking, necessitate contextual awareness (e.g., brake lights, traffic signals, and lane markings), these low-level actions are embedded within sub-goals, such as maintaining safe following distances from traffic, obstacles, and pedestrians, and maneuvering within traffic. These low-level operational actions, often classified as skill-based behaviors, can either be consciously and thoughtfully executed or may become cognitively automated (which we'll delve into in more detail later). Even routinely traveled routes, like the daily commute home, can become highly automated.

2.3 SA Model

The cognitive model of SA, illustrated in Figure.2 (Endsley, 1995), serves as a framework for comprehending the factors influencing a driver's SA within the dynamic road traffic environment. Each of these factors will be examined. Based on the factors within this model, we can subsequently delve into the role and impact of automation and vehicle design on SA.

At the bottom of Figure.2, we can observe the vital cognitive processes and structures that constitute the functioning of an individual driver. These encompass pertinent information processing mechanisms such as attention, working memory, goal-oriented processing, and data-driven processing approaches.

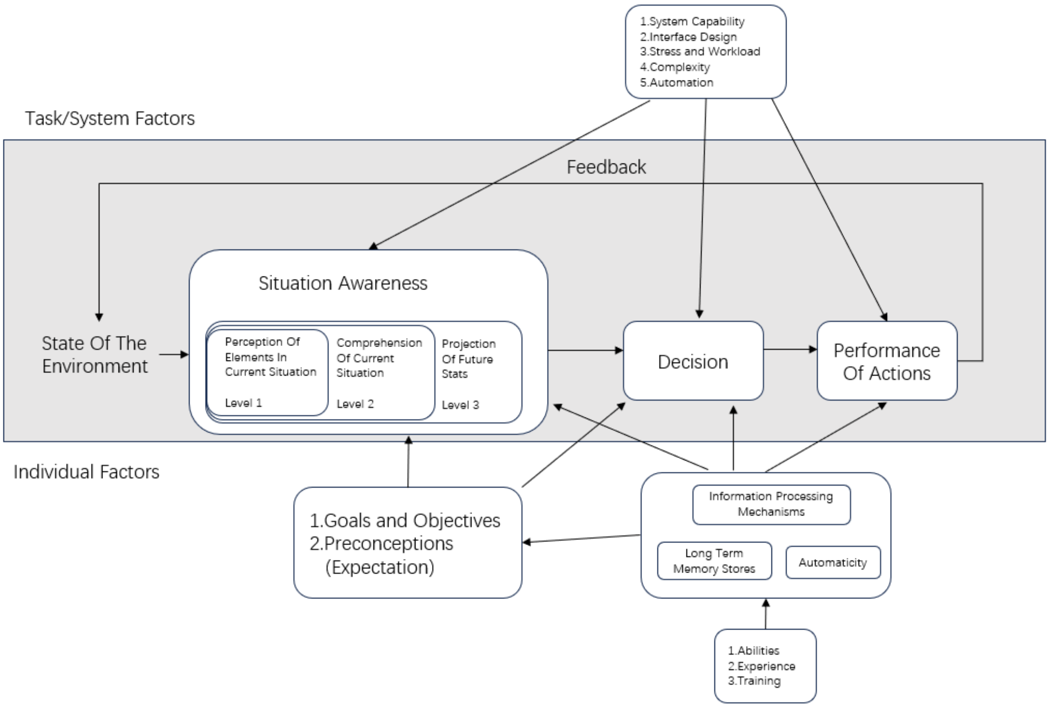

Figure.3 Model of SA in dynamic decision-making. (Endsley, 1995)

2.3.1 Limited Attention

In many instances, drivers may find themselves juggling multiple elements that demand their attention, necessitating a form of divided focus. For instance, when attempting a lane change, a driver might have to simultaneously monitor several surrounding vehicles, the traffic ahead, and upcoming road signs. Similarly, drivers making a left turn at an intersection must be vigilant of oncoming traffic and pedestrians crossing at crosswalks. Given the finite nature of human attention, this places significant constraints on a driver's ability to accurately perceive multiple streams of information simultaneously. While the capacity to allocate attention between different types of information can alleviate this challenge to some extent (Damos & Wickens, 1980; Wickens, 1992), attention remains the primary limiting factor in a driver's ability to maintain situation awareness (SA) (Fracker, 1989).

In other situations, attention may not be fully dedicated to the driving task, particularly on uncongested highways, where drivers may become susceptible to distractions, such as thinking about other tasks, events, or even daydreaming, due to excess cognitive capacity. Yanko and Spalek (2014) discovered that drivers experience distraction in 39% of cases, which is significantly correlated with an increase in speed and a decrease in braking reaction time.

2.3.2 Limited Working Memory

Likewise, working memory faces significant constraints, which limit novice drivers' capacity to gather and integrate data for formulating higher-level situation awareness (SA) and their ability to deal with novel situations, such as getting lost in a new city or navigating unfamiliar roads (Endsley, 1995). Gugerty and Tirre (1997) have demonstrated a significant correlation between working memory and SA scores in driving tasks. Kaber et al. (2016) found that Level 1 SA is strongly associated with the breadth of working memory during simulated driving tasks, especially in the aftermath of hazardous events, but this isn't the case for Level 2 or Level 3 SA.

As individuals gain experience, they can significantly mitigate the limitations of working memory by tapping into long-term memory stores, such as mental models. This has been substantiated in various studies (Endsley, 1990; 2015; Sohn & Doane, 2004).

2.3.3 Goal-Driven Processing Alternating with Data-Driven Processing

In a broader context, goal-driven processing is notably more efficient when it comes to gathering pertinent information in order of priority to achieve objectives. However, if drivers solely adhere to goal-driven processing, they may overlook crucial information signaling the need to adapt their goals. For instance, if a driver intends to change lanes, they still need to remain alert to the vehicle in front braking, which should trigger a swift shift from the "lane change" goal to the "avoiding other vehicles" goal. A hallmark of good situation awareness is the interplay between these modes: employing goal-driven processing to seek and effectively process information necessary for achieving objectives and using data-driven processing to adjust the selection of the most pertinent goal at any given moment (Endsley, 1995).

When this alternating process fails, serious SA issues arise. Those overly driven by goals might overlook vital cues, such as an emergency vehicle in their rearview mirror, a low fuel gauge on the dashboard, or a stalled vehicle in the lane ahead while they are engrossed in interacting with the in-car navigation system. Those primarily driven by data might struggle to shift their focus to relevant information when required. For instance, they might get distracted by a phone call and neglect to keep their attention on pertinent details for avoiding other vehicles and maintaining lane discipline. While at times these conspicuously distracting cues may not pertain directly to driving (e.g., distractions involving phones, texting, or conversations with passengers), it should be noted that in many instances, they are relevant to the driving task. For example, a driver might become distracted by observing pedestrians near a bustling intersection, causing them to miss the sudden stoppage of traffic ahead. In demanding driving environments, maintaining awareness of all pertinent information can be a formidable challenge due to the constraints of attention.

2.3.4 Long-Term Memory Stores

Moreover, in contrast to automation systems lacking these intricate models developed through experience, these mental models may lead drivers to possess vastly different interpretations of the significance of events and objects. Consequently, they may have differing priorities and predictions compared to automation systems. This lays the foundation for viewpoints in which appropriate actions may clash, particularly when drivers are overseeing new automation technologies. Such conflicts can give rise to confusion, incorrect expectations, and added workloads.

