A Review of Personalization in Driving Behavior: Dataset, Modeling, and Validation

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Abstract—**Personalization in driving behavior research is crucial for developing intelligent vehicles that can safely coexist with human-driven vehicles in mixed-traffic environments. By accounting for the diversity of human driving behaviors, personalized modeling can improve predictive capabilities of intelligent vehicles and foster a more balanced traffic ecosystem. This paper presents a systematic review on personalization in driving behavior, evaluating their potential to enhance road safety, transportation efficiency, and human-centric mobility. It proposes a taxonomy to categorize personalized driving behaviors and surveys relevant datasets, modeling methodologies, and techniques for validating personalized driver models. Focusing on personalized driving behavior, the study emphasizes the need for intelligent vehicles to adapt to the complex and heterogeneous behaviors exhibited by human drivers to enhance predictability, responsiveness, and ultimately create a safe and efficient traffic environment. Lastly, key challenges are identified, along with promising future research directions to advance personalized driving behavior research.**

Keywords: Personalization, driving behavior modeling, data-driven techniques, human-in-the-loop simulation, field experiments

I. Introduction

A. Motivation

The study of driving behavior is a cornerstone in the pursuit of human-centered mobility [1], a concept that prioritizes the needs and experiences of people in the design and implementation of transportation systems. While traditional driving behavior study has focused on collective trends, the true complexity of driving behavior lies in its diversity among individuals, each shaped by unique preferences, skills, and purposes. This diversity is not just a challenge to the understanding of collective behavior but a vital area of study, necessitating a deeper exploration into the unique traits characterizing each person's driving behavior. In the context of emerging intelligent vehicles (IVs) coexisting with human-driven vehicles in mixed-traffic environments, the concept of personalization in driving behavior becomes even more crucial. In this study, personalization refers to the customization of driving systems to recognize and adapt to the unique driving patterns, habits, and preferences of individual drivers. Such understanding is essential for the advancement of IVs and for ensuring their integration into our traffic ecosystems in a manner that is seamless and harmonious.

In this light, personalization in driving behavior emerges as a multifaceted concept that encompasses the distinctive driving patterns (observable behaviors and sequences of actions), habits (regular practices or tendencies, often unconscious), and preferences (personal choices based on likes or dislikes) exhibited by individual drivers throughout the driving process. This concept covers the responses and adaptive strategies they employ in reaction to varying external stimuli, highlighting a driver's personalized interaction with static road elements and other dynamic road users. These specific reactions and interactions are deeply influenced by a constellation of factors including, but not limited to, individual personality traits, driving experiences, and specific situational conditions like weather, traffic, and road types, all of which collectively shape their unique driving behavior.

In recent years, research has revealed the significant implications of personalizing driving behavior across various sectors within transportation and vehicle technology. Studying these behaviors offers extensive benefits, including enhancing user experiences in human-driven vehicles, advancing technologies in autonomous vehicles, and shaping informed transportation policies. For human-driven vehicles, knowing the driver's preference enhances the user experience by providing personalized steering control setting [2] and vehicle personalized cabin climate conditioning [3], [4]. For IVs, i.e., partially or fully automated vehicles, understanding other road users' driving behavior allows IV to predict its surrounding environment [5], [6], and react appropriately to unexpected events or changes. This is where personalization plays a crucial role. By tailoring predictions to individual driving behaviors, IVs can achieve more precise assessments of their environment. Such enhanced accuracy is beneficial for various vehicular communication applications [7], which are crucial for the safe and efficient operation of these vehicles. Notably, in applications that require prediction, like cooperative maneuvering and intent sharing, the improved understanding gained from personalization is invaluable. In cooperative maneuvering, including negotiation scenarios, IVs can anticipate and coordinate their movements more effectively with other road users [8]. Similarly, intent sharing applications [9] benefit as IVs can reliably communicate their future actions, such as turning or braking, to surrounding vehicles. This level of predictive capability, underpinned by personalized behavior

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models, is crucial for fostering safer and more harmonious interactions between automated and human-driven vehicles in mixed traffic environments. As a result, personalized autonomous systems [10], [11] will become more trustworthy and reliable to be accepted and adopted by the public. Besides vehicle technologies, the study of personalized driving patterns can significantly influence the development of informed, equitable rules and regulations in sectors. For example, driving pattern learning for driving risk scoring [12], [13] can be used by insurance companies to tailor pricing, catalyzing a new era of personalized and responsible road usage.

Personalization in driving behavior lies at the intersection of two fields: driving behavior modeling and personalization. The field of driving behavior modeling has witnessed a surge in scholarly investigation, with several comprehensive surveys elucidating various approaches that have been undertaken in this domain [14]–[16]. Meanwhile, reviews on personalized Advanced Driver-Assistance Systems (ADAS) [17], [18] have summarized the approaches to implement personalization on vehicles. However, despite valuable contributions, contemporary surveys exhibits notable shortcomings:

- Overgeneralization in driving behavior modeling. A critical limitation of solely studying driving behavior without personalization is the overreliance on generalized data, which consequently leads to the overlooking of individual driver variability. Additionally, these studies often use static modeling methods that fail to capture the dynamic and evolving nature of individual driving behaviors, limiting their real-world applicability and adaptability.
- Narrow scope in ADAS personalization: Surveys for personalized ADAS emphasizes personalization primarily focuses on vehicle-level adaptations, such as human-machine interface customization and control settings. This narrow focus often misses the broader aspect of personalization, leading to an incomplete understanding and integration of personalized driving behavior into system design.
- Lack of comprehensive modeling framework: Across both fields, there is a notable absence of a comprehensive and structured process for developing models that encapsulate personalized driving behavior. This gap hinders the effective integration of individual driver characteristics into predictive models and practical applications.

