

Review and Perspectives on Driver Digital Twin and Its Enabling Technologies for Intelligent Vehicles

Zhongxu Hu, *Member, IEEE*, Shanhe Lou, Yang Xing, *Member, IEEE*, Xiao Wang, *Senior Member, IEEE*, Dongpu Cao, *Senior Member, IEEE*, Chen Lv, *Senior Member, IEEE*

Abstract—Digital Twin (DT) is an emerging technology and has been introduced into intelligent driving and transportation systems to digitize and synergize connected automated vehicles. However, existing studies focus on the design of the automated vehicle, whereas the digitization of the human driver, who plays an important role in driving, is largely ignored. Furthermore, previous driver-related tasks are limited to specific scenarios and have limited applicability. Thus, a novel concept of a driver digital twin (DDT) is proposed in this study to bridge the gap between existing automated driving systems and fully digitized ones and aid in the development of a complete driving human cyber-physical system (H-CPS). This concept is essential for constructing a harmonious human-centric intelligent driving system that considers the proactivity and sensitivity of the human driver. The primary characteristics of the DDT include multimodal state fusion, personalized modeling, and time variance. Compared with the original DT, the proposed DDT emphasizes on internal personality and capability with respect to the external physiological-level state. This study systematically illustrates the DDT and outlines its key enabling aspects. The related technologies are comprehensively reviewed and discussed with a view to improving them by leveraging the DDT. In addition, the potential applications and unsettled challenges are considered. This study aims to provide fundamental theoretical support to researchers in determining the future scope of the DDT system.

Index Terms—Driver digital twin, human-centric design, intelligent vehicles, human-machine interactions, cyber-physical systems.

I. INTRODUCTION

Digital Twin (DT), proposed by Grieves in 2003 [1] and constantly improved since by several researchers [2–4], featured among Gartner’s top ten most promising technological trends for 2018 [5]. Moreover, it is considerably popular as a multiphysics, multiscale, ultrafidelity simulation that reflects the state of a corresponding twin in real-time based on historical data, real-time sensor data, and physical models, which provides remarkable opportunities for many industrial applications [4, 6–10]. The important milestones in the development of DT are shown in Fig. 1. Recently, vehicle-to-cloud communication technology facilitated the integration of DT into the

intelligent vehicle for monitoring, simulating, and maintaining the vehicle for its lifetime, which has been explored by several studies [11–16]. Combined with the smart city technique, certain researchers have also attempted to introduce the DT technology to the intelligent transportation system, thereby improving vehicle design, critical infrastructure maintenance, autonomous driving testing, and traffic optimization [17–19].

The concept of DT can be considered as an application and extension of the parallel intelligence (PI) technology [20, 21] that can be traced back to the Mirror World [22] and Shadow System [23] from the end of the 20th century. PI is devoted to exploring the collaboration and interaction between the actual and the artificial world by leveraging advanced intelligent technologies. Another typical and popular concept related to PI is the cyber-physical system (CPS) [24–26], in which physical and virtual components are deeply intertwined on various spatial and temporal levels. The CPS, which was incubated at the turn of the century, was identified as a key research area by the US National Science Foundation (NSF) in 2008 [27]. Furthermore, it is considered as one of the critical enabling technologies of Industry 4.0 [28, 29] and has been widely adopted in several sectors of society. Owing to the unprecedented growth and influence of CPSs on human behavior, Wang [30] theorized that human and social dimensions must be included in CPSs and proposed a cyber-physical-social system (CPSS) in 2010. The CPSS concept has been utilized in several fields [31], in combination with the Artificial Societies-Computational Experiments-Parallel Execution (ACP) theory for the parallel driving (PD) framework [32–35]. This approach underscores the importance of human drivers who are active in both mental and physical worlds. Building on this perspective, the CPSS-based approach emphasizes the integration of human drivers, vehicles, and information. The fundamental principle of parallel driving is to leverage the built artificial space that includes artificial drivers and artificial vehicles, to handle the complex process automated driving while keeping the design of the real vehicles as simple as possible. However, because CPSs have to synchronize with humans, the interaction between them was investigated and highlighted by the Human Cyber-Physical System Interaction (H-CPS-I) workshop of the International Federation of Automatic Control (IFAC) in 2014 [36]. Following this, the first formal international conference of the cyber-physical and human-systems (CPHS) was organized by the IFAC in 2016 [37]. In 2019, Zhou et al. [38] reported that an intelligent manufacturing system must always be considered a human cyber-physical system (H-CPS) from the perspective

Z. Hu, S. Lou, and C. Lv are with School of Mechanical and Aerospace Engineering, Nanyang Technological University, 637460 Singapore. E-mail: {zhongxu.hu, shanhe.lou, lyuchen}@ntu.edu.sg

Y. Xing is with Centre for Autonomous and Cyber-Physical Systems, Cranfield University, United Kingdom. E-mail: yang.x@cranfield.ac.uk

X. Wang is with the Qingdao Academy of Intelligent Industries and the State Key Laboratory for Management and Control of Complex Systems, Institute of Automation, Chinese Academy of Sciences, 100190 Beijing, China. E-mail: x.wang@ia.ac.cn

D. Cao is with the School of Vehicle and Mobility, Tsinghua University, 100084 Beijing, China. E-mail: dp_cao2016@163.com

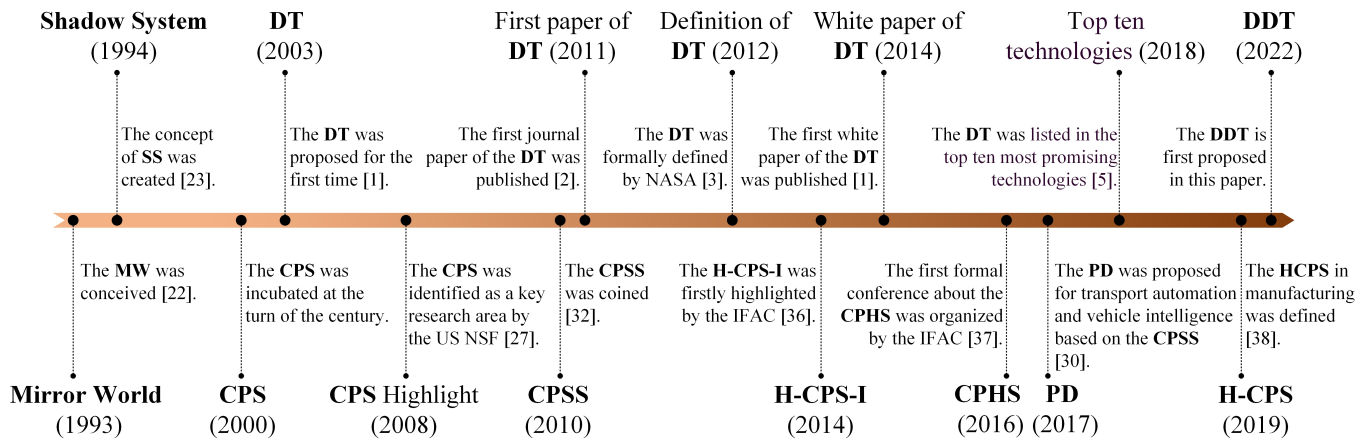


Fig. 1. History of the DT and the generalized parallel intelligence technologies.

of system constitution, i.e., it is a composite intelligent system comprising humans, cyber systems, and physical systems for achieving specific goals at an optimized level [39].

The development of the above-mentioned PI technologies, as shown in Fig. 1, show a unanimous emphasis on human involvement. A complete intelligent driving H-CPS includes three aspects: humans, vehicles, and the environmental context, as shown in Fig. 2. The current technology can better digitize and simulate the last two objects from multiple physical perspectives [40–45]; however, the digitization of humans, especially the human driver, remains challenging in view of their complexity. Existing autonomous technology requires human involvement, i.e., the driver will probably be irreplaceable for the foreseeable future. In addition, the futuristic fully autonomous vehicle must carry private passengers. Thus, their diverse personalities and preferences need to be considered to improve their acceptance and trust. The lack of a reasonable unified driver model will significantly affect the construction of the completed intelligent driving H-CPS, thereby reducing the reliability and predictability of the system. Thus, this study proposes the concept of a driver digital twin (DDT) to address the issue of driver digitization. Technologies such as advanced sensing, embedded computing, and intelligent algorithms are significant developments. They have contributed to the development of a complete DDT system that enables human-vehicle collaboration and enhances the intelligence of the automated vehicle, thereby making it more reliable. A comfortable driving environment that enables a driver to accurately feel the vehicle’s response and smoothly operate the vehicle is essential. The proposed DDT system recommends a reasonable solution to tackle the above challenges; the automated vehicle is given the ability to adapt to the driver instead of forcing the driver to adapt to it. Thus, a harmonious human-centric intelligent driving system can be obtained.

With the development of digital human technology, human DT has recently been studied in the context of the health industry to reform clinical processes and hospital management. The studies primarily focused on enhancing medical care with digital tracking and advancing the modeling of the human

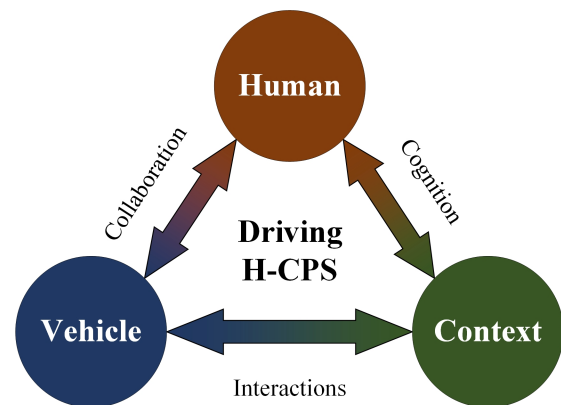


Fig. 2. A complete driving H-CPS system should include three aspects: human, vehicle, and environmental context.

body [46, 47]. The human DT can help researchers in studying diseases, new drugs, and medical devices. In the future, it is expected to help physicians optimize the performance of patient-specific treatment plans [48]. The bones and muscle model of the digital human can be utilized to prevent injury [49]. All collected health data (physiological data, genome, fitness sensors, etc.) help build a better digital human to respond to current and future medical problems in a faster and cheaper manner. However, these studies are limited to the physical level and treat the human body as a sophisticated machine. Although this approach is extremely challenging and complex, it is not sufficiently complex to faithfully model human behavior, humans are more complex than machines owing to their mental faculties. Thus, human driver digitization must be capable of modeling habits, personality traits, and decision patterns, which are crucial features defining a human driver. Leveraging the DDT, physiological state monitoring can help prevent potential accidents resulting from distraction or sudden illness, as well as enhance driving safety; individuality modeling can help build a human-centric driving system to improve the acceptance, trust, and user experience for intelligent vehicles. In addition, the collected real driver models based on historical data can be utilized to support the construction

of the multiagent system for the driving simulation. This, in turn, can increase its reliability and predictive ability and promote the development of the autonomous system. Recently, Wang et al. [50] proposed the HDT model for human-centric manufacturing, emphasizing the importance of the human in HCPS. It aims to accurately track and reflect human motion, perception, and manipulation activities, as well as capabilities, in order to construct a human digital representation and regulate human-machine alignment based on human proactivity. In comparison, the DDT focuses on the human driver for constructing the harmonious human-centric intelligent driving systems.