Mental models play a crucial role in reducing the cognitive workload associated with real-time information processing and integration. They enable drivers to (Endsley, 1995):

1. **Rapidly interpret and integrate various components to form an understanding of their meaning (Level 2 SA)**. For example, this allows drivers to comprehend the significance of warning lights on the dashboard or the impact of road conditions and weather on vehicle performance and safety.
2. **Mechanisms to predict the future state of the environment based on the current state and their dynamic understanding (Level 3 SA)**. This enables drivers to forecast potential traffic congestion on roads and at specific times or anticipate the likely behavior of vehicles in a parking lot.
3. **Identify which aspects of the environment are relevant and carry critical significance**. By incorporating information about critical cues, mental models are highly effective in swiftly grasping the situation and guiding attention. For instance, the sight of a ball on a residential street prompts experienced drivers to slow down and watch for children who may run onto the road.

2.3.5 Expertise

Inexperienced drivers exhibit notably low efficiency in their data-driven processing (Endsley, 2006). This inefficiency stems from the novice drivers' lack of knowledge about which information holds the utmost importance, resulting in sporadic and suboptimal scanning patterns (Chapman & Underwood, 1998; Underwood, 2007). They may either overlook critical information or unnecessarily over-sample data. Novice drivers lack a clear understanding of where to locate crucial information. Additionally, they struggle to focus their attention across a broad spectrum of information in their environment, likely due to the less developed mental models guiding their search efforts (Underwood, Chapman, Bowden, and Crundall, 2002).

An important consideration is the impact of vehicle automation on the development of expertise among novice drivers. If many driving tasks are handed over to automation, will novice drivers develop the deep knowledge (mental models, patterns, and goal-driven processing) crucial for situation awareness (SA)? For instance, as GPS navigation devices become widespread, the skill of map reading for navigation has become a lost art. Moreover, there's evidence that even experienced drivers may lose skills if they predominantly rely on automation. When vehicles provide automatic blind-spot warnings, drivers may no longer check their blind spots and instead become reliant on automation, which may not always be entirely reliable. It's crucial to focus on how vehicle automation influences the development of expertise among future drivers and its impact on the skill atrophy of experienced drivers.

2.3.6 Cognitive Automaticity

Through experience, individuals can also acquire a form of cognitive automation. Automatic cognitive processing is often rapid, automated, effortless, and can occur without conscious awareness, as it can happen in the background without drawing attention (Logan, 1988) or require minimal attention when needed to activate appropriate patterns, execute scripts, and follow procedures (Reason, 1984).

Automation can serve as a mechanism to overcome limited attention capacity, thus freeing up attention for other tasks, which can be highly beneficial for situation awareness (SA). However, it can also lead to a reduction in SA for familiar features in everyday situations (Endsley, 1995). Charlton and Starkey (2011) have indicated that as driving experience increases, task difficulty ratings decrease as performance becomes more automated, and object detection becomes more procedural. Additionally, drivers become more "attentionally blind" to many objects while driving, indicating a lack of conscious awareness.

The significant importance of introducing vehicle automation lies in its impact on highly automated cognitive processes. For instance, when a semi-automated vehicle takes control of steering (both horizontal and vertical), the driver will no longer engage in the low-workload automation procedures required to drive the vehicle. This implies that they will need to consciously attend to responding to traffic lights and road fragments, which previously occurred automatically from a human performance perspective. Conscious attention may be redirected or delayed in determining the need for human action, presenting new challenges.

CHAPTER3. TRUST

3.1 The Connotation of Human-Machine

Trust The definition of human-machine trust proposed by Lee and See (2004) has been widely accepted by researchers (such as French et al., 2018; Hoff & Bashir, 2015; Khastgir et al., 2017). They argue that there is an inherent connection between attitudes, intentions, and behavior: an operator's attitude toward a system influences their willingness to use the system and their reliance on it. However, relying on a system and having the intention to use it does not necessarily equate to trusting the system. Therefore, Lee and See define trust from an attitude perspective, where trust is the individual's (e.g., a driver) attitude that an agent (e.g., an automated driving system) can help them achieve a specific goal (e.g., a driving task) in uncertain or potentially harmful situations.

3.1.1 Trust Measurement

Trust measurement in the context of automated driving primarily revolves around the connotation of trust and focuses on aspects such as the driver's reliance on the automated driving system, physiological indicators, and the driver's subjective attitude. Specifically:

First, measuring the driver's reliance on the automated driving system involves behaviors such as the ratio of manual driving to automated driving during the driving process, the delay in time it takes for the driver to regain control after a takeover request, and the frequency or duration of the driver's monitoring of driving-related areas as a percentage of the total time.

Second, physiological indicators of the driver during the driving process are measured, such as heart rate and skin conductance. When the automated driving system requests control takeover, if the driver trusts the system, their emotional state will be relatively stable, with a smoother heart rate and heart rate variability (e.g., Petersen et al., The influence of risk on driver's trust in autonomous driving system. 2017), and lower skin conductance levels (e.g., Morris et al., 2017). Conversely, if the driver does not trust the system, they may become anxious and this will affect their physiological indicators.

Third, the subjective level of trust that the driver has in the automated driving system is measured (e.g., Chien, Lewis, et al., 2014; Chien, Semnani-Azad, et al., 2014; Jian et al., 2000). The Human-Machine Trust Questionnaire by Jian et al. (Foundations for an Empirically Determined Scale of Trust in Automated Systems, 2000) is currently the most widely used questionnaire for this purpose.

3.1.2 Trust Calibration

The relationship between the assessment of system capabilities and the driver's actual trust level is one of the central issues in the field of human-machine trust. Researchers typically use a two-dimensional coordinate system with system capabilities (Capability) on the horizontal axis and trust level (Trust) on the vertical axis (see Figure.4) to describe the relationship between the two (de Visser et al., 2014; Lee & See, 2004). System capabilities reflect the objective level of trustworthiness that operators should have in a specific situation based on the system's capabilities, while trust level reflects the driver's subjective actual trust level during real human-machine interactions. By measuring the relative relationship between subjective actual trust and objective trustworthiness, we can assess whether the current trust state is appropriate and, if necessary, calibrate trust (Lee & See, 2004).

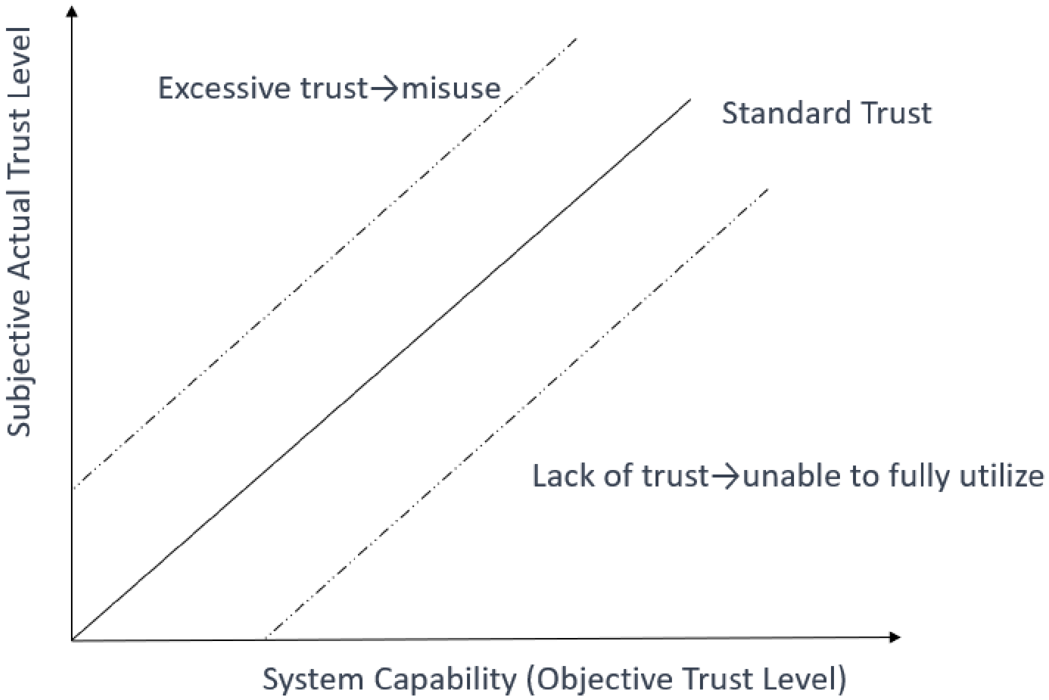

Figure.4 The relationship between system capability and subjective actual trust level (adapted from de Visser et al., 2014; Lee & See, 2004). The gray dashed area in the figure represents a zone in practical applications where trust calibration exists, with an inappropriate but recoverable or safe trust level (specific range to be further explored).