B. Contributions

Compared to existing surveys, our key contributions include:

- We performed a comprehensive review of current studies on personalization in driving behavior.
- We proposed a comprehensive taxonomy, mapping modeling strategies across various time scales, behavioral response stages, and granularity for a systematic understanding of personalized driving behavior.
- We elaborated the process of personalizing driving behavior, including data collection, behavior modeling, and model validation.
- We delivered an insightful discussion to identify promising areas for personalized driving behavior research.

C. Study Scope

This review discusses personalization in driving behavior and especially focuses on how driving behaviors are characterized and modeled for each individual driver. To be specific, it explores the theoretical foundations and methodologies of personalized behavior modeling, as well as the integration of individualized data to enhance personalization for algorithms and systems, allowing for the adaptation of general driver models to meet specific personal needs.

This study emphasizes the prevalent data-driven approaches in the field of driving behavior personalization. The rationale behind this is that individual driving behaviors are complex and diverse, influenced by a myriad of factors. Traditional rule-based and model-based approaches often fall short in capturing this complexity. By leveraging a vast amount of data and a number of modern machine-learning techniques, researchers can develop models that are both more accurate and specifically tailored to individual drivers. This data-driven methodology aligns with the trends and findings identified in our systematic review of the literature, reflecting the latest advancements and challenges in the domain.

To carry out a systematic literature search, this study follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) guidelines [19]. The literature search is conducted using two databases: Google Scholar and IEEE Xplore digital library. The step-by-step screening process is shown in Fig. 1. Initially, the title or keywords of the article must include ”personalization”, ”personal”, or ”personalized”. Secondly, the scope is narrowed to literature published within the last decade, specifically from 2013 to 2023. Subsequently, an in-depth search is executed on these filtered results, employing a combination of key terms: ’Driving’, ’Driver’, ’Vehicle’, ’Car’, ’ADAS’, ’Cruise control’, ’Driver profile’, and ’Behavior’. The final step involves a careful exclusion of duplicate articles and those not directly relevant to the central theme of personalized driving behavior, ensuring a focused and relevant collection of literature for our study.

D. Article Organization

The remainder of this paper is organized to correspond with the three main stages of the personalization process: data construction, behavior modeling and algorithm development, and model evaluation. Section II presents a taxonomy of personalized driving behavior, establishing the foundation for the subsequent sections. Section III discusses the construction of a personalized driving behavior dataset, including different categories of available datasets, data acquisition and processing, forming the basis of our data-driven approach. In Section IV, we elaborate approaches to developing a personalized model and system for driving behavior. Section V focuses on the evaluation of the personalized model. Section VI is dedicated to A detailed discussion for research gaps and future directions, synthesizing insights from each stage of the personalization process. Finally, the paper concludes in Section VII.

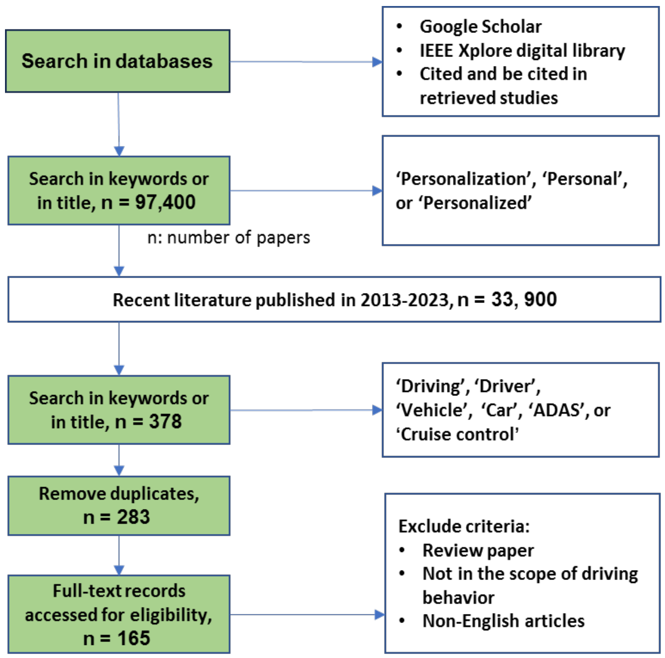

Fig. 1: The PRISMA schema for literature search in this study

II. Taxonomy

Modeling personalized driving behavior is the foundation of the personalization process, and personalized driving behaviors can be organized using an integrated and cascading taxonomy, as shown in Fig. 2. This multi-tiered approach begins with categorizing behaviors into long-, mid-, and short-term from the temporal scale perspective. Within the short-term behavior section, we further divide the behavioral response stages during driving into distinct stages based on the vehicle operation pipeline, i.e., perception, cognition, and actuation. These stages can be further detailed by classifying specific types of driver-vehicle interactions. This layered and interconnected structure effectively captures the full spectrum of personalized driving behaviors, from overarching temporal patterns down to the nuances of moment-to-moment interactions.

A. By Temporal Scale

The investigation of personalized driving behavior is complex, and we approach it by segmenting it into three distinct time scales: long, middle, and short-term. These scales each possess distinctive characteristics and are intricately interlinked with one another, influencing and being influenced in a dynamic manner. Long-term behaviors set a foundational context that shapes mid-term behaviors, which in turn have a direct impact on short-term actions and decisions. This creates a complex, interconnected web of driving behaviors across these temporal scales, necessitating different modeling strategies and focus.

Long-term: On this temporal scale, personalized driving behavior focuses on relatively stable aspects of the driver's profile, such as personality [20], [21], demographic information [22], [23], and frequently visited locations (e.g., workplace and home) that are used in activity-based modeling [24]. These features, collected and profiled over a long duration, establish the foundational layer for performing personalization, providing a consistent reference point from which we can integrate and adapt the more dynamic aspects of the driver's profile. For example, a driver's travel behavioral preference for manual versus automatic transmission, the willingness to engage in risk [25], and the impact of regional geographic and socio-economic characteristics on ride-hailing driver profiling [26]) would fall under this category.

