Towards Cross-Cultural Intelligent Vehicles: A Review

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***Abstract*—Advanced Driver Assistance Systems (ADAS) are becoming an integral part of modern road vehicles. Their deployment is demonstrating their contribution to safety and efficiency. However, as the interaction between ADAS and the driver increases, other issues are emerging that affect their performance. The driving task is influenced by a range of factors, including the driver's preferences and behavior that is conditioned by the operating environment comprising the road conditions, environmental conditions, and complex social interactions with other road users and pedestrians, etc. Driving differs also between and within cultures. In this paper, we review the current approaches in the literature that demonstrate an adaptation to the driver behavior but also the work on social interactions on the road. We then discuss issues that remain open and need to be confronted when designing a cross-cultural intelligent vehicle.**

***Index Terms*—intelligent vehicles, culture, context-based system, safety, personalized ADAS, social robotics.**

I. Introduction

Vehicles and driving are intimately connected to our individual and collective sense of self - who we are, what we believe in, what are our values, and what we aspire to achieve, as well as how we interact with others [1]. Currently, there is a rapid deployment of Advanced Driver Assistance Systems (ADAS) in the new generation of road vehicles as a means to enhance safety, riding comfort, and energy consumption. Their deployment is contributing to improvements in these areas, with modern legislation and vehicle qualification evaluations such as the EuroNcap [2]. However, the interaction between ADAS systems and drivers is becoming very symbiotic, which raises several issues.

Intelligent vehicles are mainly developed based on data collected, developments and field trials, and research conducted in North America, certain countries in Asia and Europe, where driving conditions, safety, etc. are very different from what occurs elsewhere [3]. It is to be noted that in low- and middle-income countries a growing phenomenon is occurring, road accidents are reaching almost epidemic proportions, and road safety has became a major concern. The World Health Organization [4] reported that with an average rate of 27.5 deaths per 100,000 population, the risk of a road traffic death is more than three times higher in low-income countries than in high-income countries, where the average rate is 8.3 deaths per 100,000 population, see Fig. 2. Furthermore, these countries have also witnessed a major increase in the number of road vehicles. In these countries, the road infrastructure, traffic conditions, driver training, and respect to the traffic code are substantially different [5].

The conditions and road networks where ADAS functions are deployed differ very much. Recently, research has increasingly focused on reducing bias in the development of intelligent vehicles by addressing the intricacies raised by cultural and social differences [3], [6]. In a developing country such as India, Fig. 1, in order to respond to common challenges on the road, traffic conditions, local regulations, and unwitting rules are rapidly emerging. For example, in heavy traffic, respect to the rule that should keep all cars within the boundaries of lane markings disappears, that is more cars than the number of lanes will fit across standard roads. Unlike countries within the European Union, there will be more non-verbal cues and verbal communication to create awareness and for drivers to find a consensus related to safety and efficiency. Another example would be crossing outside crosswalks that is a common behavior of vulnerable road users; this is contrary

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Fig. 1. Sample of traffic conditions in India [8]–[10].

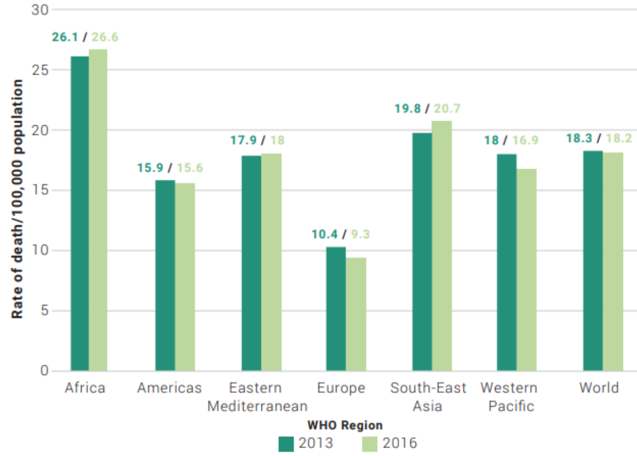

Fig. 2. Rates of road traffic death per 100,000 population between 2013 and 2016 by the World Health Organization regions [4].

to what occurs in most Nordic countries [7]–[10].