Given the growth of intelligent technologies in the past decades, researchers have studied the driver monitoring system (DMS) [51–55] from various perspectives, and related applications for advanced driver assistance systems (ADASs) have been proposed [56–59]. However, these studies primarily focused on a specific application or situation without a comprehensive perspective. Furthermore, previous studies focused on developing the autonomy and authority of the vehicle, thereby inadvertently degrading the driver’s role and importance. In the future, next-generation autonomous vehicles should be more intelligent, safe, and personalized [60–69]. Therefore, the relationship between the driver and vehicle should be discussed further to support the research and development (R&D) of the futuristic automated vehicle. The proposed DDT can be considered a reasonable solution that provides a systematic theoretical framework for integrating the related modules. The built DDT system continuously tracks and improves the driving system based on the driver’s style, preference, and capability by collecting the driver’s data and pattern in a timely manner. Furthermore, the driving process is morphed into a data generation process. The DDT can include a wide spectrum of information ranging from the high-level comprehension of driving style to fine-grained details about the driver’s behavior and attention. The generated multilevel information can be processed into big data by utilizing the intelligent algorithm, which can then be distilled into intelligence, rules, and knowledge for specific tasks and services, thereby realizing intelligent control and management as well as improving driving safety, comfort, and personalization.

The purpose and contribution of this study are to elucidate the connotation of the proposed DDT and propose its architecture and implementation approach. The enabling technologies are comprehensively surveyed and discussed, in addition to the related applications. Meanwhile, the emergence and development of DDT technology not only provides clear new ideas, methods, and approaches to realize harmonious human-centric driving but also envisage a new concept for the development of a futuristic autonomous vehicle. This study expects to establish a theoretical foundation for integrating individual research conducted on this topic and present a comprehensive review from an academically neutral standpoint.

The rest of this paper is organized as follows: Section II illustrates the concept of the proposed DDT. Section III reviews the current state of development of the enabling technologies for the DDT. The related applications are discussed in Section IV. Section V presents certain unsettled issues and potential

directions for future work. Finally, Section VI summarizes the contributions of this work.

II. HIGH-LEVEL DRIVER DIGITAL TWIN ARCHITECTURE

DDT is being proposed for the first time through this study. It can be utilized to support human-centric intelligent driving systems and futuristic autonomous vehicles. We believe that a complete DDT system should comprise four components: the real driver, digital driver, multimodal interface, and related applications, as shown in Fig. 3.

A. Human Driver in Real World

The real driver is the physical entity and the basis, who is a data generator and an application service receptor; the real driver includes drivers of various types of commercial, engineering, and special equipment vehicles. The DDT can be implemented to address the challenges of a growing shortage of skilled drivers in specific sectors and assist aging drivers in improving the safety, smoothness, and efficiency of operation. Meanwhile, humans will always play an important role and coexist with vehicles whether the vehicle is partially or fully autonomous [70–72]. Thus, futuristic vehicles should meet human needs and recognize individual preferences to form a human-centric intelligent driving system that provides a safe, efficient, and personalized user experience.

B. Digital-Twin Driver in Parallel Space

The digital driver is the core component of the DDT system. As a virtual replica of the human driver, it should reflect the behavior of the real driver realistically, comprehensively, and synchronously. However, a fine-grained 3D model of the human driver is not required, because the human is not a machine and is more sophisticated and involved with the mind [73]. Modeling the driver appropriately is crucial for building a DDT system, and it depends on the types of applications and services that must be provided. Given the complexity of a human, the digital driver can be modeled from a comprehensive perspective that combines various aspects using advanced sensing techniques and intelligent algorithms. Furthermore, the relationships between the various aspects should be thoroughly investigated considering that they may be mutually interdependent.

Driving safety and efficiency depends on the driving pattern of the individual, and an advanced intelligent driving system should be able to understand not only the human appearance behavior and physiological state, but also the human inner intention and preference [13, 74]. Thus, the goal of the digital driver should be to replicate not only the external aspects of a human driver such as biological information, physiological condition, and attention state, but also the internal characteristics such as personality, sensibilities, and capabilities. Furthermore, modeling a real person’s individuality will enable us to elicit more user-friendly and human-like interactions based on the diversity that originates from the characteristics of individuals. In contrast to the common entities with no individuality, such personalized entities can prevent misuse

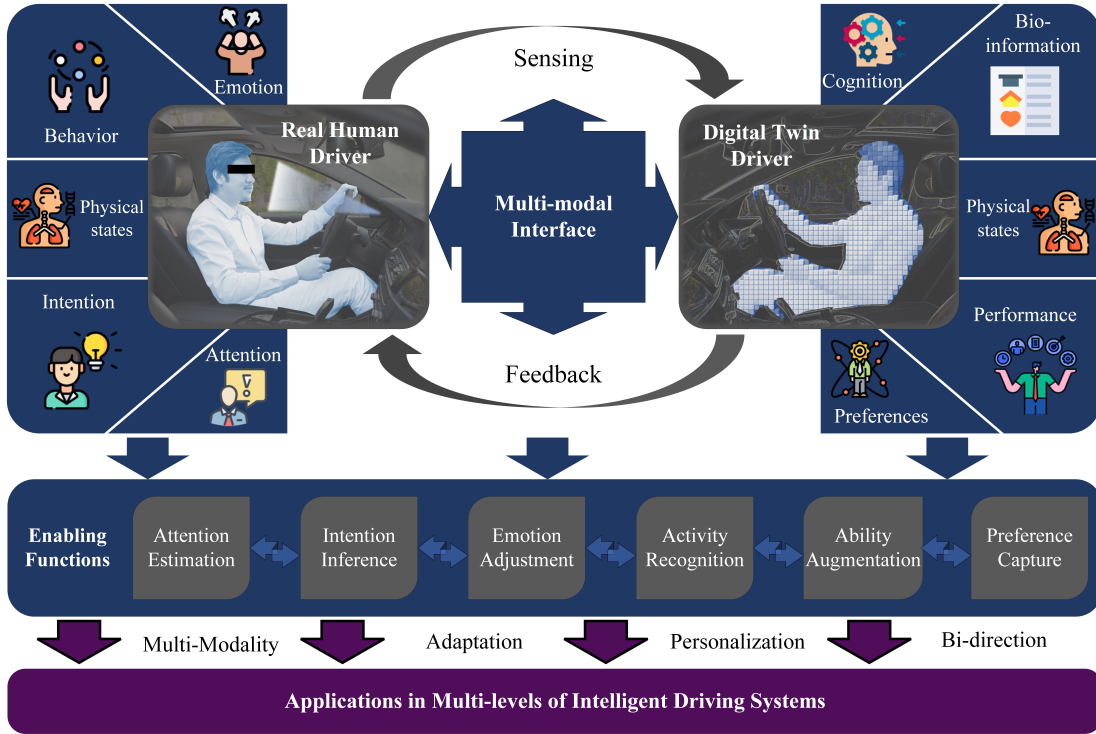


Fig. 3. Overview of the proposed DDT, including the real driver, digital driver, multimodal interface, and applications in multilevel intelligent driving systems.

of the automated vehicle and support the development of the human-centric driving system. In addition, the digital driver model should synchronize with the human driver's state in real-time to gauge mood swings and capability degradation. This personalized synchronicity with the human driver is the primary distinction between the proposed DDT and the original DT used in manufacturing.

In comparison to the current DMS system, a well-established digital driver can provide more comprehensive state information including external behavior state and internal personality pattern. Moreover, the aggregated multimodal information can improve the capability of the fine-grained analysis and recognition for the driver's state. The digital driver emphasizes entire-life-cycle monitoring, which enables the system to evaluate and predict the anomalies and the degradation of the driver's capability based on historical data; consequently, the system can provide optimal intervention to assist the driver in time. In addition, simulation is an important technique for developing autonomous driving systems [75]. The current technique can simulate the vehicle, sensors, and environment; however, real human reactions and activity in a variety of situations are difficult to simulate, which results in significant disparity between the simulation and reality. The digital driver enables a multiagent simulation supported by real models and bridges this research gap by modeling the activity patterns and personalities of various real human drivers.

C. Multi-modal Driver-Digital Twin Interface

The multimodal interface is an enabled approach and cornerstone for building the digital driver and connecting the real and digital spaces, which involves the driver's information

and the driving data. Moreover, the automated vehicle is a natural platform for deploying a variety of sensors and actuators to acquire ubiquitous data. Thus, the DDT system can provide a comprehensive perception of the state of the human driver and automated vehicle and meet the requirement of the realistic feedback of the real-time and historical state of the physical entity in the related applications by leveraging the built multimodal interface.