Mid-term: This represents the modeling of personalized driving behavior that, while exhibiting more changes, still maintain relative stability. Compared to long-term behaviors, mid-term behaviors typically span multiple trips or a single extended trip. This scale takes into account a variety of factors that can be influenced by time of day, specific events, or environmental changes. A key component of this category is the analysis of driving styles [2], [27]–[30], embodying a blend of persistent long-term habits and adaptable mid-term responses to dynamic elements like traffic states and roadway geometry. As representative driving patterns, car-following [31]–[33] and lane-change behavior [34]–[36] at this level encompass a driver's general tendencies and preferences, and reveal how the driver interacts with surroundings, providing insights into a driver's consideration of safety, comfort, and efficiency. Also, driver mood state [37], [38] falls into the mid-term category, as a driver's emotional state can fluctuate based on specific experiences or situations, but generally follows certain patterns. Similarly, temporary driver physiological state [39], [40], like drowsiness, has the same influence to driving pattern. Moreover, drivers demonstrate distinct concerns regarding fuel/energy efficiency and exhibit corresponding behavioral adaptations when operating different types of vehicles [41], especially for electric or hybrid vehicles [42]. Situational circumstances should be considered as well, and the behavior is influenced by factors like weather, traffic conditions, vehicle conditions, passenger conditions, and route elevations [43]–[47]. These mid-term elements, when combined, offer valuable insights into how drivers respond to evolving conditions and how these responses shape their overall driving behavior.

Short-term: This temporal scale pertains to immediate behaviors and operations that change rapidly during the driving process. Short-term behaviors are situational behaviors and are directly influenced by mid-term behaviors. Compared to mid-term behaviors, short-term behaviors are usually evaluated at the level of a single trip or specific events. It encompasses the whole behavioral response pipeline, including the driver's perception, cognition, and actuation, as elaborated in subsection II-B. Interactions with the vehicle's control systems and immediate responses to external events are also categorized under short-term behaviors.

B. By Behavioral-Response Stage

When modeling personalized driving behavior, it's critical to consider the entire behavioral response pipeline, which involves the stages of perception, cognition, and actuation. These stimulus-driven stages reflect the sequential process of human interaction with the vehicle and driving environment,

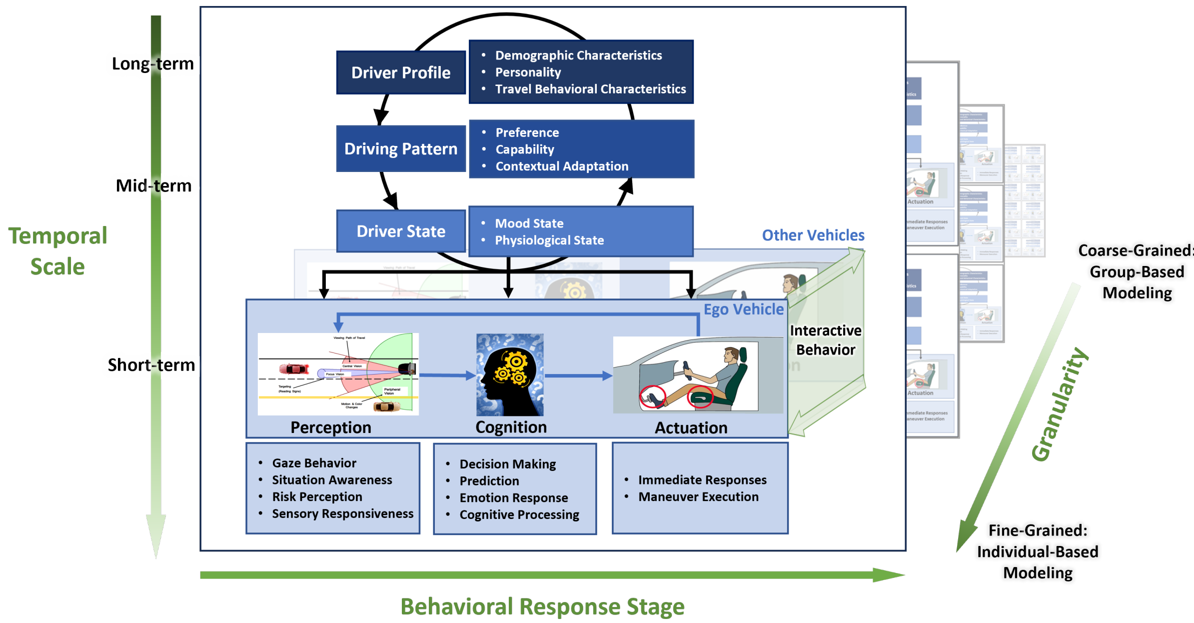

Fig. 2: Taxonomy of personalized driving behavior

and they have specific characteristics unique to individual drivers.

Perception stage: This initial stage is all about how the driver perceives the environment. As illustrated by the Drift Diffusion Model (DDM) [48], initial sensory inputs, or ”stimuli”, are actively processed to accumulate evidence towards a decision boundary. Perception is not merely a passive receipt of information but actively influences the cognition (e.g., decision making) from the outset. This stage sets the premise for all subsequent steps, as the information perceived here will influence the cognitive processing of that information and, ultimately, the physical actuation in response.

Drivers may exhibit different perceptual behaviors to gather information, and not every driver receives the same information or integrates it in the same way while driving. The focus of a driver’s gaze is another significant factor [49], [50]; some drivers may focus mainly on the road ahead, while others frequently check mirrors or allocate their attention to a secondary task [51] (e.g., instrument panels). Other factors include the driver’s awareness of the environment [52], [53], such as attention to traffic signs, other vehicles, and pedestrians, and these often involve distraction or drowsiness detection studies [54]–[57]. The perception stage also includes the study of capability (affected by midterm behavior), such as vision acuity, spatial awareness (distances, speeds, and angles), and sensory responsiveness (visual, auditory, and tactile inputs), to perceive the environment or access external signals.