The appropriateness of trust can generally be evaluated through three aspects (Lee & See, 2004):

1. **Calibration:** The matching between the subjective actual trust level and the objective trustworthiness level. Based on their relative relationship, trust can be categorized into Appropriate trust, Under-trust, and Over-trust. Appropriate trust, also known as calibrated trust, refers to the driver's subjective actual trust level being consistent with the objective trustworthiness level, as shown on the diagonal line in Figure.4 (de Visser et al., 2014). Under-trust occurs when the driver's subjective actual trust level is lower than the objective trustworthiness level (bottom-right area of Figure.4), often because the driver underestimates the capabilities of the automated driving system. In such cases, the driver may

ignore the system's valid suggestions, leading to disuse of the system's functions. Over-trust occurs when the driver's subjective actual trust level is higher than the objective trustworthiness level (top-left area of Figure.4), typically due to the driver overestimating the capabilities of the automated driving system. In this case, the driver may not monitor the current vehicle and road conditions in a timely manner, leading to the misuse of the system's functions.

2. **Resolution:** The ability of subjective actual trust to distinguish changes in objective trustworthiness. High resolution means that when the objective trustworthiness level varies significantly, the subjective actual trust level changes accordingly, while low resolution means that the subjective actual trust level remains unchanged or changes only slightly when objective trustworthiness varies significantly.
3. **Specificity:** Specificity of subjective actual trust can be divided into two categories: time specificity and function specificity. Time specificity refers to the degree to which the driver's subjective actual trust level changes in real-time as the objective trustworthiness level changes. High time specificity indicates high time sensitivity, with the subjective actual trust decreasing when the system makes mistakes and increasing with a time lag. Function specificity refers to the driver's varying levels of trust in different subsystems, functional modules, or driving modes of the automated driving system. High function specificity reflects differentiated trust levels for different subsystems, while low function specificity indicates the opposite. Current research on human-machine trust in automated driving mainly revolves around the first aspect, i.e., how to mitigate under-trust and over-trust in human-machine co-driving and help drivers achieve or maintain an appropriate trust level.

3.2 Dynamic Trust

Framework We have constructed a dynamic trust framework for automated driving based on the development process of trust. This framework elucidates the dynamic nature of trust in automated driving and the related influencing mechanisms, by delineating the factors and their underlying logical relationships at different stages of trust development (see Figure.5) (Chen et al., 2021). In this section, we will provide a detailed introduction to this framework. It should be noted that this framework is applicable to different levels of automated driving systems (excluding L0), and the impact of relevant elements may vary across different system levels.

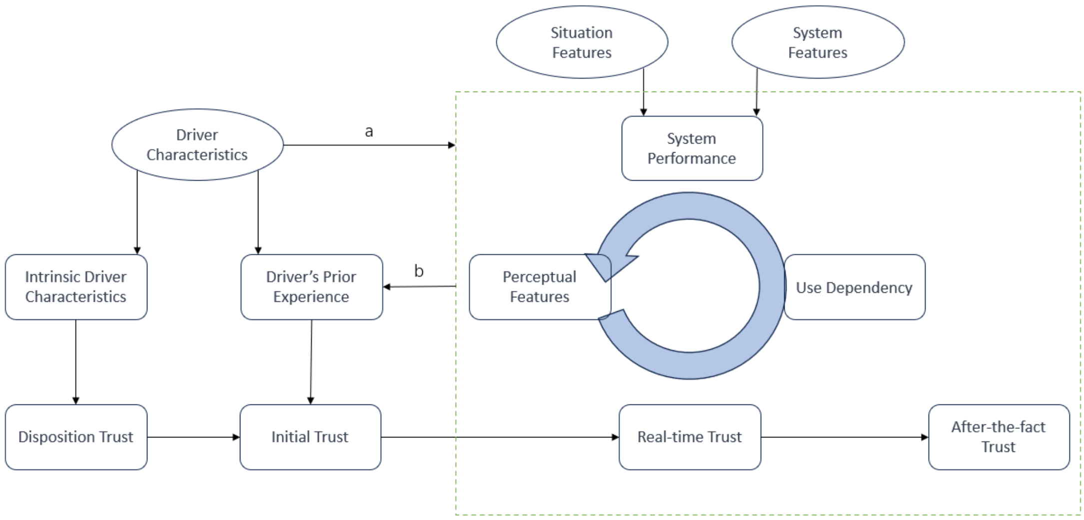

Figure.5 Dynamic Trust Framework for Autonomous Driving based on the Trust Development Process. The a line represents how driver characteristics affect all four factors, except system performance, while the b line indicates that all factors within the framework can be translated into the driver's prior experience.

3.2.1 Framework Elements

From the perspective of trust development, Merritt and Ilgen (2008) propose that an operator's trust in automated systems lies on a continuum between dispositional trust and history-based trust. Dispositional trust represents an inherent trust people have in automated systems, while history-based trust is trust formed through interactions with automated systems. An operator's trust level constantly falls somewhere along this continuum. As the operator continues to use the system, their trust gradually shifts from being primarily dispositional to being predominantly history-based, and it goes through three historical trust states: initial trust, ongoing trust, and post-task trust (French et al., 2018; Merritt & Ilgen, 2008). Therefore, this framework divides trust development into four stages: dispositional trust, initial trust, ongoing trust, and post-task trust. Initial trust develops from dispositional trust and refers to the trust an operator holds for an automated system they are about to use. They have some cognitive awareness of the system but have not yet used it. Ongoing trust refers to the trust an operator has in the system during human-machine interactions, while post-task trust pertains to the trust an operator holds for the system after the interaction has ended, representing an overall assessment of trust in the system post-interaction. The factors influencing post-task trust and ongoing trust significantly overlap, so this model primarily focuses on the factors affecting dispositional trust, initial trust, and ongoing trust.

Regarding the factors influencing trust, this framework identifies three main aspects: operator characteristics (human), system characteristics (the automated driving system), and situational characteristics (environment). Operator characteristics can be divided into inherent traits and prior experience. Inherent traits encompass an individual's physiological and stable long-term characteristics, such as gender, personality, age, cultural background, and more, which are unrelated to the system and environment. Prior experience refers to information about the system and environmental characteristics acquired through learning and largely reflects the driver's mastery of the vehicle.

During a driver's use of an automated driving system, system characteristics and situational characteristics are objectively reflected through the system's performance.

These objective system performance characteristics are then transformed into subjective perception characteristics (which also include an individual's perception of potential risks associated with the system's performance) through the driver's cognitive processing of the system. These subjective perception characteristics are the direct factors that influence trust.