In the past, researchers have explored various types of sensors in various applications including vision-based (RGB, depth, IR, Lidar, etc.), physiological-based (EMG, EEG, ECG, etc.), and driving-based sensors (steering, pedal, speed, IMU, etc.) [51, 76]. The collected data from these sensors can reflect the various behavioral patterns, conditions, and preferences of the driver from several perspectives. The DDT system must integrate these sensors and actuators to create a multimodal interface that can provide comprehensive sensing and feedback. To this end, the sensors should complement one another to support the development of a complete digital driver; all elements must communicate, interact, integrate, and merge. Meanwhile, it entails data acquisition, definition, transmission, calibration, source protection, fusion, and mining among other processes to handle large amounts of real-time, multidimensional data. Furthermore, multimodal fusion is potentially a key technology, which can be implemented at different levels, including feature-level, model-level, and decision-level [77]. The feature-level fusion requires prior knowledge to integrate the multimodal features that might enhance the interpretability of the model. However, it requires significant data calibration and synchronization. Model-level fusion includes different structure models that are utilized to

handle and extract the multimodal representations. Fortunately, the advancement of neural networks (NN) provides various types of models that can tackle varying kinds of input data, and can be easily integrated. These types of NNs such as many multi-branch or multi-streams networks are proposed to handle the multimodal input [78, 79]. The NN-based methods enable the model to learn the fusion pattern in a data-driven way, leading to a robust and accurate fusion performance. Decision-level fusion means that the result vector of each modality feature is respectively obtained by their suitable model. Thus, the rule-based approach can be utilized to allocate the different weights for each modality result. However, this approach is sensitive to outliers and cannot tackle complex and high-dimension vectors. To improve the decision performance, the machine learning (ML) classifier and regressor can be adopted to learn the internal pattern. In addition, ensemble machine learning can also be leveraged to increase decision efficiency.

Sensors should achieve precise recognition for driver activities to improve the quality of the digital driver; further, ultralow latency and ultrareliable communication technology should be investigated [80–85]. The interaction design is also critical because it must address the issue of seamless interaction and state feedback to support the dynamic collaboration and resource sharing between the physical world and digital world. The interface must consider human acceptance, such as the human’s resistance to some intrusive sensors, which requires the unobtrusive and miniaturization of the sensors. Thus, the researcher must thoroughly and carefully investigate the appropriate and available configuration of the multimodal sensors and interaction interface.

D. Key Applications of the DDT

The applications are the ultimate goal of the DDT system. They must be capable of leveraging the various enabling functions to assist the driver intelligently and securely. Furthermore, as the applications are a vital link between the virtual and real worlds, enabling the DDT system to operate in a closed-loop mode. Several related applications such as ADAS, shared control, and driver safety monitoring have already been studied for decades. Implementing the DDT system can further improve the user experiences of these applications and lead to new possibilities.

The applications can be classified into three paradigms: *physical-to-digital*, *digital-to-digital*, and *digital-to-physical*, which are applicable to different levels of autonomous driving systems. The physical-to-digital paradigm focuses on leveraging human intelligence to optimize the intelligent driving system by learning the real driver’s behavioral pattern. The DDT system provides a possible implementation solution by digitizing the driver’s behavior and decision-making pattern in a variety of situations. The digital-to-digital paradigm focuses on the ability to develop group intelligence and leverage expert models to improve the individual ones, which overcomes the physical limitations. Moreover, the mutual interactions between the various functions lead to an improvement in each function. Finally, the digital-to-physical paradigm focuses on using the assistance of the digital system to improve the

real driver’s control and state. If a life-long DDT system is constructed, the real driver’s capability can be enhanced by a past driving model of themselves in the event of degraded driving capability.

Based on the DDT system, the applications can exploit the real-time and historical data of drivers and vehicles, thereby shifting the system’s operation from the prior knowledge-driven approach to a data-driven one. Moreover, the development of related applications can be changed from passively demand-driven to positively DDT-mined innovation. Thus, data-driven DDT can reinforce the related applications that adapt to the driver’s preferences, styles, skills, and patterns, which makes the driver-vehicle coexistence and collaboration safer, more efficient, and user friendly. Furthermore, more virtual-reality-fusion applications can be explored to improve interactivity by leveraging the built-in digital drivers.

III. KEY FUNCTIONS OF DRIVER DIGITAL TWIN TECHNOLOGY

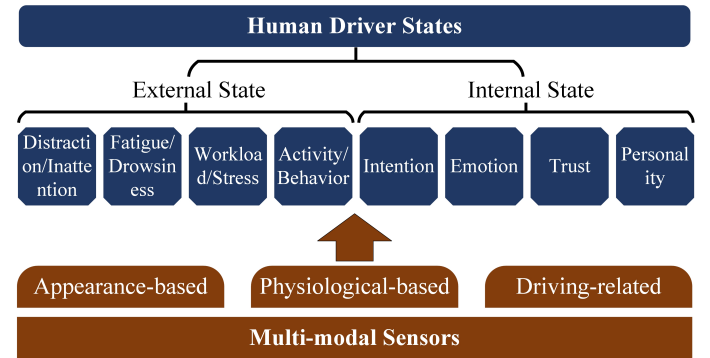


Fig. 4. Taxonomy of the existing studies for the human driver monitoring system.

To build a complete digital human driver, a variety of driver states should be obtained, modeled, and incorporated. The current research for driver modeling revolves around the DMS that has been widely used in intelligent vehicles [86]. Researchers have investigated it from various perspectives to monitor various driver states as shown in Fig. 4. These monitored conditions can be classified into external and internal conditions. The external state primarily comprises the state that exists consequent to external behavior such as distraction activity and drowsiness. The internal state is related to the inner consciousness and personality of the driver, including components such as intentions, emotions, and trust. The states are monitored by the multimodal intrusive and nonintrusive sensors that can be summarized into three categories: appearance-based, physiological-based, and driving-based. Appearance-based sensors include the RGB camera, depth sensor, infrared sensor, etc. They are utilized to obtain facial and bodily movements. The physiological-based sensors monitor the various physiological factors, including the heart rate, brain waves, and blood pressure. The driving-based sensors collect vehicle-related data during the operating process, such as the steering data, braking information, speed, etc.

Existing studies focus on a specific task and ignore the collaboration between various functions, thereby limiting recognition performance. Therefore, a unified digital model of the driver involving external and internal conditions is indispensable to endow the system with robust, precise, and time-variant sensing capabilities to assist the human driver. The data structure shown in Fig. 4 can also be utilized to model the DDT but from a unified perspective.

A. Driver Distraction Detection



Fig. 5. General framework of driver distraction detection.

Driver distraction is a primary cause of road accidents and has attracted considerable research attention [76, 87]; it has consequently become one of the typical tasks of the DMS. A variety of nonintrusive and intrusive sensors are utilized to detect the driver’s distractions at different levels of granularity by leveraging ML algorithms [88, 89]. The nonintrusive sensors, including the vision-based and vehicle-related sensors, can be used to tackle high-level behavior-related distractions such as abnormal activity [90–93], distracted pose [94–97], false operation [98, 99], and inappropriate focus area [100–103]. In contrast, intrusive sensors can precisely assist in evaluating the driver’s inner consciousness and cognitive state [53, 104–106]. However, some intrusive sensors can cause significant discomfort and affect the driver’s movements and pose. Consequently, the obtained distraction detection results are biased and affect the final interpretation. Furthermore, this limits the potential application of some of these sensors to research-related endeavors.

Currently, the definition of distraction is ambiguous, and previous studies have approached it with varying degrees of granularity. One typical approach is recognizing distractions based on the driver’s activity. [107] designed a typical driver

activities recognition system based on a vision-based sensor leveraging deep convolutional neural networks (CNN). The sensor could identify seven common driving activities by detecting the driver’s body posture; similar work can also be found in [108–111]. This approach typically achieves almost 99% accuracy in detecting the limited driver activity. It performs the classification task by leveraging the powerful representation capability of the deep learning (DL) based models. However, this method has several limitations. Firstly, actual human activities are diverse, which may adversely affect the performance and robustness of the trained models. Thus, technology capable of grasping context, such as the video-text approach [112], can be utilized to tackle this challenge. Second, these CNN-based methods typically rely on large labelled datasets to improve recognition performance, which necessitates further investigation into advanced semi-supervised and self-supervised approaches, such as the contrastive learning method [113]. Moreover, the computational efficiency is an inevitable barrier for practical applications. Thus, further model compression and optimization technologies are required [114, 115]. In addition to the activity of the body, the driver’s head and gaze is also indicative of distractions; accordingly, several studies focused on detecting the driver’s gaze on the corrected area or road [100–103]. These methods adopt a similar approach to those focusing on bodily movements and tackle distraction recognition as a classification task by leveraging the various CNN-based models, which achieve more than 90% accuracy. The primary difference is that the model input is a facial image or features rather than a full-body image.

The driver’s distraction is also related to the mental state in addition to the appearance-based distraction. Therefore, the electroencephalographic (EEG) signal is utilized to measure the brain activity for the early detection of driver distractions [105, 106]. Furthermore, measurements of the reaction time in addition to other physiological signals can be leveraged to evaluate the driver’s concentration [116]. [117] combined the various physiological data including palm electrodermal activity, heart rate, and breathing rate with facial-related features to detect the four types of distractions, and a spectro-temporal ResNet (STRNet) was proposed to handle the multimodal features. In addition, this study also analyzed the different modality features for the final detection performance. Consequently, it demonstrated that the most informative modality depends on the type of distraction, with visual features providing the most information overall. Similar work can be found in [118], which adopted physiological (electrocardiogram (ECG), galvanic skin response), behavioral (accelerometer and gyroscope), and vehicular (CAN-Bus) signals with various ML-based recognition models.