Cognition stage: At this stage, the mental processing of perceived information takes place. Drivers interpret what they see, anticipate potential outcomes, and make decisions based on their experience, understanding and judgement. Studies focusing on this stage cover a variety of aspects. To name a few, drivers’ risk assessment [58], [59] might greatly influence how they react to potential dangers on the road. Also, decision-making studies [60], [61] evaluate how drivers respond under different circumstances, noting differences between more aggressive or cautious behaviors. On the other hand, intention prediction studies [62]–[67] anticipate a driver’s next actions based on current behaviors, as a typical use case of cognition process modeling. Additionally, studies on cognitive processing, such as cognitive load assessment [68]–[70] contribute further to understanding the cognitive demands on a driver during various situations. Likewise, research into drivers’ emotional responses [38], [71] dives deep into how emotions influence decision-making and overall driving behavior, further enriching our understanding of the cognitive aspect of driving. These aforementioned cognitive factors together shape the comprehensive profile of a driver’s behavior on the road.

The inherently abstract nature of these cognitive processes necessitates indirect methods for their assessment. Recent advancements in physiological measurements have offered promising methodologies to bridge this gap. For instance, Luo et al. [72] studied how personal comfort system affects the cognition performance based on heart rates. Najafi et al. proposed to use Electrodermal Activity (EDA) Skin Potential Response (SPR), their Electrocardiogram (ECG), and their Electroencephalogram (EEG) for driver attention assessment [73]. Govindarajan et.al. [74] adopted headband and camera to measure EGG signals and thermal facial data, which are used for personalized reaction time prediction. By correlating physiological signals with driving behaviors, researchers can infer the underlying cognitive and emotional processes for more personalized and adaptive driving assistance systems that cater to the individual cognitive profiles of drivers.

Actuation stage: The Actuation stage is the dynamic and observable component of the behavioral response in driving, where the cognitive choices formed from perception are translated into physical maneuvers. In this conclusive phase, the driver’s mental activities—encompassing the assessment of environmental conditions and cognitive judgments—are translated into direct interactions with the vehicle’s controls.

As shown in Fig. 2, this phase serves not only as the execution of a driver's behavioral response process but also completes a feedback loop via perception. It involves two primary response types, and they are 1) immediate responses: these are the direct, often reflexive actions taken in response to immediate and unexpected driving situations. They represent the driver's ability to quickly process and act upon the information perceived, illustrating the practical application of cognitive decisions in real time, which includes quick adjustments to the steering, throttle, and brake [75], [76]. 2) Maneuver execution: in contrast to the reactive nature of immediate responses, maneuver execution encompasses the strategic implementation of complex driving maneuvers planned by the driver. This includes performing overtaking [77], as well as the dynamic adaptation required for car-following and lane-changing [78]–[81].

Actuation is more situational compared to the mid-term driving pattern, characterized by higher intensity in reaction and interaction. These situational behaviors are the main prediction target of many literature because they are highly affected by a driver's characteristics of perception, and cognition under various traffic conditions. As such, the Actuation Stage is not only about action but is integral to a cyclical behavioral response process that feeds back via perception, forming an iterative loop that shapes and is shaped by the driver's continuous interaction with the surroundings. This loop is central to enhancing driving safety and the development of personalized driving assistance systems that can adapt to an individual's driving style in real time.

C. By Granularity

Granularity, within the context of personalized driving behavior modeling, refers to the level of detail and individualization applied when analyzing and modeling driving behavior. This concept acknowledges that while drivers may share similar patterns, each individual also possesses unique traits that merit distinct consideration. Therefore, adopting both group-based (coarse-grained) and individual-based (fine-grained) modeling methods is a prudent approach to comprehensively capture the range of driving behaviors.

Individual-based modeling (fine-grained) is the focus of this review. It concentrates on tailoring behavioral predictions and interventions to the specific traits and behaviors of individual drivers. This level of granularity involves detailed data collection and analysis for each driver, enabling highly customized and accurate behavior models.

Group-based modeling (coarse-grained) categorizes drivers into clusters based on shared behavior patterns, such as driver type clustering [64], [82] and classification [21], [83]. This approach helps in the initial understanding and segmentation of driver data, facilitating the identification of broad behavior patterns and commonalities among different driver groups. It serves as an effective strategy for segmenting driving behavior, which can be refined for more detailed analysis.

Transitioning from coarse-grained to fine-grained modeling involves not only increasing the number of driver clusters but also deepening the analysis within each cluster. This refinement enhances the model's ability to differentiate between drivers on a more granular level. As more detailed data are incorporated—such as specific situational reactions, driving conditions, and temporal behaviors—the clusters become increasingly refined. This refined clustering approach allows the model to capture unique driver traits and tendencies more accurately, thus moving the analysis from a broader group-based perspective to an individual-focused one. Techniques such as incremental learning are employed to continuously update the model as new data becomes available, particularly individual-specific data. For instance, Zhao et al. [80] utilized an incremental learning method to retrain their model based on human feedback, developing a personalized adaptive cruise control system that better matches each driver's preference during each trip. Federated learning is another effective technique. Once a group-based model is established, it can be customized for individual drivers by continuing to train locally on each driver's data. Du et al. [84] implemented a clustering-based personalized federated learning framework to model lane change behavior, enabling the learning of individual behaviors based on a general model.

This granularity spectrum, ranging from coarse-grained group-based to fine-grained individual-based modeling, illustrates a flexible approach to personalizing driving behavior analysis, adapting the level of detail to the specific needs of the research or application.

D. Interactive vs. Non-Interactive

Drivers engage in continuous interactions [85] with other road users, and within the scope of this paper, we mainly focus on vehicular interactions. These interactions, pivotal in personalized driving behavior modeling, predominantly reside within the cognition and actuation subsections of our discussion. **Interactive behaviors** cover a driver's dynamic interactions with other vehicles, involving their predictive, decision-making, and vehicle operation capabilities. Examples include adjusting speed to both react to and influence the movements of other vehicles [86], [87]. Conversely, **non-interactive behaviors** refer to reactions with static or predictable elements, such as road conditions, traffic signs, and traffic signals [88]–[91]. Diving deeper, the study of **personalized interaction** patterns seeks to understand the tendencies of individual drivers, focusing on how they distinctly react to and influence other vehicles.