3.2.2 Influence Mechanisms of Different Types of Trust

3.2.2.1 Dispositional Trust and Initial Trust

Dispositional trust is the initial stage of trust development and reflects a person's innate trust propensity. Dispositional trust is primarily influenced by driver's inherent traits such as age and personality. Research has shown that driver age can affect dispositional trust (Molnar et al., 2018), with older drivers tending to trust and use automated driving systems more. When using automated driving systems, driver control preferences can affect trust. Drivers with lower control preferences are more inclined to trust automated driving systems (Molnar et al., 2018). Driver personality traits can also influence trust propensity (Chien et al., 2016). For example, individuals with higher agreeableness are more likely to trust automated systems, which may be related to the fact that agreeableness encompasses traits like trust and compliance. There is currently no significant evidence to suggest that gender has a significant impact on dispositional trust (Molnar et al., 2018).

Initial trust develops from dispositional trust. In addition to being influenced by a driver's existing trust propensity, it is also affected by the driver's prior experience with the automated system. Prior information can facilitate the driver's understanding of the system, influence the driver's psychological model of the system, and subsequently affect trust. During the initial encounter with the system, prior information primarily comes from descriptions by others (especially brand reputation generated by advertising) and experiences with similar systems. Drivers tend to have higher trust in automated driving systems with strong brand reputations (Celmer et al., 2018). Information about the possibility of system errors can affect a driver's initial trust level (Beggiato & Krems, 2013). The higher the level of automation, the higher the driver's initial trust level in the system may be. After multiple interactions with the system, the driver's experience with the automated system is transformed into the driver's prior knowledge, influencing their initial trust in the next driving session (as shown by line b in Figure.5). Research has found that takeover experiences allow drivers to experience system shortcomings, which can help them better understand the system and, in turn, increase their trust level (Molnar et al., 2018).

It's important to note that the impact of takeover experiences on trust may not be a singular effect. For example, takeover experiences may expose system shortcomings in the short term, leading to a decrease in trust. However, in the long term, these experiences may enhance the driver's understanding of the automated system, leading to a more accurate psychological model of the system and ultimately promoting the attainment of an appropriate trust level (Payre et al., 2016).

3.2.2.2 Ongoing Trust

Ongoing trust develops from initial trust. A driver's level of ongoing trust directly influences whether they use an automated system and to what extent they rely on it. During the use of automated systems, the system's characteristics and context-related features of driving are objective factors and direct influences on trust. Objective factors determine the objective level of trust that a driver should have in the automated system. However, these objective factors do not directly impact ongoing trust. Instead, drivers need to process them cognitively to transform them into subjective perceptual features, which are the direct factors influencing ongoing trust, as illustrated in Figure.5.

Ongoing trust is mainly influenced by system characteristics and context features. System characteristics encompass system purpose, system processes, and system capabilities. System purpose refers to the intentions of the designer or the functionality of the system, such as adaptive cruise control or lane-keeping assistance. Users typically perceive the system's provided functions as reliable and trust them. System processes refer to how the automated system accomplishes driving tasks. Research has found that automated driving systems providing driving-related information through alerts enhance trust. Systems that provide driving guidance are more trustworthy than those that only offer vehicle information (Cramer et al., 2008). Systems with proactive feedback have higher levels of trust than systems with reactive feedback (Du et al., 2019). System capabilities are essential factors influencing trust, such as system reliability (Petersen et al., 2018), system errors (Kraus et al., 2020), and the level of automation. The more severe the system errors and the lower the reliability, the more trust is eroded. System failure (false alarms) can seriously undermine trust. Context features include task difficulty, road conditions, and weather. Existing research has found that traffic density affects a driver's trust in the system.

Subjective perceptual features are a core element influencing ongoing trust, and thus, the appropriateness of ongoing trust depends on a driver's accurate perception of the system and contextual features (i.e., the driver's situation awareness level; Endsley, 1995, 2016). As depicted in Figure.5 with the circular arrow-containing ring, ongoing trust impacts a driver's reliance on the system during the process of automated driving. Drivers dynamically perceive system characteristics and contextual features through the system's performance and adjust their ongoing trust level accordingly.

When the system's performance consistently remains excellent, a driver's trust in the system gradually increases. Conversely, when the system experiences errors, a driver's trust level decreases (Kraus et al., 2020). Systems can enhance a driver's accuracy in perceiving these features through the Human-Machine Interface (HMI) by providing information about system characteristics and contextual features.

Regarding system characteristics, research has found that presenting information about system reliability or uncertainty through visual means (such as using bar graphs to illustrate the automated driving system's response capabilities under the current situation) helps drivers establish an appropriate level of trust and prevents over trust (Kunze et al., 2019).

In terms of contextual features, environment reconstruction views allow drivers to perceive environmental risks more accurately, enabling their trust level to dynamically adjust with actual traffic risk levels.

Recent research has begun to focus on the impact of social cues within the Human-Machine Interface (HMI) on trust. Relevant social cues carried by automated systems can be perceived by drivers through specific aspects of automated driving systems, such as their appearance, driving behavior, and decision-making patterns, thus influencing drivers' trust in the system.

These social cues include anthropomorphism, system-driver similarity, and driving style. Anthropomorphism involves giving automated driving systems human-like characteristics, such as voice, appearance, or gender. Anthropomorphic features enhance a driver's understanding of automated systems (Niu et al., 2018), foster emotional connections, or create a sense of social presence (Lee et al., 2015), all of which contribute to higher levels of trust among drivers (e.g., Waytz et al., 2014).

System-driver similarity encompasses visual similarity, behavioral similarity, and cognitive similarity between automated systems and drivers. Cognitive similarity, such as having common driving goals, can increase a driver's trust in the system (Verberne et al., 2015). This effect may be due to the principle that similarity breeds trust (Verberne et al., 2015).

Regarding the driving style of automated systems, it can mirror human driving styles in behaviors such as lane changes, acceleration, braking, following distance, lateral safety margins, and other driving patterns. Research has found that drivers tend to trust automated vehicles with a conservative driving style more than those with a more aggressive driving style (Ekman et al., 2019). This preference may stem from drivers perceiving lower risks in vehicles with conservative driving styles. When considering both driver and vehicle driving styles, Hartwich et al. (2018) found that automated systems with driving styles similar to the drivers are more trusted.

3.3 Trust Calibration

The ultimate goal of trust research is trust calibration, ensuring that drivers maintain an appropriate level of trust in automated systems. Trust calibration essentially aims to ensure that real-time trust remains at a reasonable level (i.e., along the diagonal line in Figure.5). Based on the dynamic trust framework for automated driving discussed earlier, trust calibration can be approached from three aspects: monitoring and correction, driver training, and optimizing HMI design. We will discuss the first two sections for now and delve deeper into HMI in the next chapter.

3.3.1 Monitoring and Correction

The most direct way to calibrate inappropriate trust is to monitor the driver's real-time trust level and provide appropriate interventions when the driver either trusts the system too little or too much. When the driver exhibits over trust, the system can provide warning feedback and information about system reliability to indicate the current system and environmental risks. This helps recalibrate the driver's inappropriate cognition and adjust their trust level in the system (Kunze et al., 2019). When the driver lacks trust, their trust can be increased by providing information about system reliability and using various forms of feedback such as visual and auditory cues (e.g., Kunze et al., 2019). Interpersonal techniques like apologies, denial, explanations, and commitments can be used to repair trust between the driver and the automated driving system (trust recovery, de Visser et al., 2018; Khastgir et al., 2017).