The differences in road networks and operating conditions are more notable when deploying the Society of Automotive Engineers (SAE) Level 4 vehicles (e.g., robot-taxis); that is, the machine should understand its situation before making any decision; however, situations will vary from country to country, from rural land to dense urban areas, even within the same country. Most field trials of robot-taxis have been so far confined to limited areas, and scaling up has proved more difficult than expected. Therefore, the manner of how all road users will behave is a major constraint to full-scale deployment.

Intelligent vehicles comprising ADAS functions or different levels of automation will not achieve their promise if drivers and the environment rounding do not accept and use them in a sustainable manner [11].

Designing a cross-cultural intelligent vehicle is one of the challenging problems faced by researchers in the automotive sector but not yet seriously addressed. Through this paper, we tackle the following questions:

- What do we mean by a culture with respect to driving? What are the main cultural differences in driving behaviors?
- What do we mean by a cross-cultural adaptive intelligent vehicle? What are the cues to pay attention to on the road?

The remainder of this paper is organized as follows. In the following section, Section II, we define culture, introduce its dimensions in the context of driving, and we emphasize the bias in the development of intelligent vehicles to date. Following that, in Section III, we discuss personalization in Advanced Driver Assistance Systems and drivers models in the literature. In Section IV, we will review the state of the art in social intelligent vehicles and discuss where attention is turned to on the road. Section V discusses what a context-based intelligent vehicle would consider and highlights challenges and open issues in the design of such a system. Conclusion and future work are drawn in the last Section VI.

II. Culture's impact on driving task and road traffic

The driving task is not only what is measured objectively on a road, nor only the professional conceptualization of the traffic system. It is also the "world view" that lay people have of the traffic system [12].

It is in the human being as a mirror of one's personality, one's expectations and risk assessment, also one's culture. In this context, How could intelligent vehicles gain their place in society and be accepted by the driver? The intelligent vehicle is involved in more than just trajectory optimization, obstacle avoidance, and driver cognition testing. To become a part of the surroundings and to incorporate the driving culture, it needs also to be merged with the driver and represent him/her.

Before diving into the role of culture in the driving task and why it is primordial to include the context in the design of intelligent vehicles, we first define the concept of culture.

In "What is Culture?" by Edgar Schein [13], culture is defined as a pattern of shared assumptions (knowledge and values) that have served a group well in the past, that is learned to new members and that can be adapted to external circumstances. Culture is essentially a social indoctrination rule that people learn as they try to fit into a particular group.

Culture can also be defined through its characteristics. It has collective representations - vocabularies, symbols, and codes [14], [15]. More often on some roads and less on others, drivers, to find a consensus, tend to communicate verbally their decisions and understand common non-verbal cues, while in Europe for example, we notice a certain individualism as rules are respected and traffic is structured. The work in [16] and [17] explicitly addresses the need for an external HMI for autonomous vehicles to communicate with other vehicles and pedestrians. Culture has social norms and values. All these elements structure the thinking and acting of the individuals within the same group to respond to the survival challenges of their environment by learning through reward and punishment, by conforming to social norms, laws, and regulations, by accepting persuasive messages, anticipating others' behavior, and compensating for the errors of other traffic participants.

As illustrated in Section III and concluded in [1], the ADAS systems can compensate for the perceptual constraints that affect driver performance when responding to roadway demands, but less when overriding a driver's attitudes, goals, and priorities. Driver behavior, then, may ultimately have the most influence on traffic safety. Research on driver behavior has focused almost entirely on individual differences (e.g., cautious, aggressive), distraction, or cognitive level as contributors to unsafe driving behavior. However, in [18], the authors investigate the relationship between the three factors of the Driver Behavior Questionnaire (DBQ) (errors, aggressive violations, ordinary violations) reflecting culture differences and the difference in the rate of fatalities in six countries (Finland, Great Britain, Greece, Iran, The Netherlands, and Turkey). Findings demonstrated that the addition of driving styles, especially aggressive violations and errors not only improved the models for predicting the number of traffic accidents but also mediated the relationship between culture/country and accidents. The results show that 84.6% of traffic accidents are caused by vehicle violations, which is the crucial factor within all traffic accidents [15]. In the road safety annual report in 2019 [19], it is emphasized that traffic-related mortality rates differ widely between countries, e.g., the risk of being killed in a road crash is six times higher in Argentina than in Norway. Although traffic car accidents are a major problem everywhere, significant differences between countries are encountered. The results emphasize the critical role that culture plays in driving safety. The authors in [20] discuss road accidents related to the interactions among drivers instead of single attitudes. A recent review [21] discusses the factors influencing driving behavior and the causes of road accidents.