III. Personalized Dataset

The foundation of personalization in driving behavior lies in the construction of a personalized dataset, which is both the initial step and the cornerstone of the personalization process. This dataset's primary goal is to capture the unique driving patterns and characteristics of each individual driver. A robust and effective personalized dataset has three vital characteristics:

a) Individual Identifiability: This aspect emphasizes the need to distinguish and label the unique behavioral traits of each driver, facilitating a truly personalized analysis.

TABLE I: Personalized Dataset Summary

Data Category	Collection Methods	Collection Instruments	Typical Data	Utilization
Vehicle Operational and Contextual Data	NDS, FOT, Simulation (HuiL)	OBD II, IMU, GNSS, On-board Sensors (LiDAR, Radar, Cameras)	Vehicle Speed, Throttle position, Engine RPM, Location, Surrounding Objects Information	• **Dynamics Insight**: Provides comprehensive understanding of vehicle operation behavior and driver interaction with the control systems in various driving scenarios. • **Environmental Contextualization**: Captures essential data to evaluate the interaction of vehicle dynamics with environmental and situational variables.
Driver Physiological and Behavioral Data	NDS, FOT, Simulation (HuiL)	EEG, ECG, In-Cabin Cameras, Wearable Devices	Eye or Body Movements, Heart Rate, Facial Expressions, Skin Conductance, Gestures	• **Behavioral Insight**: Delivers key metrics on driver states, such as attentiveness and emotional states, crucial for assessing mental workload and predicting potential driving distractions. • **Physiological Correlation**: Enhances the modeling of personalized driving behavior by correlating physiological markers with cognitive and emotional driver states.
Demographic and Subjective Evaluation Data	Interviews, Questionnaires	Questionnaires, User Feedback, Driving Reports	Attitudes, Psychological Characteristics, Social-Economic and Demographic Information, Personal Experiences	• **Personalized Profiling**: Aids in creating in-depth driver profiles by gathering subjective data on individual driver characteristics and preferences. • **Behavioral Explanation**: Offers explanations for specific driving behaviors by linking them to socio-economic, demographic and psychological data points.

b) Adequate Volume: To effectively feed and optimize data-intensive algorithms, the dataset must possess a substantial volume of data. A rich dataset allows for a more comprehensive analysis and understanding of varied driving behaviors, enhancing the accuracy and reliability of the resulting models.

c) Appropriate Data Type Variety: It's essential that the dataset includes a diverse range of data types (e.g., driver data, vehicle data, and driving environment data), tailored to capture the various aspects of driving behavior. This variety ensures that the dataset comprehensively addresses the specific nuances and needs of different driving styles.

This section presents the data acquisition and processing, with a special focus on categorizing data for driving behavior personalization, surveying available data sources, and outlining the collection of customized datasets for particular study objectives, as summarized in Table I.

A. Data Categories for Driving Behavior Personalization

The potential data type for driving behavior personalization includes:

a) Vehicle Operational and Contextual Data can be obtained from onboard information systems, like OBD II (On-Board Diagnostics II), GNSS (Global Navigation Satellite System), IMUs (Inertial Measurement Units), and vehicle sensors (e.g., front cameras, LiDAR, Radar, etc.). These systems together provide insights into vehicle speed, throttle position, engine RPM, location, acceleration, braking, cornering forces, and surrounding environment information. This data helps to shed light on a driver's operational behavior and how the driver interacts with others in various traffic conditions, enabling the customization of driving assistance systems to better support the driver's needs [47], [64], [83], [92]–[94].

b) Driver Physiological and Behavioral Data can offer an understanding of attentiveness, emotional state, mental workload, and potential distractions. This data can be collected by in-cabin cameras and wearable devices like Electroencephalography (EEG) and Electrocardiography (ECG). These tools monitor various indicators, such as the driver's eye movements, body movements, facial expressions, gestures, heart rate, skin conductance, and other physiological signals [68], [72]–[74], [95], [96]. By correlating these physiological signals with driving behaviors, researchers can infer the underlying cognitive and emotional processes that dictate the driver's responses. This deeper understanding allows for the development of more effective personalized and adaptive driving assistance systems that can adjust interaction modes, prioritize information delivery, and manage alerts to accommodate the driver's current state.

c) Demographic and Subjective Evaluation Data can provide insights into why certain driving behaviors manifest and what drivers think or feel in certain situations. These data are essential for building a comprehensive driver profile, which includes the driver's attitudes, psychological characteristics, situation awareness levels, and self-identified driving styles. Such information is typically gathered through questionnaires and interviews, allowing researchers to personalize driving models based on the driver's background, personality, and self-identification, which can greatly influence driving behavior and the effectiveness of tailored driving interventions [20], [52], [71], [97], [98].

B. Personalized Real-World Data

Having discussed the various data types integral to model personalized driving behavior, it's crucial to consider the sources of these data. Two principal sources of real-world data, namely the Naturalistic Driving Study (NDS) and Field Operational Test (FOT) data, are indispensable in this context [99]. As depicted in Fig. 3, while FOT data offers some experimental control, NDS operates with considerably less or none, capturing genuine behavioral dynamics in natural driving scenarios [100].