In addition to the state of the driver, manual information can also be utilized to evaluate the level of driver distraction. [98] as well as the [99] leveraged the eye-steering correlation structure to indicate the driver’s state. These studies demonstrate that the correlation is useful, but not more robust than the previously discussed features. [119] utilized the broad learning and incremental learning system (BLILS) to recognize vehicle misbehavior using the vehicle steering information,

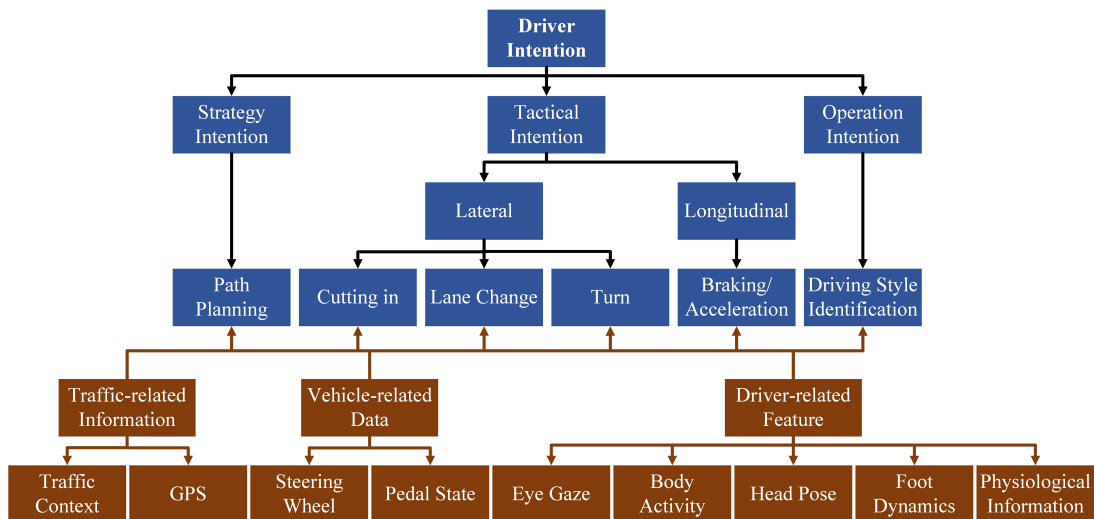


Fig. 6. Overview of the driver intention prediction.

such as vehicle speed & acceleration, direction of travel, vehicle position, transmission delay. The experimental results show that the proposed BLIS can recognize distractions faster and more accurately than the conventional ML and DL methods, while possessing excellent robustness and scalability for practical applications. [120] presented a driver workload detection approach based on the driver’s physiological, and vehicle signals as well as traffic contexts such as congestion level and traffic events, and evaluated the proposed method on the real driving scenarios data. In addition, smartphones have been utilized in several studies to monitor the driver’s behavior by leveraging the mounted multimodal sensor of the phone [91, 121–124]. However, the mobile-based approach, with approximately 80% accuracy, cannot compete with the methods using the driver states, unless combing of the driver face image is performed to detect distractions.

Existing studies can be summarized as shown in Fig. 5. The detection of multigranular distractions can be implemented by various types of features by leveraging the multimodal sensors. Previous studies have reported impressive performances in recognizing specific distractions with more than 95% accuracy. One study [117] demonstrated the varying importance of a variety of modalities for monitoring different types of distraction. In contrast, the literature highlights the absence of a unified solution that can handle all types of distractions for various scenarios. Furthermore, the existing methods, despite their excellent performance, largely ignored individual diversity. The proposed DDT concept can be utilized to overcome these challenges by providing a unified approach with multimodal sensors to extract various types of features. It can achieve this by leveraging the representation learning approaches and the DL-based recognition models. Moreover, studies have demonstrated that utilizing multiple sensors can improve the overall performance [98, 99, 111, 117, 118]. In the future, an approach with multiple sensors must be explored to enhance the reliability and intelligence of the distraction detection system.

B. Driver Attention Estimation

Driver attention estimation aims to determine the driver’s focus area to support the conditional driving system and provide intervention or assistance in critical scenarios [125, 126]. Attention estimation is related to distraction detection; however, it goes a step further in understanding the driver’s state and not only detects whether the driver is distracted but also estimates whether the driver’s attention is on the right area such as the road, traffic light, and crossing pedestrians.

A typical approach is to build a mapping model between the context of the external scenario and the driver’s field of attention. The visual field of the driver is divided into several sub-fields or targets. In [103], a naturalistic driver behavior dataset with six predefined attention zones was created for various driving scenarios. A random forest classifier was utilized to generate a set of probabilities for each gaze zone based on the features of the head and face, and a recognition accuracy greater than 90% was achieved. A driver focus corpus was built for a parked vehicle in [127] that divided the driver’s attention into 18 zones based on RGB and depth sensors. A pre-trained VGG16 model was fine-tuned to classify the gaze zone with an 84% accuracy. In this study, an end-to-end approach was adopted using the color driver image without extracting the facial features. A similar CNN-based approach was utilized in [128], where a driver gaze in the wild (DGW) dataset was collected with 9 labeled zones. However, compared with other datasets, the DGW employs more subjects to improve the diversity of the dataset, thereby resulting in a lower accuracy of approximately 60%. AutoPose [129] collects driver attention data from an infrared camera and an RGB-D camera using a driving simulator; these data include six gaze zones, as well as head poses and driver activities. A multimodal driver monitoring dataset with 21 gaze targets and driver head poses was presented in [130]. A head-mounted inertial sensor was used in [131] to determine the ten focus spots of a driver in a vehicle cabin, in which several ML classifiers were utilized to predict the gaze attention. Furthermore, the experimental results demonstrated

TABLE I
EXISTING DATASETS FOR DRIVER ATTENTION ESTIMATION

Dataset	Scenario	Sensors	Gaze Annotation	Subjects
MIT [103] (2016)	Highway	RGB-driver	6 Gaze zones	50
DG-Unicamp[127](2019)	Parking	RGB-driver Depth-driver Infrared-driver	18 Gaze zones	45
DGW[128] (2020)	Parking	RGB-driver	9 Gaze zones	338
Autopose [129] (2020)	Simulator	RGB-driver Depth-driver Infrared-driver Mo-Cap	6 Gaze zones Head pose Driver activity	21
MDM [130] (2021)	Parking Driving	RGB-driver,back,mirror,road Depth-driver,Infrared-driver Fi-Cap,Microphone,CAN-BUS	21 Gaze zones Head pose Driving data,Audio	59
DR(eye)VE [132] (2018)	Highway Countryside Downtown	RGB-road Eye tracking(collecting)	Gaze attention map	8
BDD-A[133] (2018)	Critical driving situations	RGB-road Eye tracking(collecting)	Gaze attention map	45
DADA-2000[134] (2019)	Accidental driving scenarios	RGB-road Eye tracking(collecting)	Gaze attention map	20

the efficiency of the head-mounted inertial sensor that can achieve an accuracy greater than 96%.

Another focal point of driver attention estimation is predicting the driving gaze map of the scenario, which indicates the area that might attract the driver’s attention rather than that the driver actually focuses on. A representative study of this type is the DR(eye)VE project [132] that assembled the driver’s gaze map with the use of gaze tracking glasses worn by the driver while driving in various scenarios with varying conditions leveraging. Furthermore, several datasets, such as the BDDA dataset [133] that focuses on critical driving situations, and the DADA-2000 dataset [134] that focuses on accidental driving scenarios, were developed. To predict the driver’s gaze map, U-Net [135] type of models were adopted to learn the attention pattern. In addition, the optical flow and semantic information were also utilized to improve predictive performance. According to the existing experimental results, predicting driver attention remains challenging because of the complexity of the scenario and the human driver’s individuality.

The typical datasets for driver attention estimation are listed in Tab. I. Existing appearance-based approaches of gaze zone estimation can perform well and achieve outstanding accuracy by leveraging deep-learning-based technology. Leveraging complementary information, such as head pose, can further improve the estimation performance compared with the end-to-end model. However, these methods only consider the external appearance information of the driver. Thus, in scenarios where the focus of the gaze and mind do not coincide, estimation accuracy declines drastically. Thus, the DDT model combined with cognitive state information can help improve the robustness and accuracy of driver attention estimation.

C. Driver Intention Inference and Prediction

In addition to the external driver state information, the vehicle needs to understand the driver’s intention to generate appropriate assistance and collaborative control strategies. Current studies focus on specific tasks or scenarios such as lane change intention [136–138], braking intention [139–141], and acceleration intention [142], and they can be summarized as shown in Fig. 6.

When predicting driver intention, lane change is the most commonly encountered intention. Here, the target includes the ego-vehicle [136, 143] and surrounding vehicles [144]. The prediction of surrounding vehicles utilizes trajectory information, obtained based on the GPS and Internet of Vehicles(IoV) technology, as the input to infer the intention. Such methodologies found in studies on ego-vehicle [144–149] and several deep learning-based models, particularly the recurrent neural network (RNN), are proposed for handling the traffic information of the ego-vehicle and surrounding vehicles. Vehicle maneuvering patterns are also investigated to predict and estimate the vehicle lane-changing state [150]. In addition to the driving data, the driver’s states and posture are frequently utilized to improve the prediction accuracy. Head pose is a common indicator of driver intent, and measuring the head pose is less time-consuming and more reliable in unfavorable driving conditions [94]; therefore, it is often used to infer driver intent [151–153]. Furthermore, gaze can accurately reflect driver attention, and is commonly adopted to act as a classifier that predicts driving intention, as demonstrated in [138, 154–156]. In [137], a vision-based driver lane-change intention inference system was introduced; this system utilized multiple driver-related signals and the vehicle data acquisition system to handle time-series driving sequences and temporal behavioral patterns. According to the survey in [136], lane change intention can be predicted with an accuracy greater than 90% in the driving simulator. In contrast the on-road

accuracy is generally 70%-90%, where the CAN bus data is essential for the on-road inference. Moreover, the driver's facial information can also be captured by leveraging the RNN-based model to achieve an accuracy greater than 90%.

Longitudinal maneuvers such as braking and acceleration can cause the automobile to lurch and can result in potential safety issues. The reliable prediction of the intention to brake or accelerate can enhance safety of driving through preventative actions. [142] proposed an intention-oriented model for longitudinal dynamics based on the commonly available signals on the CAN bus of modern vehicles. [139] presented a novel braking intention identification model based on the LSTM network to recognize three levels of braking: slight, normal, and hard, in which braking-related data obtained from the speed sensor, gyroscope, and pedal force sensor, were utilized to achieve a predictive accuracy greater than 95%. Further, the driver's cognitive signal was investigated to detect the intention to perform emergency braking [140, 141], with an experimental accuracy greater than 90%. [157] investigated the mechanism of intentional behavior and proposed a psychological perception-action (P-A) model that enables the intentions of drivers to be characterized at each level of the P-A hierarchy in terms of a variety of driver signals.

The steering intention exhibited by the driver was studied in [158] to enhance human-vehicle understanding. A novel deep learning-based time-series model was proposed to model the relationship between the neuromuscular dynamics and the steering torque by leveraging the electromyography (EMG) signals of the upper limb muscles; this model can be utilized to predict both the continuous as well as discrete steering intentions. [159] demonstrated a personalized driver intention prediction system at T intersections devoid of traffic signals by learning in-depth driving behaviors; various classifiers were evaluated to link low-level vehicle states to high-level driving behaviors. An ensemble learning-based driver steering intent recognition strategy was developed in [160], and a nonlinear model predictive control algorithm was designed and implemented to generate haptic feedback for lateral vehicle guidance, assisting the drivers in accomplishing their intended action.