Moreover, culture provides the subtext to driver behavior by shaping the beliefs, values, and ideas that people bring to the driver's seat. It highlights the influence of societal expectations and practices among drivers from the same culture. For example, "honking" clearly reflects aggression in Scandinavia, whereas in Southern Europe and Iran, drivers use their horn frequently to give various messages, such as thanking other drivers. Furthermore, in Turkey, the speed of traffic flow on many roads is much higher than the speed limit. Consequently, drivers do not see their speeding as a serious offense as the Western Europeans might do. Thus, it is important to consider that traffic culture or context determines the criteria but also both formal and informal rules for acceptable driving style, and thus, develop nation-specific items for reflecting informal rules that reflect the cultural behavior in each country/environment [18]. Understanding the context is what will give the intelligent vehicle fluidity, motion involved in social exchanges, the socio-acceptance and it is what is going to increase the driving safety by anticipating other drivers behavior and making up for errors made by other traffic participants.

Transferring the ADAS technology as designed by automotive manufacturers from one culture to another can be problematic. In [22] and [23], research was conducted to indicate different cultural areas that need to be focused on when developing ADAS for China. One of the major problems in China is the complex traffic environment with congestion, motorized three-wheeled vehicles, and poor lane markings. It has been reported that ADAS such as Forward or Lateral Collision Warnings or Adaptive Cruise Control can be just annoying in such crowded environments where people obey authority norms less than social ones. Consequently, an ADAS that is of great value to the drivers of one country may be of less value than to those in another if not adapted.

The intelligent vehicles are integrated into hybrid roads where drivers tend to possess a model of their environment, allowing them to predict the intentions of road and non-road users, and thus, their safe driving is predetermined based on meeting the expectations of others. The intelligent vehicle should possess this set of knowledge, skills, and competencies to recognize, understand, and adapt to social and cultural differences.

III. Personalized Driving Assistance systems: State of the art

Due to the greater market penetration, the field of advanced driver assistance systems has grown to include aid functions that are increasingly complex but designed for the average driver or all drivers [24]. To assure the best user experience throughout such a wide range of use conditions and usage patterns, personalization techniques have been created. Personalized ADAS are developed by learning driver models from the observation of driver behavior and then parameterize the vehicle controllers to meet the personal driving style. In this section, we review recent work on the driver models and the personalized ADAS.

A. Driver modelling

Since their pioneering theoretical study of Automobile-driving, human driving behavior, by Gibson and Crooks in 1938, scholars have contributed to driver behavior mimic and driver psychology modeling [25].

The models proposed went from simplistic mathematical models to represent the correlation between the state metrics of the host vehicle (acceleration, relative speed, distance headway, etc.) [26]–[28] to more sophisticated models reflecting the internal mechanisms of the decision making that drivers must hold in their minds. The authors in [29] model the driver behavior in the ACT-R cognitive architecture. In [30], J.A. Michon discusses the driver behavior model types; behavioral (Mechanistic, adaptive-control, etc.) and psychological (motivational, cognitive, etc.). The authors of [31] review two hundreds models on driver behavior modeling.

Each driver is individually influenced by the social environment consisting of other road users, general social norms, traffic-related rules of conduct, and their representations [32]. The models proposed in the literature either suggest that a group of similar characteristics, or stereotypes, exist about a set of users [33], [34] or they are tailored to meet personal driving styles. However, driving style is supposed to vary in the degree to which it is shaped by both intrinsic (e.g., age, sex, experience, cognitive biases, and emotions [35]) and extrinsic (e.g., social context) factors [18], which are rarely considered. In the same sense, driver behavior modeling as proposed in the literature lacks a connection between models of individual driver behavior and the (presumably) resultant population behavior as reflected in traffic characteristics, informal rules conducted, or the accidentology level in the environment, which greatly influence the driving skills, the other main component of human factors in driving [36], [37]. [38] models the driver behavior along with demonstrating how the contextual information affects its performance.