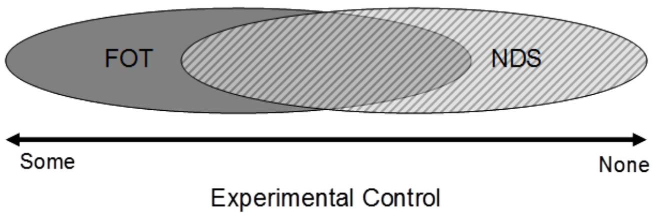

Fig. 3: Real-world data from naturalistic driving studies and field operational tests [100]

The FOTs typically involve a series of structured stages, starting with the design of the test objectives. During the execution phase, pilot testing is conducted to refine the systems and procedures, followed by the main phase of data collection, where specific vehicle technologies and driver behaviors are monitored under predefined conditions. Post data collection, the analysis phase focuses on evaluating the data against the test objectives, ensuring compliance with ethical standards. Similarly, NDS employs an unobtrusive approach where data collection equipment is installed in vehicles without influencing or altering the driver's normal behavior. This method allows for the capture of authentic driving behavior under natural conditions. The data gathered is then analyzed to understand how various driving patterns correlate with different driving contexts.

1) NDS data: There's a growing recognition of the value of NDS datasets. NDS employs advanced in-vehicle technologies to discreetly record drivers' behaviors during routine driving scenarios. It allows researchers to observe and analyze drivers' authentic reactions and decision-making patterns in real time, offering insights into their adaptive strategies across varied traffic and environmental conditions.

To facilitate personalization in NDS datasets, driver identifiability is paramount. Several open-source NDS datasets have been introduced to bolster studies on personalized driving behavior. These datasets not only capture authentic reactions and behaviors across a myriad of driving contexts but also ensure driver identifiability, fostering the evolution of more personalized models. Notable examples include the 100-Car Naturalistic Driving Study dataset [101], [102] and the Candrive study dataset [103]. Both offer comprehensive data by non-intrusively capturing vehicle states and driver maneuvers. These datasets are obtained using the participant's vehicle, ensuring familiarity, and are equipped with cameras and sensors. While sensors track vehicle states and the surrounding environment, cameras record the facial expressions and reactions of the drivers throughout their sessions. This setup not only captures drivers' emotions and responses but also facilitates data segmentation for each individual, paving the way for the creation of customized datasets for every participant. Moreover, datasets like Brain4Cars [104], Drive&Act [105], SHRP2 [106], UAH-DriveSet [107], and MIT AVT [108] further expand the scope of available naturalistic driving datasets.

However, These datasets were primarily constructed for generic or broader applications and might not fully cater to the intricacies required for personalization. While they offer significant advantages, such as capturing a wide range of driving contexts and ensuring driver identifiability, they often fall short in meeting the requirements for data volume and variety of data types necessary for comprehensive personalization. Specifically, these datasets are collected from a restricted set of drivers and certain scenarios, making it challenging to extrapolate findings to a broader population, traffic conditions, and different personalization objectives. Additionally, these open-source naturalistic datasets focus more on collecting short-term actuation driving behavior but ignore the data required for personalizing other stages of driving behavior, compelling researchers to create their customized datasets for different research purposes. Therefore, in the context of NDS, many researchers create customized datasets based on personalized objectives, in addition to the dataset of vehicle operation. For instance, Hu et al. [3] compiled in-vehicle temperature, humidity, car speed, pressure, and window state to build a personalized driver climate control behavior recognition model. Banerjee et al. [49] extracted eye gazing data to model the driver's perception behavior. For modeling the driver workload during each trip, Xie et al. [69] collected ECG, heart (HR) heart rate variability (HRV), breath rate (BR), galvanic skin response (GSR), vehicle speed, and acceleration.

2) FOT data: Conversely, FOT is designed to evaluate specific vehicle functions in their usual operational environments and traffic conditions. Structured to identify the real-world impacts and benefits of these functions, the data from FOT is invaluable for enhancing performance and safety attributes.

Summarizing different types of FOTs, Barnard et al. [109], [110] presented a systematic and scientific procedure for implementing an FOT. They categorized these tests into three main domains: user-centered, vehicle-centered, and context-centered evaluations. Using the FOT dataset created by the Dutch Ministry of Transports [111], Viti et al. [112] investigated how the adaptive cruise control system influences driving behaviors. Instead of using existing FOT data, Lyu et al. [113] carried out a small-scale (44 participants) naturalistic-FOT (N-FOT) to collect naturalistic driving data for establishing a driving style recognition framework. Taking a step further to studying personalized behavior, Liao et al. [66], [114] built an FOT testbed and used the collected data to train and validate a personalized lane-change prediction model.

Many extensive N-FOT projects, along with the datasets they generate, are utilized for algorithm development, as highlighted in [115], [116]. While these datasets also serve as proof of concept, their primary role is in performance evaluation. The level of experimental control directly corresponds to the suitability of the dataset for algorithmic assessment, which will be further discussed in Section V-B2. Yet, the domain of personalized driving behavior through FOT data still offers ample opportunities for further research.

C. Human-in-the-Loop (HuiL) Simulation Dataset

Real-world driving datasets are often collected in ever-changing environments influenced by various temporal factors (e.g., traffic conditions, vehicles nearby, weather, time of the day), leading to inconsistencies. This variability makes it difficult to discern if these temporal factors directly impact a driver's behavior or if they're merely coincidental. A comprehensive understanding truly necessitates longitudinal studies to capture the recurrent pattern over extended periods. Driving simulations, in contrast to real-world datasets, provide a controlled environment for consistent data collection. Human-in-the-loop (HuiL) driving simulations in an immersive simulation platform (e.g., NADS-1 driving simulator [117]) present an opportunity to mimic real-world scenarios while ensuring that the conditions remain standardized, facilitating more precise analysis and comparisons across different drivers and driving behaviors.

Just as in real-world datasets, driver identifiability remains a fundamental prerequisite for personalized simulation datasets. Doubek et al. [118] introduced an open-source Human-in-the-Loop (HuiL) driving simulation dataset to examine automation-to-manual takeover behavior, capturing data from 25 drivers. Similarly, a multi-HuiL simulation was carried out and dataset was published [119], [120], aimed at exploring interactions between two human drivers across diverse traffic scenarios. Simulation datasets tailored to specific research needs are increasingly prevalent, primarily due to their ease of collection compared to real-world datasets. As an illustration, researchers [2], [36], [76], [121] utilized HuiL driving simulations to collect targeted personalized driving behavior data. This approach allows researchers to deliberately replicate specific traffic scenarios or vehicular interactions, facilitating a more precise identification of primary behavioral indicators and reducing the impact of incidental factors. Moreover, HuiL allows for the exploration of rare or extreme scenarios, granting insights into driver reactions in situations seldom or never seen in reality.