There are two challenges in implementing current monitoring and correction approaches. (1) How to dynamically measure real-time trust: Real-time trust monitoring in laboratory studies can be achieved through the measurement of behaviors (e.g., eye movements) and physiological indicators (e.g., heart rate, skin conductance) during driving. However, accurate measurement of indicators directly related to trust, such as eye movements and skin conductance, remains challenging in real-world driving due to factors like ambient light, body movements, and emotional states. Future research needs to strengthen real-time measurement methods and indicators. (2) How to identify inappropriate trust: The core issue of appropriate trust lies in whether there is a match between system capabilities and the current actual trust level. However, these two aspects do not exist in the same measurement dimension. Even with a given level of system capabilities and the driver's real-time trust level, determining whether the trust state is appropriate is still challenging. A possible solution is to construct a mapping between system capabilities and objective trust levels. For example, researchers can attempt to construct objective trust levels for different levels of automated driving and scenarios. For instance, for Level 3 vehicles performing automated driving on highways, drivers must reach a minimum monitoring frequency or minimum monitoring time; otherwise, they must intervene. Overall, the implementation of monitoring and correction requires further exploration in terms of trust indicators selection and the identification of inappropriate trust in real-world driving.

3.3.2 Driver Training

According to the dynamic trust framework, a driver's prior experience determines their psychological model or expectations of the automated driving system, which subsequently affects the dynamic change in real-time trust (as indicated by line "a" in Figure.5). Therefore, inappropriate trust can be calibrated through training to accumulate a driver's prior experience and foster correct perceptions of the system. Through training, drivers can learn about the system's capabilities and limitations, acquire the ability to use the system to gather environmental information, and form correct psychological models of the automated system in advance (Ekman et al., 2018). This helps reduce the impact of initial system failures (first failure, Manzey et al., 2012) and enhances the driver's ability to maintain an appropriate trust level (Molnar et al., 2018).

In addition, in-depth training, involving exposure to complex scenarios like overtaking, being overtaken, and takeover events, can mitigate the negative impact of over trust on takeover responses (Payre et al., 2016). Some researchers have suggested incorporating automated driving training, including control transfer operations, into driver's license assessments. However, existing studies often involve short driving experiences and may not represent systematic, long-term training. Moreover, the psychological models formed through training may have lower ecological validity. Future research should consider the long-term impact of training on drivers of automated vehicles and explore the mechanisms of training based on real-world automated driving scenarios.

CHAPTER4. OPTIMIZE HMI DESIGN

According to the dynamic trust framework, drivers can perceive system characteristics through the system's performance. Therefore, inappropriate trust can be calibrated through optimizing HMI (Human-Machine Interface) design, providing drivers with information about system characteristics and situational features to enhance their situation awareness. This approach primarily focuses on increasing the transparency and comprehensibility of objective features by providing information about the system and the context, helping drivers process objective features more effectively, and enhancing their perception, understanding, and prediction of the system and the context to calibrate trust.

The key issue in this approach is what information HMI should provide. De Visser et al. (2014) and Mirnig et al. (2016) proposed HMI design frameworks for trust cues. These two design frameworks include two dimensions: system characteristics and driver information processing. Regarding system characteristics, de Visser et al. proposed that HMI should provide system information across five dimensions: system purpose, system capabilities, system processes, presentation format, and system design background and reputation. Mirnig et al. framed HMI design from the perspective of different levels of automation in system functionality, suggesting that HMI should provide information across three levels: operational, tactical, and strategic system information. It's worth noting that there is some overlap between the five dimensions proposed by de Visser et al., which could be further simplified into system purpose, system capabilities, and system processes. This simplification aligns with the explanation provided in this chapter's model framework of the elements of system features. For instance, to convey system capabilities, drivers can be presented with sensor recognition results or sensor reliability under different weather conditions. To convey information about system processes, drivers can be shown schematic representations of processes like overtaking and lane-changing.

Regarding the driver's information processing dimension, the two frameworks (de Visser et al., 2014 and Mirnig et al., 2016) essentially revolve around enhancing the three levels of situation awareness (Chen et al., 2018; Endsley, 1995, 2016): perception, comprehension, and projection of how the system operates in different situations.

4.1 Automated Vehicle HMI Design

Through surveys, mock-ups, driving simulators, test tracks, and real-world driving, extensive research has been conducted on driver preferences, behaviors, and performance. Much of this research has been summarized and incorporated into design guidelines (e.g., Campbell, Richard, Brown, & McCallum, 2007; Campbell et al., 2016), as well as into standards and best practices published by organizations such as the Society of Automotive Engineers (SAE) International and the International Standards Organization (ISO). However, relatively few published research studies provide actionable insights into the questions surrounding how to design the human-machine interface (HMI) for vehicles with higher levels of automation. In many respects, this reflects the early stage of maturity of the technology. But perhaps a broader challenge is the multitude of uncertainties surrounding the circumstances and scenarios in which automated driving system (ADS) HMIs will be deployed. Specifically, automated vehicle (AV) warnings may need to be richer and more carefully designed than the simple hazard warnings that have been the focus of much of the published research. For example, driver warnings and even status information in AVs serve additional long-term goals of aiding the driver in developing and maintaining a functional mental model of the system, as well as supporting and increasing the driver's trust in the system. Information may also be frequently presented in situations where the driver is not fully engaged in the driving task and may be unaware of current conditions.

With these considerations in mind, we provide the following tentative design principles:

- Providing both basic status and mode information.
- Identifying key principles for presenting warning information.
- Facilitating the transfer of control (TOC).
- Supporting improved situation awareness (SA).

4.1.1 Communicating AV System Status and Mode

The automation mode refers to the specific level and type of automation that is active at a given time. This includes specific driving functions under automation, such as steering, speed control, and/or braking, as well as other information that helps the driver understand the current operation of the system. Appropriate feedback regarding automation status and modes is crucial for the following reasons: (1) maintaining the driver's situation awareness (SA), (2) communicating if the automation has received a driver's request (e.g., transfer of control request), (3) notifying the driver if the system's operations are executed correctly, and (4) informing the driver if issues or errors occur (Toffetti et al., 2009).

Principles for Presenting System Status Information in AV		
Type of Status Information	**What Information to Provide**	**Why Information Is Provided**
System activation or on/off status	A display indicating which automation feature/function/mode is currently active.	To support driver awareness of current automation mode when the driver seeks this information.
Mode transition status	A display indicating that a TOC is occurring or that one will occur in the near future.	Under normal operating conditions, this information is presented to help drivers maintain awareness of the driving tasks.
Confirmation of successful transfer from automated to manual control	A display or message confirming for the driver that control has been transferred to the driver as they would expect, or communication of a failed/incomplete TOC if the transfer is unsuccessful.	To indicate a successful TOC from the automation system to the driver.
System fault or failure	A display or message indicating that part of the system has failed, is not functioning correctly, or that the system has reached some operational limit.	To alert drivers that they must intervene and reclaim control of driving tasks that have previously been performed by automation, due to a system fault or failure.

Table3. Principles for Presenting System Status Information in AV

4.1.2 HMI Guidelines for AV Warnings

Past research and guidelines can support the design of visual, auditory, and tactile warnings (see, for example, Campbell et al., 2007, 2016, 2018). However, it's important to note that there is limited research supporting a range of warning situations and conditions related to Levels 2-4 automation. In general, the effectiveness of specific warning methods may vary depending on the level of automation, the implementation of automation, and the driver's level of engagement with driving situations and conditions.

Therefore, we will focus on three warning design parameters that are easy to understand and highly applicable to automated vehicles: selecting warning modes, reducing false and nuisance warnings, and using staged (or tiered) warning methods.

4.1.2.1 Selecting Warning Modality

The mode of warning presentation can influence a driver's response and behavior. The choice of message mode depends on the driving environment (e.g., anticipated vehicle/cabin noise and vibration, hazardous situations), message severity (e.g., critical vs. non-critical situations), the location of visual displays (assuming these locations cannot be changed), and other factors.