Figure 6 shows that the utilized input data for driver intention includes traffic context information, driver states, and vehicle dynamic data, in addition to their various combinations to predict the various maneuvering intentions. Existing studies demonstrate that driver intention prediction is a context-aware and multimodal representational task. Thus, current models suffer several limitations. In conclusion, a unified model integrated with multiple indicators is indispensable for improving the robustness, generalizability, and accuracy of the prediction to tackle various scenarios rather than a specific situation.

D. Driver Drowsiness Detection

Driver drowsiness is another important factor that causes traffic accidents with a high fatality rate. Therefore, it has attracted considerable attention among researchers [51, 52]; however, despite its similarity to driver distraction, they are not identical. The drowsiness alert function is becoming

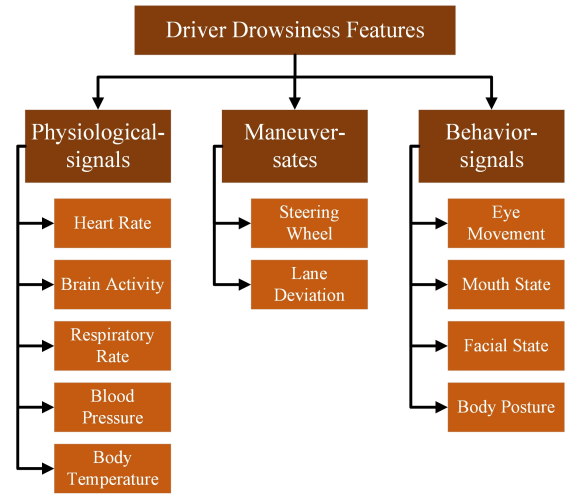


Fig. 7. Commonly used features for driver drowsiness detection.

increasingly common in intelligent vehicles [161]. From a methodology perspective, a driver's drowsiness can be detected in a manner similar to that used to detect driver distraction, as shown in Fig. 7, where three types of features are commonly used: physiological [162–164], maneuver [165–167], and behavioral [168–170].

Drowsiness is more concentrated in the facial [169, 170] and cognitive-related features [171]. For example, [162] established a technique for detecting driver fatigue by analyzing two distinct features: eye movement and bio-signals. A wireless, wearable brain-machine interface (BMI) system was proposed in [104] for signal sensing and processing the detection of driver drowsiness. In addition, the correlation of the EEG power spectrum and the driver's behavior was demonstrated in [172]; they found that the EEG pattern of the drowsiness varies with the individual. Therefore, subject-dependent and generalized cross-subject detection models for driver drowsiness were investigated. [173] combined the electrooculogram (EOG) with the EEG to monitor the driver's vigilance to improve model performance, and a novel LSTM-based model with a capsule attention mechanism was proposed to learn the multimodal representation. The respiratory signal was utilized in [174] to detect drowsiness using an inductive plethysmography belt, which analyzed the respiratory rate variability (RRV) to determine the driver's state.

Like driver distraction, current research on driver drowsiness focuses on specific types of drowsiness by leveraging specific types of features. The advancement of DL networks has also contributed to impressive predictive performance in such systems. Certain studies [173] attempted to fuse multimodal sensors in a simulator that enable systems to detect the fatigue more robustly and accurately but lack real driving evaluation. Furthermore, [172] found that system performance may decrease rapidly when the non-personalized drowsiness detection models are applied to different drivers. These studies indicate that a personalized and multimodal integrated representation in a real driving scenario is required to enhance the performance of the drowsiness monitoring system.

E. Driver Emotional State Monitoring

The emotional state of the driver is critical for driving safety, particularly in cases of road rage, which has been investigated in several studies [175–178]. These studies indicate that the driver’s emotional state critically impacts driving performance, and that the negative state is associated with aggressive driving that leads to numerous traffic accidents. Emotion recognition has attracted considerable attention in the past decades [179, 180] because emotions influence human decision-making during driving [181]. Consequently, the emotional state of humans is investigated in a range of research areas of psychology and cognitive science. Two types of approaches have been adopted to analyze human emotional states: discrete [182] and continuous [183, 184]. The discrete approach categorizes emotional states into specific states such as happiness, surprise, sadness, and anger. The continuous approach uses a continuous space to indicate the emotional state. In view of its importance to automated driving systems, emotion recognition has been studied from various perspectives with a variety of sensors using machine learning technology [185].

Emotional conditions are associated with discernible physiological responses [179], which include ECG [186], EEG [187], EDA [188, 189], and BVP [190]. Several studies utilize wearable physiological sensors to detect the emotional state of the human driver. For example, [187] presented a multimodal database that comprises EEG and ECG signals recorded during affect elicitation via audio-visual stimuli, and an SVM-based method was proposed to recognize the emotions of individual participants. [191] leveraged the nonlinear complexity of heart rate variability (HRV) to assess an individual’s emotional state. Similarly, [192] suggested that increased HRV can be an indicator of the ability to recognize human emotions.

The vision-based approach was investigated by several researchers owing to the fact that emotions are readable from facial expressions. For instance, [193] proposed a probability and integrated learning algorithm for high-level human emotion recognition in music videos. This algorithm adapted emotion classification fuzziness based on the mechanism of uncertainty artificial intelligence. [194] presented an integrated network approach for recognizing facial expressions using facial landmarks. [195] combined head poses and gaze with facial expressions for continuous emotion recognition; an attention mechanism was used to guide the model to extract highly relevant information. The asymmetric bilinear factorization model was used by [196] to decouple linguistic and affective information from the face. [197] proposed a facial dynamics map combined with optical flow to characterize the movements of microexpressions at various granularities.

Other studies combined the physiological information with the appearances feature to improve recognition performance. [198] proposed a DL-based framework for recognizing the driver’s emotions using visual images of facial features and heart rate data over time. A novel convolution bidirectional LSTM model was developed to extract the features and classify them into five general categories. [199] used the heart rate and animation units to aid in the detection of

facial expressions in videos. [200] presented a multimodal sensor fusion framework for studying both basic and complex emotions, including eye tracking, biometrics, and EEG signals. Acoustic features were also leveraged in certain studies. For instance, [201] demonstrated an acoustic features-based speech emotion recognition approach, and [202] used an SVM model to classify five emotional states for automatic speech emotion recognition.

According to existing research, emotion recognition relies on multiple features or sensors because emotions are related to the physiological condition, cognition state, and facial features. An accuracy greater than 80% can be achieved using classic ML models and over 90% with DL models [179]. However, considerable research and development is required before vehicles can recognize the full spectrum of the emotional states of drivers. Therefore, an interdisciplinary approach including psychological investigations must be considered. The fusion of multimodal data can certainly provide additional information to improve accuracy. Ubiquitous, flexible, and pervasive wearable technology should also be further investigated. Existing wearable devices equipped with physiological sensors, such as smartwatches, are a good starting point and can be integrated into the driver monitoring system. Furthermore, emotions are specific to individuals. For example, the reasons behind the driver’s negative emotions typically depend on traffic conditions to which the driver is subjected over a certain period. In addition to external influences, certain internal personal factors can also frustrate the driver, such as the personality reaction to stimulation and the cognitive state, which includes pressure, stress, and anxiety. Different drivers exhibit various cognitive and emotional patterns. Thus, DDT with comprehensive modeling can achieve robust recognition by focusing on modeling the individual emotional pattern.

F. Monitoring of Driver Trust on Vehicle Automation

In addition to the aforementioned factors, the driver’s attitude toward the assistance provided by the automated vehicle (AV) in uncertain scenarios can be reflected in their level of trust [203]. Accidents can occur when drivers mistrust the AVs, especially in complicated and unanticipated scenarios. In such scenarios, ensuring that the driver completely understands the automated decisions can be impractical [204]. Thus, building an appropriate level of trust becomes a crucial issue for safe operation, which has attracted considerable attention [205–207].

Human trust is a sophisticated implicit variable that involves several factors such as the psychological, sociological, and neurological status [208]. According to existing studies, human trust relies on the driving performance of the AVs [209–211]. Moreover, high levels of initial trust generally stem from an excellent illustration of the system capability [212, 213]. In addition to increasing the capability, comfort, predictability, and transparency of the AV to gain human trust, we can also investigate human factors to avoid inducing over-trust or distrust. This is typically time-variant, and it can be influenced by the stress, workload, cognition, scenario, and personality of the driver [214, 215]; even the educational

background and usage experiences can be associated with trust [216, 217]. Li et al. [218], for example, investigated the relationship between driver personality and driver trust in the AV and discovered a significant correlation between Openness and driver trust. Xing et al. [74] summarized all influential factors into three categories: prior, short-term, and long-term factors. Prior factors include the personal traits and background that can affect the human's acceptance of the AV prior to usage. Short-term factors include driver-related states and driving performance, whereas long-term factors include user experience and familiarity after a certain period. Several studies have proposed different approaches to measure the level of trust and optimize the AV to determine the driver's trust status. The different approaches include questionnaires, workload & anxiety estimations, detection of trusting behaviors, and preference studies [219–223]. Other studies have attempted to evaluate trust using external driver behavior features and response time, and their results indicate that the level of trust varies with the reaction times of control recovery [224, 225].

Trust is a crucial factor that should be considered in the design of the AVs; otherwise, it will tend to treat the driver as a by-product of the AV and easily cause automation misuse. Dynamic trust monitoring is indispensable for providing timely intervention to ensure that the human driver trusts the system to an appropriate level. Furthermore, trust evaluation remains a challenging problem because it involves multidisciplinary knowledge and information. DDT provides a reasonable solution to this problem based on comprehensive modeling and time-variable characteristics.

G. Personalized Driver Behaviour Recognition

Drivers can have various types of driving behaviors, and they prefer automated vehicles with a driving style that is similar to theirs [226]. Ensuring such parallelism can enhance the acceptance and comfort the human driver experiences. However, a human is more flexible when tackling different scenarios. Therefore, a personalized driving system is necessary and important, and it can be built by observing and learning the driver's behavior and decision-making patterns.