However, it's important to acknowledge the limitations of HuiL datasets. One significant drawback is the potential for domain shift, where the simulated environment does not perfectly replicate real-world conditions, leading to discrepancies in driving behavior. Additionally, the psychological and physiological responses elicited in simulations might differ from real-life situations, leading to behavioral discrepancies. These factors highlight the importance of complementing HuiL studies with real-world data for a more comprehensive validation. Further exploration on developing HuiL driving simulations and addressing these challenges is discussed in Section V-B1.

D. Personalized Interaction Dataset

Modeling personalized interaction behavior requires understanding how a driver reacts to and influences other road users. Consequently, it necessitates data from the perspectives of all involved road users, which is crucial in understanding driving behavior in traffic or group dynamics. Currently, however, there is a significant gap due to the absence of interaction data involving multiple vehicles. The aforementioned datasets are predominantly generated from the perspective of the ego vehicle and its driver.

The development of connected vehicles (CVs) has made data sharing more accessible. Specifically, the data collected from CVs can include aspects such as the driver's profile, their current state, and intricate details of their actuation maneuvers. Based on shared data of two connected vehicles, Liao et al. [6] discovered personalized interaction patterns exhibited by aggressive and cautious drivers in a ramp merging area. Their study illustrates the different strategies adopted by these two drivers when they attempt to influence or react to the maneuvers of other vehicles in conflict situations. While this rich information enables collaborative analyses across multiple vehicles, the process still faces challenges. Factors like communication delays [114], communication range, and signal blockage [122] hamper data synchronization and sensor fusion, thereby posing constraints on the generation of datasets utilizing CVs. Therefore, HuiL driving stimulation is still the main tool to collect driving for multiple drivers. Zhao et al. [121], [123] established a multi-driver co-simulation platform to study personalized interaction behaviors. This platform integrates SUMO (a traffic simulator) and Unity (a game engine simulator), equipped with two driving simulation kits with steering wheels and pedals. Supported by AWS service, it can also simulate vehicle-to-cloud communication, in addition to vehicle-to-vehicle communication.

E. Data Analysis and Preprocessing

In the quest for a robust personalized dataset, the primary challenge often lies not just in collecting ample data, but in ensuring its quality, relevance, and diversity to accurately represent the individual driver's behavior across varying scenarios. This stage involves processing and understanding the acquired data. Analysis techniques such as statistical methods, data mining, or machine learning can be used to extract meaningful information about driving habits, decision-making processes, and reactions to different situations. It also involves identifying important features that significantly impact driving behavior and separating the noise or less relevant information. Thus, data analysis and preprocessing are usually conducted in parallel.

Data noise removal can be accomplished using low-pass filters such as the median filter, wavelet filter, and Kalman filter, as well as the moving average filter [14]. Following noise removal, an integral preprocessing step is segmentation. In the context of trajectory data, segmentation is typically based on events, actions, or defined time intervals, and these data can be labeled manually or through automated labeling techniques [124]. For image and video data, distinguishing between the foreground and background is particularly crucial.

Data analysis helps understand the data, and hence researcher can decide on approaches for personalization. Besides the descriptive statistics analysis (e.g., measuring the data distribution), analyzing feature importance is a usual practice, and some popular approaches include correlation analysis [125], permutation feature importance (PFI) Analysis [126], principal component analysis (PCA) [127], etc. In addressing dataset limitations, researchers often engage in data balancing and augmentation [128]–[130]. Besides data processing, transfer learning (TL) [69], [76] is adopted to overcome the data constraint.

IV. Approaches to Personalization in Driving Behavior

Having established the vital role and characteristics of personalized datasets, we now shift our focus towards the methodologies. Leveraging the rich insights derived from personalized data, we aim to create models that precisely mirror individual driving behaviors, a process denoted as model personalization.

In this section, we will explore approaches researchers employ to characterize personalized driving behavior, discuss the potential benefits of personalized behavior modeling in the context of driving, and review the key algorithms that effectively meet these objectives. We will also evaluate the advantages and disadvantages of these algorithms, as summarized in Table II.

A. Personalizing the Driver Model

This approach is based on fitting the parameters of a predefined model for the characteristics of a specific driver. This type of parametric model can be explainable cost functions, neural networks, probabilistic models, and regression models.

Cost function is widely used to illustrate the preference of a driver. Inverse reinforcement learning (IRL), as one type of imitation learning, is an effective method to recover the cost function given the driving demonstration. Some studies [66], [133] used cost functions to describe the personalized lane change preference of a driver and adopted IRL to recover the weights of the cost function based on the driver's historical driving trajectories. Since drivers adjust their car-following gaps at different speeds, Zhao et al. [32] modeled the personalized car-following behavior with a cost function in speed-gap space using IRL. Also, based on IRL, Bao et al. [131] used a personalized cost function to depict how a driver perceives risk in a lane change, as the core of a subjective risk model, which is then integrated into a controller to generate a user's preferred lane change maneuvers. Along the same lines, based on end-to-end imitation learning, Tian et al. [132] personalized the parameters for the cost function of the planning and control module, using limited historical samples.

Personalized neural networks, specifically trained for individual drivers, have proven to outperform general networks. Leveraging the capability of neural networks for reusability, Dang et al. [136] employed a pre-trained long short term memory (LSTM) network to a new dataset as a personalized network to the time-to-lane-change of specific drivers. The study in [49] demonstrated enhanced accuracy in driver distraction detection using a personalized encoder-decoder module. The individualized neural networks developed for each driver, as per [37], showed superior performance in recognizing driver emotions when compared to a general model. Furthermore, Abdelraouf et al. [7] introduced a personalized approach for vehicle trajectory prediction using temporal graph neural networks. Combining Graph Convolution Network (GCN) and LSTM, their model, pre-trained on large datasets and fine-tuned for individual driver, significantly improved prediction accuracy, particularly for longer horizons.