1. Auditory warnings are effective at quickly capturing the driver's attention and can be used to present short messages that require rapid or immediate action (e.g., simple or complex tones or voice messages), including high-priority alerts and warnings (Lerner, Kotwal, Lyon, & Garder-Bono, 1996).

2. Visual messages are most suitable for presenting more complex information (Deatherage, 1972), information that is non-safety-critical and doesn't require immediate action. This includes continuous information presented over an extended period (uninterrupted information throughout a journey, trip, or even an entire drive) and lower-priority information, such as navigation instructions or advisory messages.

3. Tactile feedback (similar to auditory warnings) can quickly capture the driver's attention and can be used when auditory information might not be as effective.

4. Depending on the vehicle's level of automation and the implementation of automation, drivers may not always have physical contact with certain parts of the pedals, steering wheel, or even the seat.

4.1.2.2 Reducing False and Nuisance Warnings/Alarms

From Campbell et al. (2016), false alarms are alerts that indicate a threat when there is none. They should be avoided as they can distract drivers, lead to incorrect decisions and/or responses, and even increase a driver's reaction time to real warnings. Nuisance alarms, on the other hand, are correct alerts of potential threats that drivers perceive as unnecessary or not needed, possibly because they are already aware of the threat or believe that it can be resolved without driver intervention. Importantly, drivers may not always distinguish between false alarms and nuisance alarms. Excessive false or nuisance alarms can increase workload and decrease driver trust in AV systems. Strategies to minimize the frequency and impact of false/nuisance alarms, as provided by Lerner et al. (1996) and Horowitz and Dingus (1992), include:

- Automatically deactivating the warning device when it's not needed in specific driving conditions (e.g., requiring the gearshift to be placed in reverse to activate the backup warning device).
- Allowing drivers to reduce detection sensitivity to a limited extent to minimize false/nuisance alarms without significantly affecting the device's target detection capability.
- Issuing warnings only after a specified minimum time has elapsed when a target or critical situation is continuously detected.
- Allowing drivers to reduce the warning intensity or volume to mitigate interference.
- Changing modes with increasing severity (e.g., issuing visual warnings initially and adding auditory components as severity increases).

Recent examples of staged warnings include a system that, if it detects that the driver is not paying attention to the road, activates a series of warning lights, sound alerts, and/or seat vibrations on the steering wheel. The system only applies the brakes to bring the vehicle to a stop if the driver fails to respond appropriately to these warnings.

The advantages of two-level or multi-level warnings are that they provide drivers with continuous information, offering more time to identify and respond to emerging threats. They can also help drivers build a functional and consistent mental model and a better understanding of the operation and limitations of automated systems (Campbell et al., 2016).

4.2 Interaction Design Space for Automated Vehicles

When designing human-machine interfaces (HMI), the design space for communication between systems and humans is closely tied to the vehicle's technology, interior, and human capabilities (senses and actions). Modern vehicles have already integrated numerous high-end technologies such as touch panels, microphones, cameras, GPS sensors, light sensors, and algorithms that analyze the driver's steering behavior. Future vehicles will further integrate additional technologies and expand the possibilities for interaction. For best practices related to sensing and feedback, we refer to Riener et al. (2017).

Figure.5 illustrates the evolution of cockpits over the past three decades in a BMW 3 series (a-c) and various modern approaches (c-e). These designs exclusively represent the current design space for lower levels of automation (SAE 0-2). They have not yet been designed for higher levels of automation (SAE 3-5) and do not include design solutions for automation cooperation or fully automated driving. Presently, tactile and touch interfaces with visual or vibrotactile feedback dominate interface design. Vehicle system designers may consider that some of the human senses and actions, like human brain interfaces, lack practical value because they require additional effort. However, technology evolves rapidly, and concepts that seem impractical today may become feasible tomorrow with advances in technology. The less critical the primary driving task becomes, the higher the potential for other control mechanisms to become more relevant.

Figure.5 The evolution of cockpit design. Credits: a (Witzel, 2011), b (Doerfer, 2009), c (Wagner, 2019), d (Jurvetson, 2017), e (Verch, 2019).

4.3 Some Key Points and Cases Related to HMI Design in AV

More and more automakers today are promoting automated driving capabilities as a selling point for their vehicles, from Tesla's FSD to NIO's NAD. Vehicles without automated (assisted) driving capabilities are hardly considered intelligent electric cars. While accidents involving this still immature technology are frequent today, it is undeniable that automated driving is getting closer to us. As all manufacturers are pushing for automated driving, how will the experience design of the Human-Machine Interface (HMI) develop?

4.3.1 Safety Remains the Top Priority

Recurring accidents related to "automated driving" have provided harsh lessons that demonstrate there is no absolute safety in current automated driving technology. In the design of HMI interfaces, safety remains the most critical factor. Information presentation and interface color schemes must prioritize safety to help users better understand and complete interactive operations quickly.

1) Placement of Road Safety-Related Icons at the Highest Level

According to national standards and regulations, mandatory icons related to driving safety, such as front windshield defogging, should be placed at the top level of the interaction hierarchy to ensure the quickest possible completion of the operation.

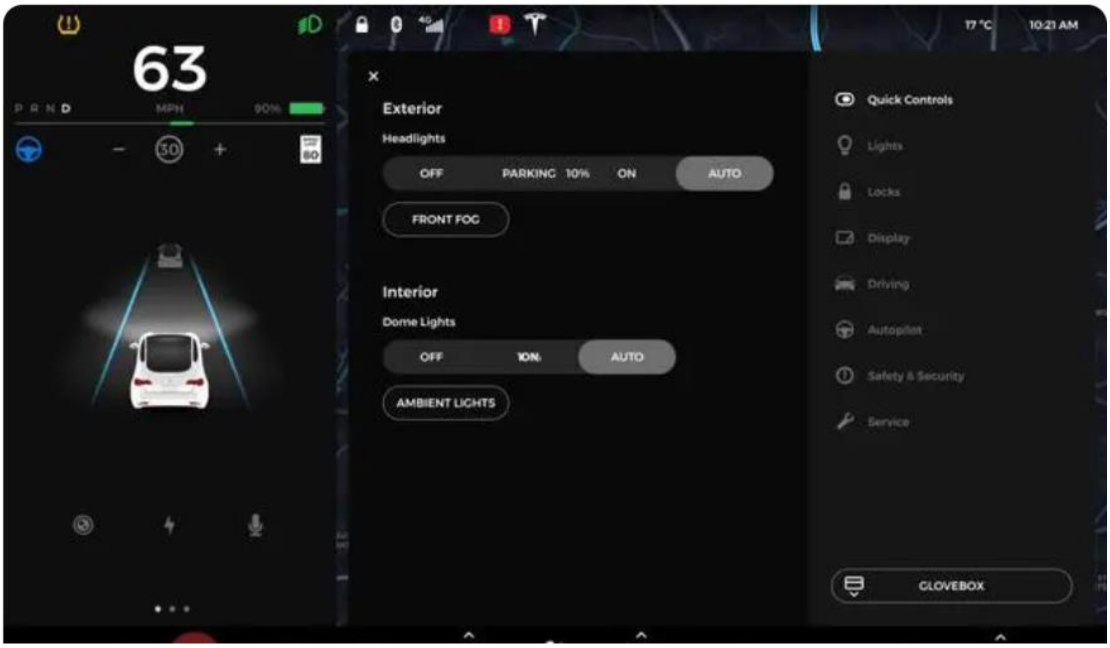

Figure.6 Tesla dock

2) Clear Visual Contrast

Appropriately sized fonts and clear color contrast assist users in completing operations quickly, avoiding prolonged visual attention that could pose safety risks.