The acceptance of different driving styles by different drivers and their influence on the drivers have been discussed in [227] and [228]; the designed experiments demonstrated that younger drivers exhibited a greater preference for their own style compared with older drivers. Furthermore, it was demonstrated that different drivers have diverse requirements and preferences. A similar study was conducted by [229]. They investigated the preferences of the human drivers including assertive and defensive styles, under three autonomous vehicle driving styles (defensive, assertive, and light rail transit). The results showed that the defensive driving style was preferred and that variations exist between participants related to their own driving style. Furthermore, the study indicated that future autonomous vehicles should indicate and adjust the driving style to the preferences of the human driver to maximize comfort in the travelling experience. [230] also found that drivers prefer a driving style significantly more defensive

than their own, and that they tend to think it is their own. Furthermore, the preference was found to depend on specific scenarios.

Based on the above assumptions, [231] proposed a human demonstration learning approach to teach the vehicle to learn the desired driving style instead of using manual settings. This approach modeled the driving style of each individual by leveraging the inverse reinforcement learning approach to obtain suitable driving parameters. [232] presented a human-like decision-making system for autonomous vehicles that formulated different driving styles and social interaction characteristics based on game theory to enhance driving safety, ride comfort, and travel efficiency. [233] proposed a new predictive control method based on the models of human behaviors and vehicle dynamics to improve the performance of the longitudinal brain-control driving; this method was developed with the intention of maintaining vehicle rear-end safety and driver ride comfort while ensuring drivers have maximum control authority.

Furthermore, personality is a diverse and sophisticated characteristic and involves various indicators that are difficult to obtain unless it is observed from a comprehensive perspective. The driving data and reaction information for a variety of situations can be collected to reflect the driver's personality by leveraging the DDT system. Personality modeling is one of the most critical enabling functions of the DDT that can lead to the development of a personalized intelligent driving system.

The above subsections reviewed studies focused on driver modeling; these studies investigated the different functions from various perspectives. Certain studies showed that the combination of multiple sensors can improve system performance. For example, [121] utilized a smartphone's multimodal sensors to identify the states of the driver that signaled danger, including drowsiness, distraction, aggressive driving, and high pulse rate. Furthermore, they proposed a cloud system architecture to collect statistics from vehicle drivers, analyze them, and finally personalize the driver's smartphone application. [234] proposed a novel danger-level analysis framework for dealing with high variety and high volume problems of multisource driving data including driver-, vehicle-, and road-related information. Therefore, the integration of multimodal sensors into the DDT can further enhance the capability of driver modeling. Furthermore, the existing methods rely on the data-driven approach, and the utilized data are collected from various human drivers. However, humans are diverse, and it is impractical to utilize the same criteria to evaluate the state of different people. This is demonstrated in [235], which established a framework for analyzing the driving behavior of professional drivers and evaluating the impact of novel safe driving concepts on different driver profiles. The results revealed that drivers with varying levels of experience exhibited varying levels of performance when applying safe and anticipative driving behaviors. Consequently, the DDT system can be utilized to build a personalized model to achieve precise detection. Furthermore, the different states of the driver are interdependent and can be supplemented with others to improve the performance of the recognition model,

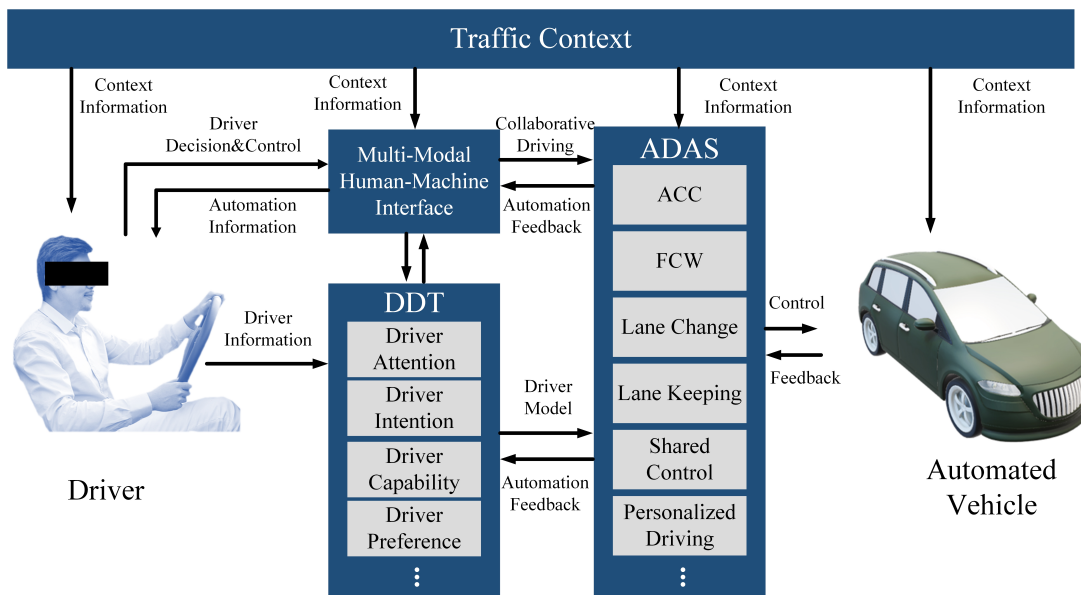


Fig. 8. A general framework of the ADAS leveraging the DDT system.

as demonstrated in [236]. They developed a driver intention recognition model that involves the driver's emotions; various resources including visual features, auditory information, and olfactory data were used to induce the driver's emotions.

The literature survey reveals that existing studies tend to fall into a kind of stagnation. Although several models have been developed to tackle a specific task for certain scenarios, hardly any have performed ideally in practice owing to the complexity of the actual scenarios and human driver. In contrast, the DDT system could provide a comprehensive, personalized, and time-variant representation of the driver's state that enables the AV to thoroughly understand the driver's state and improve its performance. In addition, existing studies focus on recognizing the explicit activities or states of the driver to achieve a specific function; however, implicit driving patterns and styles also need to be investigated further to ensure support for downstream applications. This remains challenging owing to the non-deterministic nature of the implicit patterns and the high degree of inter- and intra-driver variability. Therefore, the DDT is expected to provide a novel avenue of research for future studies, and consequently lead to significant development in this field.

IV. REPRESENTATIVE APPLICATIONS OF DDT IN INTELLIGENT VEHICLES

This section aims to summarize the DDT-enabled key applications and discusses how the DDT can be utilized to further improve the intelligence, personality, and adaptivity of driving automation systems at multiple levels.

A. DDT in Advanced Driver Assistance System

The partially autonomous vehicle is expected to play a dominant role in the future based on the current pace of development of automated driving technology. ADAS would be a standard configuration for intelligent vehicles, and it can

be enhanced with more assistance functions and utilized in a broader range of applications. The ADAS system can mimic or predict the driver's behavior and intention by leveraging the driver's pattern and style information provided by the DDT, such as [237] proposed an LSTM-based model which utilizes data on the driver's gaze and head position as well as vehicle dynamics data to predict the driver maneuver. Thus, it can provide personalized and adaptive assistance to improve the driving safety or experiences, as shown in Fig. 8.

1) *DDT for Adaptive Cruise Control*: Adaptive cruise control (ACC) is a typical assistance function for longitudinal control of vehicles. It simultaneously maintains a constant speed set by the driver and a desired time gap to the leading vehicle. Conventional ACCs pre-define a set of time gaps from which to select. Certain studies have attempted to involve the personality factor to improve the self-adaptation of ACCs [59, 238–240]. In [241], a human-like car-following nonlinear model predictive control controller is developed based on a calibrated human-like Wiedemann model. [242] collected the driving data of multiple drivers and built several driving style profiles. Subsequently, the driver was assigned to one of these profiles for determining the ACC control strategy; this strategy included the engage and disengage ACC [242], and the stop and go strategy [243]. [244] and [245] adopted another approach. The individual driving style was observed and a personalized strategy was developed to improve user experience. In this study, different learning algorithms were proposed to acquire the individual driver's driving style [246–249]. Other studies developed two distinct modes to achieve personalization: learning and running [250]. The driver could manually activate the learning mode to observe the driving parameters, while the running mode was utilized to deploy the learned control model. Meanwhile, other researchers recognized the significance of online learning and proposed the personalized ACC system, which can adapt to driver control

strategies in a dynamic traffic environment [246].

2) *DDT for Forward Collision Warning*: A forward collision warning (FCW) system can alert the driver to avoid an impending collision with the leading vehicle or object. [251] and [252] proposed a statistical approach to model driver behavior, which can be used to adaptively determine the warning activation threshold and reduce the false warning rate; this is similar to [253]. [254] utilized facial information and EEG signals to estimate the brake reaction time of individual drivers to optimize the timing of the warning. Moreover, different drivers behave differently in a given scenario. Thus, personalized FCW systems can reduce the false alert rate and adaptively adjust the warning time to provide drivers with a reaction time appropriate to their driving capabilities.

3) *DDT for Lane-keeping and Lane Change*: Lane-keeping and lane change are typical functions of the ADAS system. They aim to assist the driver to stay in or change the lane by estimating their intention based on the personalized driving model. [255] proposed a learning approach to model driver behavior and improve the lane departure alarm system. [256] developed a personalized vehicle steering system that can adaptively assist the driver to follow a given path based on the driving style. [257] built a personalized vehicle steering pattern to predict the driver's behavior and avoid vehicle collision. [258] proposed an efficiency desired path generation system by modeling the driver's personalized steering mode. [259] proposed a sinusoidal lane change kinematic model based on the driving style. It could adaptively adjust the related parameters according to individual driver behavior, to enhance the safety and comfort of the lane change assistance system. [260] presented a lane change decision model that could detect implicit maneuvers using a data-driven approach while satisfying the comfort and safety constraints.