B. Personalized ADAS

In this part, we are interested in defining the personalization of the ADAS as studied in the literature, revealing the key human/environment features considered in this personalization and presenting the process behind including those features in the loop. We have considered functions representing the three types of driver efforts: strategic (route planning), tactical (Adaptive Cruise Control [46], [47] – Lane Change Assistance), and operational (Forward Collision Warning) in the aim of identifying which features are relevant to each type/function and coming across models that have an eye in and out of the vehicle. A recent survey [48] and a review of personalization in ADAS and autonomous vehicles [49] concentrate on methods that combine individual driver models and controllers for designing personalized ADAS.

Table I summarizes some of the papers reviewed. In the personalization of the ADAS, we can distinguish between group-based and individual-based approaches to personalization. In the former case, drivers are assigned to one of a small number of representative driving styles (e.g., aggressive, cautious, etc.). In the latter case, the ADAS strategy tries to best reproduce the driving style of an individual driver [50]. In the table, we make also the point on the driver's characteristics relevant for the function, the environmental dynamic information, etc. We also refer to the methods used for Driver/context behavior recognition and the models used for Adapting. Finally, the personalization as demonstrated today, lacks a continuous learning of the human preferences or proposes that on demand with a recalibration of the process of personalization, we distinguish between the two approaches in the table.

We have presented some ADAS functions referring to self-driving capabilities (Adaptive Cruise Control), maneuver assistance (Lane Change Assistance), and monitoring capabilities (Lane Keeping Assistance) to show how they share some common features and differ on others to approach the driver modeling.

The use of neural networks or fuzzy logic (with capabilities of approximation, generalization, and self-learning) is suitable for modeling driver behavior with nonlinear characteristics. The research showed that artificial intelligence could offer some potential advantages in driver behavior analysis and modeling. However, the current studies present some limitations listed below:

- The driving style and the driver behavior are studied mostly from the control viewpoint, e,g., mimicking the acceleration/deceleration profiles [41]. Although, this operation is the result of different traffic situations, intra-individual differences, etc.
- Current customized personalized systems are mainly implemented through manually adjusting warning trigger thresholds for example, which would be less feasible for overall drivers as a certain domain expertise is required to set personal thresholds accurately and it becomes a tedious task as the number of ADAS is continuously increasing.
- Personalization techniques exploit individual drivers' data to build personalized models. Such an approach could learn personal behaviors but requires impractical large-scale individual data collection or the data are mostly based on simulation and not close to reality.
- We did not come across papers studying different functions under the same framework and this is problematic as the ADAS functions are increasingly added.
- The personalization of the ADAS to meet the driver's preferences and to mimic his behavior is bottom-up and when it is top-down, it is not validated.
- Artificial intelligence has proven its potential in modeling driver behavior. However, it presents some disadvantages when coming to the model stability, the computational load required and the complexity of it.
- Two approaches exist for the trajectory modeling: stochastic (Hidden Markov Models, Neural Networks, Fuzzy logic, etc.) and kinematic [42]. the stochastic modeling has proven its capability to approach different driver behaviors, it is flexible and accurate but lacks the physical meaning contrary to the kinematic modeling.

Despite the aforementioned efforts, it is missing the inclusion of the driver skills which are related to the environment from which he gains experience and constructs this toolkit to respond to the road needs. The objective of a driver model is to represent the process by which a driver transforms some perceived information about the driving situation into an action on the vehicle's actuators (steering wheel, pedals). We believe that regenerating this behavior is not mimicking the brake and acceleration profiles but understanding the why of these maneuvers as the driving task is about the driver's behavior toward a certain situation.

IV. Social Autonomous vehicles

Research on social robotics and in particular social autonomous vehicles is demonstrating the importance that play the social and the cultural dimensions when it comes to situation understanding [51], decision-making, and motion planning [52]. [53], [54] reveal the gaps in the development of autonomous vehicles navigating in uncertain environments and the lack of sufficiently detailed understanding of how humans interact in such conditions and how that understanding

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TABLE I
REVIEW OF PERSONALIZED ADVANCED DRIVER ASSISTANCE SYSTEMS.