A mature in-car font system should have distinct font hierarchies, differentiating various interaction functions and usage scenarios based on font thickness and font size. Highly legible text aids drivers in reducing browsing and decision-making times, thus minimizing cognitive and visual distractions.

Since different users may perceive font sizes differently, adjustable dynamic font systems are also increasingly used in in-car operating systems.

Style	Font Weight	Font Size
H1 Headline	Medium	56sp
H2 Headline	Medium	48sp
T1 Title	Medium	40sp
T2 Title	Medium	36sp
Operation	Medium	32sp
C1 Content	Regular	32sp
C2 Content	Regular	28sp
Caption	Regular	24sp
Caption-lmtd	Regular	20sp

Table4. Baidu In-Car Ecosystem Open Platform Font Guidelines

The interface color of HMI directly affects user operational safety and user experience. Traditional automotive manufacturers often use dark interfaces with strong contrasts to reduce glare, even in strong light. With the improvement of in-car capabilities and the growing diversity of user needs, more and more automakers are providing users with the option to choose between light and dark themes.

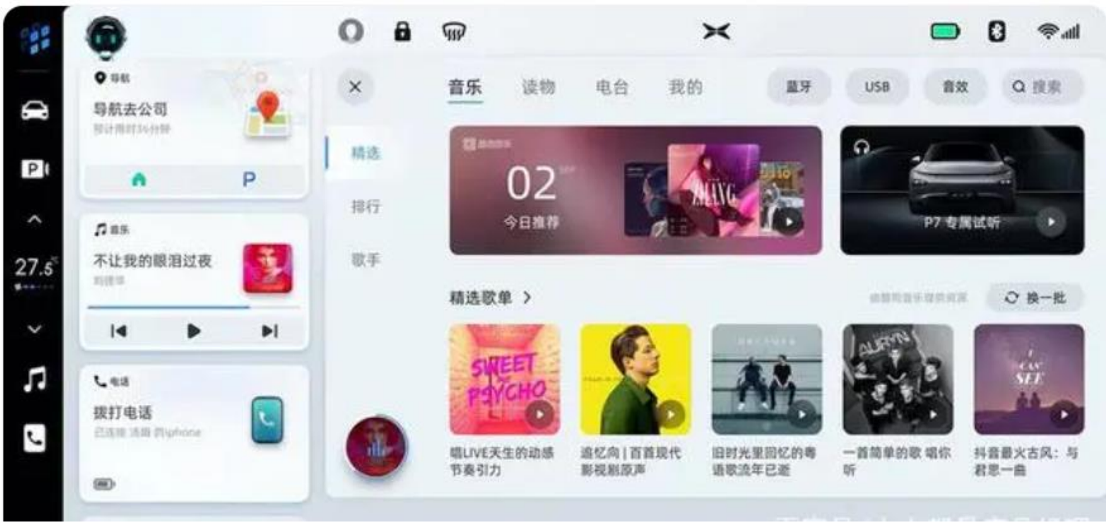

Figure.7 Xiaopeng Xmart's Light Interface

Taking into account the impact of real-world lighting conditions, the contrast of icons, text, and other images must be at least 4.5:1. In NIO's 3.1.0 update's light mode, the text-to-background contrast is 9.9:1, ensuring accurate information presentation while providing comfortable reading for users.

4.3.2 Instantly Understandable Interface

As vehicle functions continue to expand, the volume of information in HMI interfaces is also increasing. HMI serves as a platform for users to input and receive information within the car. Designing an interface that balances the amount of information with readability is crucial for enhancing user experience.

QQ Music offers different presentations on PC and in-car systems, representing two distinct approaches to displaying information. One is business-oriented, and the other is efficiency-oriented.

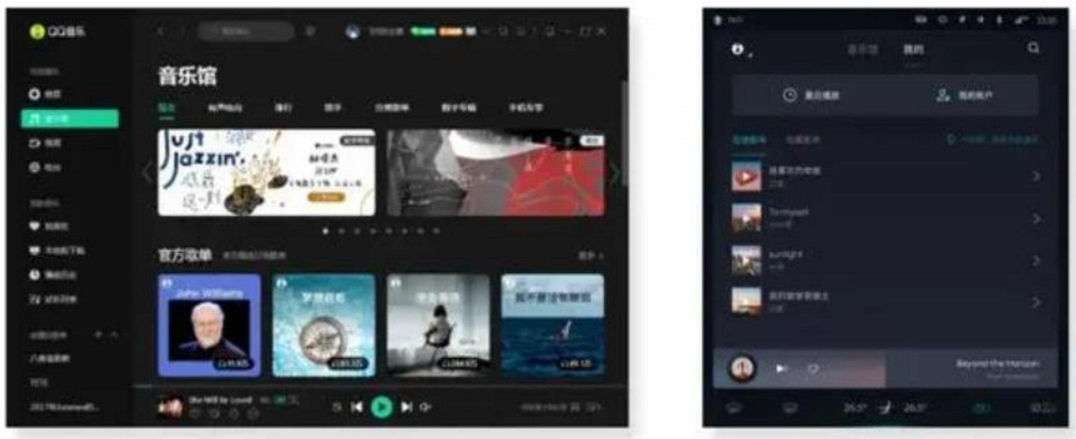

Figure.8 The differences between different platforms of Music software.

The improvement in automated driving capabilities can certainly free up the user's attention inside the vehicle. However, it also increases the demands on information interaction and places a higher focus on enhancing the user experience.

A car interface equipped with automated driving capabilities should achieve the following:

1. Accurately and quickly convey the vehicle's current performance status.
2. Provide pre-event notifications to guide user actions.
3. Communicate information about the driving environment and anticipate potential interactions with the surroundings.
4. Implement standardized interaction processes to avoid overly complex interaction methods.