4) *DDT for Human-centric Shared Control*: Highly automated driving will play an important role until fully autonomous vehicles are developed. These systems will retain a human driver in the control loop. A shared-control system enables a human driver and an automation system to share control authority and cooperatively operate a vehicle [261–263]. However, one critical issue is identifying how to appropriately transfer and allocate the control authority [263–269]. [270] proposed a data-driven approach for estimating the driver's take-over readiness based purely on observable cues from in-vehicle vision sensors. [271] highlighted the importance of the personalized ADAS. It proposed a method to identify the competence and capacity of the driver and the ADAS that could be used to enhance the reliability, acceptance, and even the attractiveness of the system. [272] showed a personalized cooperative control system which could automatically adjust the related parameters based on the individual driving pattern, to make the assistance system easier to accept. [273, 274] proposed a collision probability-aware human-machine cooperative planning and tracking method by evaluating the risk level of the human driver's behavior; the system could be adaptively activated to incorporate the driver's intention and improve the automated vehicle's safety. [275] presented a human-machine adaptive shared control method to tackle automation performance degradation, wherein the

control authority can be adaptively allocated by monitoring the driver state and automated vehicle performance. [276] created a shared control driver assistance system to avoid obstacles based on driving intention identification and situation assessment. Another method is that of inductive classification. It adopts an unlabeled data approach to recognize a human driver's driving intention and determine the desired maneuver based on the lateral offset and lateral velocity relative to the road center line. Three fuzzy controllers in different conditions determine the cooperative coefficient, which denotes the percentage of control authority resting with the controller and the human driver. To build the cooperative control framework for the human driver and the active rear steering system, the human driver model is established in [277] while taking into account different driving characteristics.

The goal of ADAS is to assist the driver in achieving a more intelligent, safe, and efficient driving experience. A wide range of personalities, sensitivities, and preferences have to be considered to ensure that all types of drivers are represented. A single driver can also have dynamically varying emotional states and abilities over time. Thus, the system should be personalized and adaptively cooperate with the driver to enhance user experience and make the ADAS easier to accept. Thus, ADAS-related studies need to not only focus on the specific modules and functions from a vehicular perspective but also consider the driver's personality, preferences, capabilities, etc. The proposed DDT provides a reasonable solution to address this requirement. The DDT system achieves this by leveraging the built unified model to optimize the ADAS module in terms of adaptability, predictability, and time-variable ability. Several studies reviewed in the previous section attempted to incorporate the driver's personality into the ADAS and, consequently, demonstrated its benefits. This encourages us to further investigate intelligent and personalized ADAS by leveraging the DDT system.

B. DDT in Personalized Human-Machine Interface

A human-machine interface (HMI) not only determines how good the user experience is, but also contributes to the trust-building process for drivers. A well-designed HMI requires the vehicle to adaptively recognize the driver's behavior and command, assess the driver's emotional state, and provide timely feedback [278]. Consequently, DDT effectively serves to improve the HMI for enhancing interaction efficiency and driver trust in the vehicle.

A typical area of interest in HMI is command recognition, which involves two widely studied tasks: activity and speech recognition. Hand gesture recognition is a commonly used activity recognition technique and has been implemented in several commercial vehicles [279–281]. In-vehicle hand gesture recognition enables the user to interact with the vehicle through static or dynamic gestures. The advancement of pattern recognition technology and intelligent hardware has popularized online hand gesture recognition. Significant breakthroughs in several aspects such as recognition accuracy, response time, computational memory consumption, user availability have contributed to this. According to one report [282],

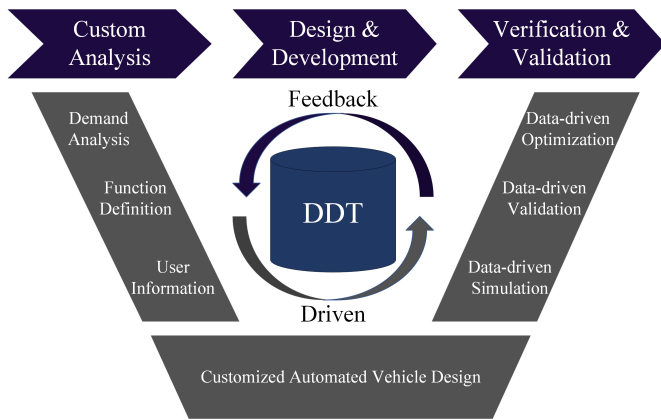


Fig. 9. DDT is utilized in the autonomous vehicle development.

speech control is expected to become the second most popular interface, and 80% of automobile man-machine interfaces will adopt speech control in the near future. Speech recognition has played a role in several applications such as automatic navigation, speech search, command input, and speech assistant. The use of the deep-learning capability of spoken dialogue system has been improved and has helped achieve impressive performances in audio processing applications. In addition, other modality interfaces, such as the brain control [283] and the haptic interface [284], have also been investigated. However, these approaches are currently limited to laboratory demonstrations and far from the practical deployment stage. Further investigation is required to integrate these approaches with other interfaces to achieve robust interaction.

Currently, most HMIs are designed using average modeling, wherein most functions are fixed for every driver. This means that unless users adapt to specific interaction gestures and pronunciations, the recognition accuracy will degrade. For instance, several real use-cases have demonstrated that speech recognition systems fail to handle diverse dialects, which hinders user experience. Thus, the HMI system should be able to adaptively tackle the diverse behavioral patterns and speech accents to improve the experience of end-users and make them feel like the system is customized. To accomplish this, the DDT can be utilized to fine-tune recognition models.

C. DDT in Automated Vehicle Development

Apart from enhancing the ADAS for a low-level autonomous driving system, the DDT can also be leveraged for high-level systems as shown in Fig. 9. These autonomous cars from the same factory or vehicle type were installed with the same decision algorithm and default configuration. The DDT system aids the autonomous vehicle in providing enhanced personalization and enables it to drive like a human, thereby enhancing passenger comfort and confidence. Furthermore, surrounding drivers can naturally interact with it and better understand its behavior and purpose. In addition, it can be used provide more reliable simulation systems for the development of autonomous vehicles. Validating the safety of autonomous vehicles in the real world is costly, dangerous, and time consuming [285]. Thus, performing this validation

in simulated environments can help address these problems. However, the simulation of real and complex traffic scenarios is a challenging task owing to the highly dynamic nature of human behavior that results in diverse driving patterns. The DDT overcomes these challenges by providing diverse realistic driving models.

Several studies have introduced the human factor to autonomous driving systems [286]. For instance, [287] presented a proof-of-concept investigation to demonstrate that the autonomous driving design can be benefited from the cognitive work analysis. [288] presented an autonomous vehicle model based on dynamic human behavior. The model enabled vehicles to drive appropriately by mimicking the behavioral features of the driver. It achieved this by analyzing the drivers' characteristics such as gender, age, driving experience, personality, and emotion, thereby enabling personalization. [289] proposed a human-like autonomous car-following planning framework based on deep reinforcement learning. Human driving data were fed into a simulation environment to train the autonomous vehicle system to acquire human-like characteristics, thereby increasing the naturalism of its interactions with passengers and surrounding vehicles. [290] integrated social psychology tools into controller design for autonomous vehicles by predicting driver behavior and quantifying the driving style. The interactions between human and autonomous agents were modeled using game theory and the principle of best response. By studying certain common-yet-difficult traffic scenarios, they determined that autonomous performance can be significantly improved by incorporating the driver's behavior into the model. Owing to the intelligent transportation system comprising the human-vehicle-infrastructure-roadside units, [291, 292] introduced the parallel internet of vehicles concept, where the human factor is highlighted and modelled in the framework to flexibly adjust and allocate the available resources according to social acceptance.

Owing to the lack of real-world connected and autonomous vehicle (CAV) exposure data, evaluating the safety impacts of CAV has been a major challenge. Studies that attempt to simulate CAVs using a single simulation platform or by integrating multiple simulation platforms have limitations; in most cases, they consider only a small portion of a network and do not perform safety evaluations because of its inherent complexity [293]. [294] addressed this issue by constructing multiple solid human driver models based on real-world driving data. [295] utilized generative adversarial imitation learning to help representative human driver models learn and increase the realistic nature of the simulation. [296] proposed a driving training data rendering approach leveraging actual human-collected trajectories, which enhanced the ability of virtual agents within the previously unseen scenarios and situations. [297] presented a human-in-the-loop agent-based simulation that incorporated human crowd characteristics and behaviors to enhance the efficiency of crowd control for unmanned vehicles. They developed the individual path model by leveraging the social-force-based model to predict the near-future location of individuals for improving the path planning performance of the UV. To facilitate the visual intelligence testing of intelligent vehicles, [298] created a realistic artificial

scenario simulator to generate synthetic images, and a virtual driving scenario dataset was developed, called ParallelEye-CS. Leveraging this simulator, [34] proposed a novel theoretical framework to address the long-tail problem using parallel technology. Here, a novel parallel vision actualization system (PVAS) capable of leveraging the constructed virtual parallel simulator was presented. It was used to search for challenging scenarios for improving the perception capability of autonomous vehicles. A similar concept was utilized in [299], which presented a virtual-real interactive point cloud generation framework for autonomous driving, called parallel point clouds (PPCs). To accelerate the evaluation and development of autonomous vehicles, [33] designed a human-in-the-loop parallel testing system to implement more challenging tests via virtual-real interaction. In these tests a human expert vaguely defined the tasks and performed qualitative judgments, following which the simulation system defined the tasks more precisely, generated further testing scenarios, and collected feedback from humans to validate the test results.

The DDT model can be utilized throughout the whole R&D process of autonomous vehicles in a data-driven manner from the custom analysis to the functional development and validation, and finally during on-road operation. Thus, the customization and personalization of the autonomous vehicles can be progressively achieved.

V. OBSERVATIONS AND RECOMMENDATIONS

Existing driver modeling studies and DDT-related applications for multilevel autonomous vehicles were comprehensively reviewed. The various technologies and models proposed by these studies have been crucial in establishing DDT technology in the automotive industry; however, DDT has a considerable amount of untapped potential. However, numerous obstacles need to be overcome before DDT can become commercially viable. This section presents the opportunities and challenges that will govern the future research objectives in this domain.

A. Unified Modeling Framework

Driver modeling is the foundation of the successful operation of DDT systems. Existing driver models are based on isolated perspectives or individual parameters instead of being generalized. However, the driver's performance is multimodal and can have different physical or psychological reactions to different driving scenarios. Therefore, the first critical task in the implementation of DDT is to construct a practically viable unified digital model. However, the complexity of humans makes modeling and massive data fusion analysis challenging; in addition, the diversity of data sources, data variability, and heterogeneity present further obstacles [300]. A consensus should be reached on the framework of the DDT model and how to construct it based on the aggregated multimodal data trove. The corresponding algorithms and tools should be thoroughly investigated. Thus, the unified model of the DDT remains insufficiently defined and needs to be further explored and discussed.