Function	Approach	Driver/context in the loop	Model-used	Driver/Context behavior recognition	Methods for adapting	The learning rate	Reference
Adaptive cruise control	Group-based	average, maximum and minimum of relative speed, time headway and jerk	learning-based	Self-organizing feature map neural network with K-means then PNN classifier	MPC as an upper-level Controller, and feedforward and PID for lower-level controller	On demand	[39]
Adaptive cruise control	Individual-based	Demographics: Age, sex, income level, educational level - location of the vehicle: distance to the lead vehicle, vehicle speed, longitudinal acceleration, road density, road type, weather - driver's behavior	learning-based	Regression model – decision tree model	-	-	[40]
Adaptive cruise control	Individual-based	Motion states of the leading vehicle and the host vehicle (vehicle speed, acceleration, accelerator pedal/throttle depression, brake pressure, relative distance/speed to lead vehicle, and Global Positioning System information)	Model-based	Self-learning algorithm based on RLS to identify the model parameters	a linear driver behavior model with a lower PID controller	Continuous learning	[41]
Lane change assistance	Individual-based	Max/average absolute value of steering-wheel angle, average steering-wheel angular velocity, standard deviation of steering-wheel angle, max/average absolute value of lateral acceleration, maximum absolute value of slip angle, maximum absolute value of yaw angle, maximum value of yaw rate, average value of yaw rate, and standard deviation of yaw rate	Rule-based and learning-based	Fuzzy c-means algorithm for classification then back-propagation (BP) neural network optimized by a particle swarm optimization (PSO) algorithm	a sinusoidal lane-change model	Continuous learning	[42]
Forward Collision Warning	Individual-based	Time headway, Time to collision, longitudinal speed of ego vehicle	Model-based	recursive least squares method for warning threshold	Adaptive algorithm	Continuous learning	[43]
Forward Collision Warning	Individual-based	Gas pedal position, range with neighboring vehicles, turn signal, yaw rate, longitudinal acceleration, velocity…	learning-based	Neural network – Support Vector Machine	Adaptive algorithm	Continuous learning	[44]
Route planning	Group-based	The vehicle's absolute motion, the vehicle's relative motion to surrounding vehicles and/or objects, Distance, Time, acceleration profile…	Model-based	HMM models – classifiers – fuzzy-based classifier - …		Continuous learning	[45]

might be quantified in computer models. Considering the lane change maneuver, scholars are formulating the problem as a non-cooperative game [55] when considering the social behaviors and the intentions of the surrounding vehicles [56], [57] while in [58], the authors are imitating the stimulus-based selective attention mechanism of human vision systems to recognize the lane changing intention of the surrounding vehicles. Based on a higher level of cognition, human drivers have this capability to pay attention to relevant information on the road related to their actual maneuvers, the authors in [59] review the modeling of where and when the drivers look on the road. Additionally, human drivers consider the stochastic variability in their interaction with vehicles/pedestrians, [60] is addressing this problematic at uncontrolled crosswalks. Learning to drive has emerged as an efficient alternative to hand-crafted rules, especially when considering interactive behaviors [61]–[66]. To tackle the social, ethnographic, and legal dilemmas in the urban environment, [67] offers insights into a new automated driving strategy by introducing a general learning-based framework based on maximum entropy inverse reinforcement learning and the Gaussian process. In [68], the authors introduced the learning by watching others framework enabling the vehicle to learn new skills in a new situation or geographic location, which finds its inspiration in the driver capabilities to fit in new environments and cultures by watching demonstrations from other drivers. To fit into an environment and to gain this social invisibility [69], drivers are learning from countless experiences by possessing this device of permanent memory, inferring, and experiential updating in addition to their event-related mechanism. The authors of [70] are discussing how to implement a cognitive computing framework for autonomous driving with selective attention and event-driven mechanism. A direct measure of performance for autonomous vehicles is their level of similarity to human drivers, and emulating human driver behavior just adds more challenges to countless ones.

V. DISCUSSION

In order for an intelligent vehicle to gain in intelligence, performance, robustness, and acceptability, we posit that it should take a culturally and socially cognizant path. We define cultural awareness as the capacity to infer such favorable actions based on knowledge about the driver and others' intent and behavior, of understanding road and non-road users' interactions and complying with mutually-accepted rules but also compensating for the uncertainties and non-stationarities, thus, formulating their social insights.