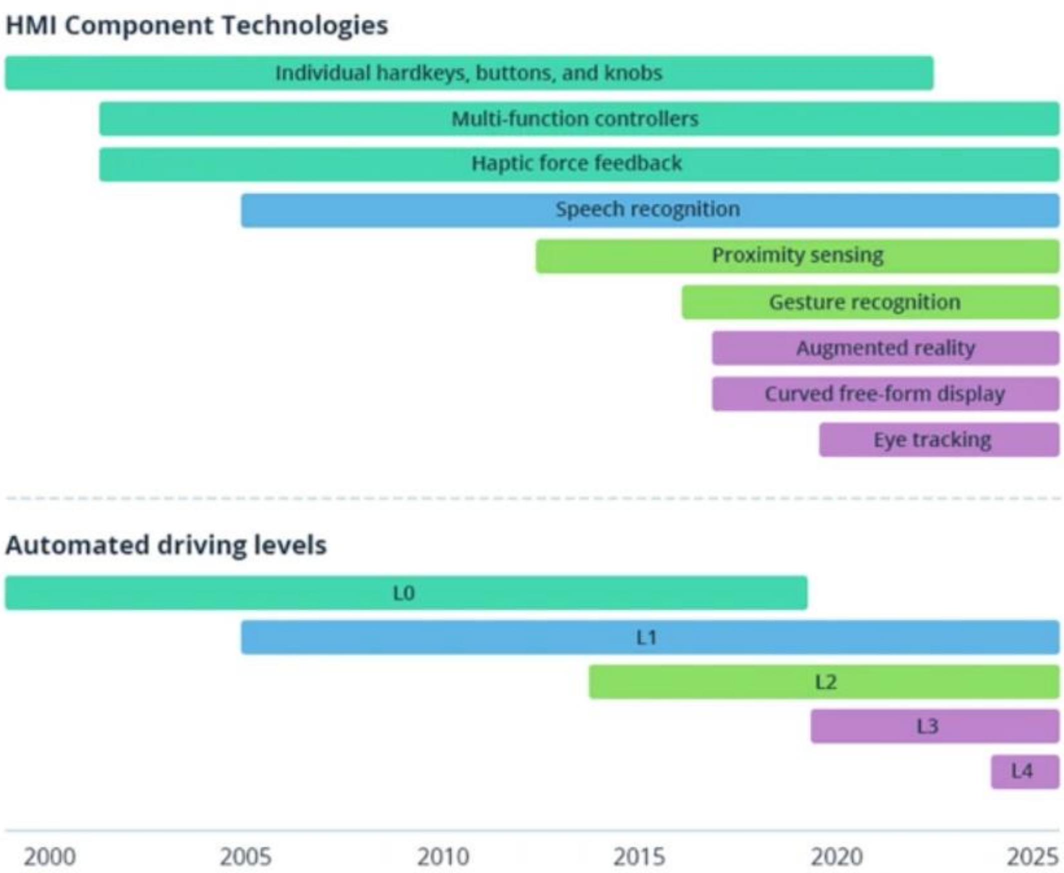

Figure.9 Interactive capabilities continue to improve with automated driving capabilities

4.3.3 Usability Improvements

Improving usability is one of the major challenges for HMI designers. Enhancing usability relies on user insights and research in the early stages and is also influenced by technological factors and continuous iterations.

In the era of automated driving, user demands have surged, placing higher requirements on HMI usability compared to the previous approach of keeping in-vehicle systems as simple as possible to ensure usability.

1) Design Consistency:
Consistency here doesn't only refer to visual consistency but also consistency in interaction methods. Many people have experienced the need to relearn various vehicle operations when switching to a new car, which is caused by cognitive differences due to different feature layouts and sign prompts.

In the design of assisted driving modes, companies like Tesla and XPeng use gear lever controls, while NIO employs a separate start button. If there are significant inconsistencies in this aspect, it can directly impact the user experience.

NIO: button

Tesla: column shift

Figure.10 The differences in interaction between different brands.

2) Meeting More Specific User Needs

Today, the age range of drivers is expanding, and different age groups have varying user requirements. In HMI design, visual cues such as size and color, auditory indicators' volume and sound frequency should be optimized to cater to the specific needs of different user groups.

In an increasingly aging population, various mobile phone manufacturers are exploring elderly-friendly mobile operating systems. In the not-so-distant future, we might see senior-friendly versions of in-car systems.

4.3.4 Enhance Trust between People and Vehicle

The process of people accepting new technologies is essentially a process of building trust. As automated driving gradually matures, establishing trust between HMI and users becomes crucial. During automated driving, it's vital that the vehicle operates as per the user's expectations and that the in-car system enhances the overall experience. All of this is built on the foundation of trust between the user and the vehicle.

To increase user trust in HMI, the following aspects can be considered:

1. Informing users about the current status of the vehicle's automated driving.
2. Providing driving event notifications during automated journeys.
3. Offering timely feedback for user operations.
4. Granting users more control over HMI settings and interactions.

Building trust in automated driving systems is fundamental for their successful adoption and integration into the daily lives of users.

4.3.5 Human-Centered Design Thinking

At every stage of human-machine interface design, human-centered design is the most crucial consideration. In-vehicle systems, serving as information bridges between people and their vehicles, need to convey information about the vehicle's status, environmental conditions, media, entertainment, and more to the users.

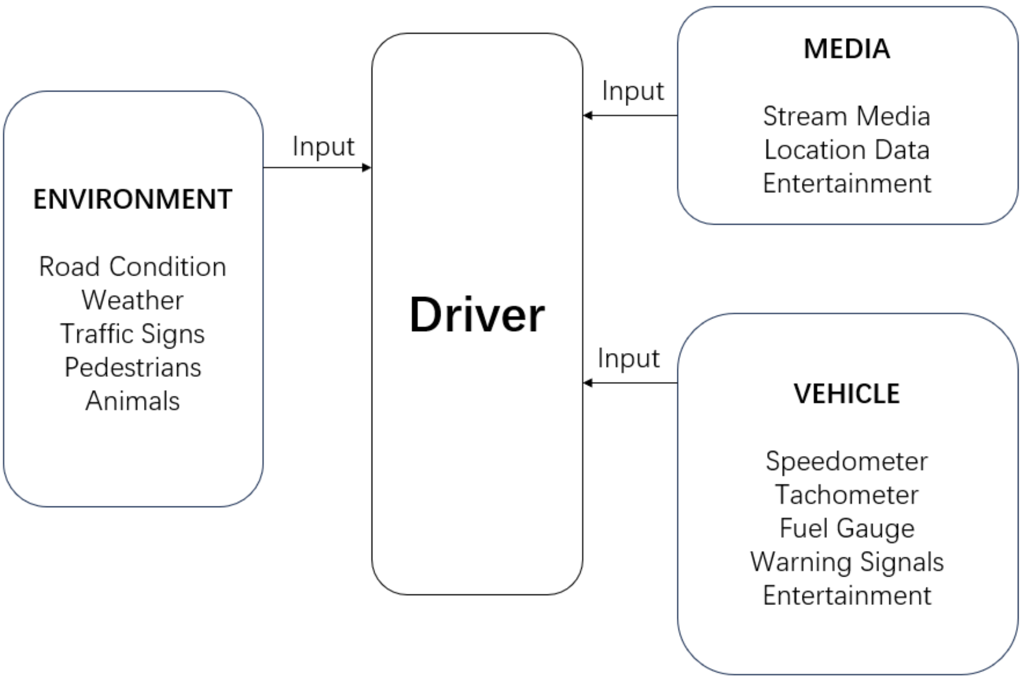

Figure.11 Drivers simultaneously receive various types of information during the driving process.

The improvement in automated driving capabilities also means that in-vehicle systems will have more diverse functions, leading to a rise in personalized user demands. Through recommending functions based on usage habits, prioritizing high-frequency applications, and intelligently categorizing information, the in-vehicle system should be able to predict user needs more effectively and provide a seamless user experience. NIO offers customizable quick control pages, allowing users to prioritize functions according to their needs.

Figure.12 NIO's customizable quick control pages

CONCLUSION

In this thesis, we reviewed and delved into the human factors of automated vehicles, as well as issues closely related to trust and situation awareness in human-machine interfaces. We provide profound insights into these topics through a review of relevant research and case studies.

First and foremost, we emphasize the extensive potential applications of automated vehicles and their significant impact on the future of transportation. However, we also point out the numerous challenges that must be overcome before realizing this vision. These challenges include technical feasibility, regulatory requirements, road safety, and other issues, but the primary focus of this chapter is on human factors and human-machine interfaces.

We delve into the importance of trust in automated vehicles. Trust is a key factor in user acceptance and effective use of new technology. We underscore the necessity of establishing and maintaining user trust in automated systems to ensure they can realize their full potential. Additionally, we discuss how building and maintaining trust require time and appropriate information communication.

On the other hand, we also emphasize the significance of situation awareness. Automated vehicles must accurately perceive their surroundings to operate safely. Human-machine interfaces play a critical role in providing information about the vehicle's surrounding context. By designing intuitive and efficient interfaces, driver awareness of road conditions can be enhanced, thus improving safety. We illustrate some attempts made by automated vehicle companies in this regard through specific cases.

In summary, the thesis underscores the crucial role of human factors and human-machine interfaces in the field of automated vehicles. Efforts must continue in future research and development to address these issues and ensure the success of automated vehicles on real roads. We anticipate that these future endeavors will further promote the advancement of automated technology and bring about positive transformations in the way we travel.

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