B. Unsupervised Data Analysis

Data analysis relies on an intelligent method to recognize or detect specific states. Deep learning techniques are known for their powerful learning capability, and are currently the most popular approach in many applications [301–304]. However, deep learning-based methods require large datasets, which presents a challenge for the DDT system. In particular, a large multimodal corpus dataset of driver performance is yet to be developed. In addition to the effort of collecting data, unsupervised learning models are required for investigating approaches to tackle this challenge [305–308]. In addition, human driver performance is complex, diverse, and personalized. Therefore, building a dataset applicable to all scenarios is difficult. Thus, advanced unsupervised approaches should be further explored to overcome the lack of labeled data [309–313].

C. Multi-modal Sensor Fusion

A well-established DDT system is expected to involve multimodal fusion of massive volumes of data on various drivers, in addition to real-time, historical, virtual, and physical data. This requires multiple techniques including data cleaning, conversion, calibration, and mining, among others [314–318]. The related intelligent algorithm and method should be improved to handle the iteration and optimization of the massive data [319]. The corresponding connection and communication protocol is also crucial for the successful operation of the DDT system and needs to be standardized. Thus, multimodal data fusion should be carefully studied to support the efficient interaction between modules.

D. Regulation

In addition to new technologies, DDT comprises various regulatory aspects. To ensure wide applicability and feasibility of our research results, a wide variety of technical areas need to be considered. Furthermore, non-technical aspects including ethical issues, personal privacy, and the reliability of simulation outcomes, need to be scrutinized when considering the utilization of DDT [320, 321]. Moreover, DDTs operate on heterogeneous data sources that must be protected by strong digital security and data governance policies to secure highly sensitive data; in addition, they must meet evolving legal/compliance requirements. To achieve this, we will need the cooperation of experts in various fields of research and technology, including social sciences, natural sciences, humanities, and other interdisciplinary fields.

E. Other Recommendations

The comprehensive digitization of the driver means that the DDT can be effectively merged and exchanged in cyberspace. This automatically enables the driver to temporarily acquire the driving skills of an expert and the ability to maintain control in risky scenarios. Furthermore, the DDT can be utilized to continuously mine potential requirements to generate novel, unique, and valuable product concepts, which can then be transformed into detailed customized products to cooperate

with smart manufacturing. In addition, the vehicle design scheme continuously reduces the inconsistency between the vehicle's actual behavior and the design's expected behavior.

VI. CONCLUSION

Digitization is of utmost significance in the future in view of the development of advanced sensing and intelligent systems. Consequently, DT is potentially one of the most promising enabling technologies; it has already been introduced to several fields including intelligent vehicle and transportation systems. The driver, who remains indispensable to the system, must be incorporated with the other elements to form a complete driving H-CPS. However, systematic research into the digital human driver is rare. Therefore, this study proposes the concept of a DDT to introduce a more comprehensive model of the human driver. Compared with the original DT used in manufacturing, the DDT emphasizes the personality and capability of the driver instead of the external physiological-level state. Thus, it is expected to provide a theoretical basis for a human-centric intelligent driving system.

The DDT has significant potential for development considering the rapid growth of computing capacity, low-cost intelligent devices, data storage, convenient data acquisition, and AI. This study systematically illustrates the concept of the DDT and outlines its key enabling aspects. Current related technologies and applications have also been comprehensively reviewed. Furthermore, we have discussed how the DDT can be leveraged to further improve these technologies and applications. Unsettled technical issues and potential applications have also been presented. The proposed DDT is a work in progress that must be refined and allowed to evolve. In addition, several urgent issues must be addressed to increase its practical viability. For instance, a unified DDT modeling method based on multi-modal data is urgently required; the intelligent algorithms and data fusion approaches should be further investigated; and the corresponding regulations need to be established and followed. The DDT is expected to become a central research topic in the future as our ability to manipulate DT-enabled technology and our understanding of the human aspects in driving grows. In conclusion, this study aims to serve as a guide to peer researchers seeking to determine the future direction of DDT research and its possible applications.

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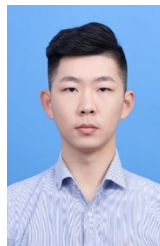
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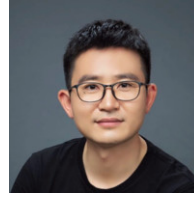
Zhongxu Hu received a mechatronic Ph.D. degree from the Huazhong University of Science and Technology of China, in 2018.

He was a senior engineer at Huawei. He is currently a research fellow within the Department of Mechanical and Aerospace Engineering of Nanyang Technological University in Singapore. His current research interests include human-machine interaction, computer vision, and deep learning applied to driver behavior analysis and autonomous vehicles in multiple scenarios.

Dr. Hu served as a Lead Guest Editor for Computational Intelligence and Neuroscience, an Academic Editor/Editorial Board for Automotive Innovation, Journal of Electrical and Electronic Engineering, and is also an active reviewer for IEEE Transactions on Intelligent Transportation Systems, IEEE Transactions on Industrial Electronics, IEEE Intelligent Transportation Systems Magazine, Journal of Intelligent Manufacturing, and Journal of Advanced Transportation et al.



Shanhe Lou received the Ph.D. degree from the School of Mechanical Engineering, Zhejiang University, Hangzhou, China, in 2020. He was a Member of the State Key Laboratory of Fluid Power and Mechatronic Systems, Zhejiang University. He is currently a Research Fellow with the Department of Mechanical and Aerospace Engineering, Nanyang Technological University, Singapore. His research interests include intelligent design and manufacturing, human-cyber-physical system for autonomous vehicles.



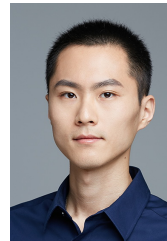
Dongpu Cao received the Ph.D. degree from Concordia University, Canada, in 2008. He is a Professor at Tsinghua University. His current research focuses on driver cognition, automated driving and cognitive autonomous driving. He has contributed more than 200 papers and 3 books. He received the SAE Arch T. Colwell Merit Award in 2012, IEEE VTS 2020 Best Vehicular Electronics Paper Award and 6 Best Paper Awards from international conferences. Prof. Cao has served as Deputy Editor-in-Chief for IET INTELLIGENT TRANSPORT SYSTEMS JOURNAL, and an Associate Editor for IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS, IEEE/ASME TRANSACTIONS ON MECHATRONICS, IEEE TRANSACTIONS ON INDUSTRIAL ELECTRONICS, IEEE/CAA JOURNAL OF AUTOMATICA SINICA, IEEE TRANSACTIONS ON COMPUTATIONAL SOCIAL SYSTEMS, and ASME JOURNAL OF DYNAMIC SYSTEMS, MEASUREMENT AND CONTROL. Prof. Cao is an IEEE VTS Distinguished Lecturer.



Yang Xing received his Ph. D. degree from Cranfield University, UK, in 2018. He is currently a Lecture with Centre for autonomous and cyber-physical systems, Department of Aerospace, Cranfield University. Before joining Cranfield, he was a Research Associate with the Department of Computer Science, University of Oxford, UK, from 2020 to 2021, and a Research Fellow with the School Mechanical and Aerospace Engineering, Nanyang Technological University, Singapore, from 2019 to 2020. His research interests include machine learning, human behavior modeling, intelligent multi-agent collaboration, and intelligent/autonomous vehicles. He received the IV2018 Best Workshop/Special Issue Paper Award.

ing, human behavior modeling, intelligent multi-agent collaboration, and intelligent/autonomous vehicles. He received the IV2018 Best Workshop/Special Issue Paper Award.

Dr. Xing serves as a Guest Editor for IEEE Internet of Thing, IEEE Intelligent Transportation Systems Magazine, and Frontiers in Mechanical Engineering. He is also an active reviewer for IEEE Transactions on Intelligent Transportation Systems, Vehicular Technology, Industrial Electronics, and IEEE/ASME Transactions on Mechatronics, etc.



Chen Lv is a Nanyang Assistant Professor at School of Mechanical and Aerospace Engineering, and the Cluster Director in Future Mobility Solutions, Nanyang Technological University, Singapore. He received his PhD degree at Department of Automotive Engineering, Tsinghua University, China in Jan 2016. He was a joint PhD researcher at UC Berkeley, USA during 2014-2015, and worked as a Research Fellow at Cranfield University, UK during 2016-2018. He joined NTU and founded the Automated Driving and Human-Machine System (AutoMan)

Research Lab since June 2018. His research focuses on intelligent vehicles, automated driving, and human-machine systems, where he has contributed 2 books, over 100 papers, and obtained 12 granted patents. He serves as Associate Editor for IEEE T-ITS, IEEE TVT, and IEEE T-IV. He received many awards and honors, selectively including the Highly Commended Paper Award of IMechE UK in 2012, Japan NSK Outstanding Mechanical Engineering Paper Award in 2014, Tsinghua University Outstanding Doctoral Thesis Award in 2016, IEEE IV Best Workshop/Special Session Paper Award in 2018, Automotive Innovation Best Paper Award in 2020, the winner of the Waymo Open Dataset Challenges at CVPR 2021, and Machines Young Investigator Award in 2022.



Xiao Wang obtained her B.E degree in network engineering from Dalian University of Technology, Dalian, China, in 2011, M.E and Ph.D. in social computing from the University of Chinese Academy of Sciences, Beijing, China, in 2013 and 2016, respectively. She is the President of Qingdao Academy of Intelligent Industries and an Associate Professor in the State Key Laboratory for Management and Control of Complex Systems, Institute of Automation, Chinese Academy of Sciences. Her research focuses on cyber-physical-social systems,

social computing, social transportation, cognitive intelligence, especially in aspects of social network analysis, data fusion, multi-agent modeling and computational experiments. She has published more than 60 publications in international refereed journals and conferences. As for the member of IEEE Intelligent Transportation Systems Society(ITSS) BoG, she always cooperates with the other BoG members to advance important initiatives of the society, give full play to the role of female researchers in ITSS activities and spread the worthy ideas to the society.

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Review and perspectives on driver digital twin and its enabling technologies for intelligent vehicles

Hu, Zhongxu

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