A generalized framework of an intelligent vehicle having an eye in and out could be a step up. It should consider the following features, which we regroup in three sub-contexts:

1) ***The vehicle with automation***
2) ***Interaction with the operating environment:*** all the elements constituting the operating environment are linked, see Fig. 3. People from the same culture develop distinct patterns of emotions, norms (informal rules, local perception of the law, etc.), and behaviors to deal with the survival challenges of their common environment (infrastructure, environmental conditions, etc.) figuring out a structure in the unstructured environment. The system should be able to reason about these behaviors, predict the intentions of traffic participants, and compensate for their errors, thus increasing safety and socio-acceptability.
3) ***Interaction with the driver:*** the personalization in the sense"to suit the automated task to the preferences and needs of the driver," we believe that it should consider the driver behavior that is understood as the intentional actions issued from the driver's inner mental thought and unintentional characteristics [71], but while answering the in which situation question. The driving task for an intelligent vehicle still needs the driver to remain active and engaged to take back the control [72], considering that the driver cognitive level is primordial for the system.

To achieve such a cross-cultural intelligent system, we are now facing the challenge of defining the value of society across different scenarios and translating the set of ethical rules into a language that the vehicle can understand independently from any human intervention. We need then to propose a cognitive architecture capable of being socially and culturally aware and in the sense of being able to abstract the situational information on the road, to retrieve what is relevant for its application. The framework should emulate the way expert drivers understand human interactions on the road and comply with mutually-accepted rules learned from countless experiences, we can do so by enabling the intelligent vehicle to memorize, reason, experiential update its knowledge, and extend the generalized knowledge learned to new scenes that were previously unknown and gain in adaptability and dynamic reconfiguration to face the environment changes and different Human/vehicles interactions [73]. We recognize that the challenges are enormous, adding to what was mentioned, the simplicity of most car simulators, especially the lack of realism when addressing the social and cultural aspects.

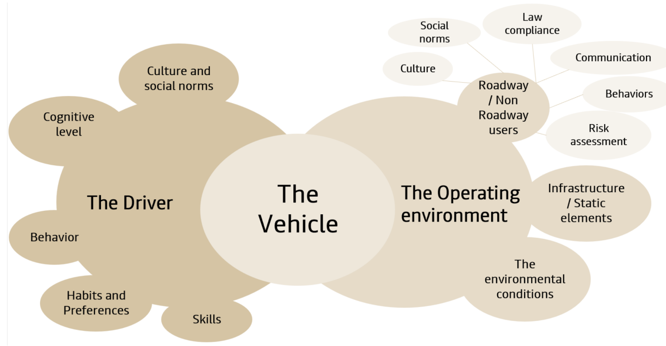

Fig. 3. Driver-vehicle-environmement in the loop.

VI. Conclusion And Future work

In this paper, we highlight the importance of considering seriously one of the most challenging problems facing the intelligent vehicle today, which is the cross-culture adaptability. We have taken a first step towards that by defining the culture with regards to driving and emphasizing the bias in the development of intelligent vehicles to date. We have provided a review of the current state of the art for personalization in advanced driver assistance systems and social autonomous driving. Our concern was the driver models used for personalization. The main objective of ADAS customization is to increase the system usability and, as a result, the driver acceptance. This is particularly crucial in applications safety-related such as Forward Collision Warning, where alarms and their timing should be tailored to the needs and skills of the driver to prevent the system underuse. The state of the art for social autonomous vehicles was then reviewed, including some studies that analyze interactions with other road and non-road users as well as anthropological and legal dilemmas in an urban environment. Finally, we discuss what a cross-culture adaptive intelligent vehicle could be considered. It should possess a model of its environment, allowing is to predict the intentions of road and non-road users, and thus, its safe driving is predetermined based on meeting the expectations of others. The intelligent vehicle should possess this set of knowledge, skills, and competencies to recognize, understand, and adapt to social and cultural differences. The challenges are enormous; defining the value of society across different scenarios and proposing a cognitive-based architecture for the system would be our next step.

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