Personalized probabilistic models are also efficient tools, such as Hidden Markov Model (HMM) and Generalized Gaussian Mixture Models (GMM). Lefevre et al. [137] adopted a personalized HMM to build a personalized lane-keeping assistance. The personalized HMM captures how a driver changes his or her decision over left/right lane change and lane keeping, revealing the transition probabilities between each action. Wang et al. [138] demonstrated a personalized HMM-GMM model that can capture better car-following behavior than traditional GMM-based models.

Similarly, personalized regression model. To search for a personalized navigation route, a personalized fuel consumption prediction model was proposed using a multivariate nonlinear regression model (MNR) [47], whose parameters were estimated based on a driver's driving style. Similarly, for developing a personalized route searching method, Chen et al. [82] initialized the weight vector of a graph-based road network as the user preference model, based on a driver's classified driving style, and then adjusted the weights once the driving behavior changed.

Training personalized models for each driver presents significant computational challenges, primarily due to the sheer number of individual models required when dealing with a large driver population. Each model necessitates separate training, validation, and testing processes, escalating the computational workload exponentially with the increase in the number of drivers. Despite their computational intensity, these personalized models have effectively bridged the gap between generic predictions and individualized insights. To mitigate computational demands, researchers [3], [135], [139], suggested categorizing driving styles and tailoring networks accordingly. This strategy balances the need for detailed personalization with computational efficiency, offering a practical solution to the challenges posed by large-scale model training.

The effectiveness of personalized models largely depends on the design and robustness of the underlying base model. A well-constructed base model is pivotal for yielding accurate and detailed predictions tailored to individual drivers. However, customizing these models for each driver is resource-intensive, requiring substantial computational resources for fine-tuning. To address challenges associated with limited personalized driving data, transfer learning (TL) has emerged as a popular tool. This technique involves pre-training a model on a general dataset and subsequently fine-tuning it with individual-specific data. Abdelraouf et al. [7] effectively utilized this approach, demonstrating its efficiency in personalization. Similarly, Li et al. [76] employed an importance-weight-based TL approach to adapt the base model for new drivers using a relatively small amount of personalized data, thus streamlining the adaptation process.

B. Personalizing the Driver Attributes

This approach learns the attributes of the driver to build a driver profile, and these attributes can be modeled independently and jointly, with researchers opting for a specific approach based on their research focus.

The process of modeling independent attributes is succinct and direct, encapsulating distinct characteristics like subjective

TABLE II: Summary of Approaches to Driving Behavior Personalization

Approaches	**Output**	**Algorithms**	**Pros**	**Cons**
Personalizing the Driver Model	Cost Functions	Inverse Reinforcement Learning [32], [66], [131]–[133]	• **Highly Specific**: The models are highly personalized, leading to more accurate predictions. • **Flexibility**: Can be applied to a variety of driving behaviors and scenarios through model personalization (e.g., fine-tuning), offering broad applicability. • **Comprehensiveness**: Bridges the gap between generic and personalized insights.	• **Complexity**: Can become complex, especially when dealing with a wide array of driving behaviors and scenarios. • **Data Dependency**: The quality and quantity of personalized driving data impact performance. • **Base Model Dependency**: The performance highly relied on the design and effectiveness of the base model.
	Neural Networks	Encoder-Decoder Modules [49], [134], CNN+SVM [37], Transfer Learning [135], GCN [7], LSTM [135], [136]		
	Probabilistic Models	HMM [137], HMM+GMM [138], Importance-Weighted Least-Squares Probabilistic Classifier [76]		
	Regression Models	Gradient Boosting Decision Tree [3], NAR [139], MNR [47]		
Personalizing the Driver Attributes	Single Attributes	Subjective Risk Level by RFGA-BLTSM [140] Aggressiveness Index by ESD [28] Acceleration, Time Headway and Pedal by statistical distributions analysis, Kernel Density Estimation [94], [141], [142], Driving Risk Probability by Power-Law Function Estimation [23]	• **Adaptability**: Capable of evolving to capture changes in driver's behaviors and preferences over time. • **Targeted Interventions**: Allows for personalized feedback and improvement suggestions. • **Clarity**: Provides clear, focused insights into particular aspects of driving behavior, incorporating various aspects of behavior and preference.	• **Partial View**: Might not capture the complete picture of driving behavior if too focused on specific attributes. • **Data Sensitivity**: Requires reliable data on various attributes, while precise and accurate data can be challenging to obtain and quantify.
	Joint Attributes	Parameters of Personality by LSTM-based MTLA network [21], Tradeoff between Presences by Optimization [91]		
Labeling Drivers	Driver Clustering	K-Means [2], [82], [83], [83], [143], HCA [71], [139], GMM [76], [144], [145], [36], [68], PRM [64]	• **Simplicity**: Straightforward in interpretation, and the outputs can be easily implemented in downstream modules. • **Efficient**: Efficient in identifying patterns and trends in driving data for generalized interventions.	• **Generality**: Might oversimplify complex driving behaviors, leading to generic insights, not capturing the detailed behaviors of individual drivers. • **Static Labels**: Lack flexibility to adapt to evolving driving behavior.
	Driver Classification	SVM [2], [37], [68], Tree-Based Classifier [64], [94], [140], LSTM [21], PNN [83], Fuzzy Inference [71], Semi-Supervised Learning [146]–[148]		
Learning Personalized Driving Strategy	Driving Policy	Reinforcement Learning [149]–[151]	• **Adaptive**: Continuously learns and adapts to the driver's evolving behavior and external conditions. • **Personalized Feedback**: Can offer real-time, personalized feedback.	• **Computational Load**: Often demands significant computational power and data. • **Slow Convergence**: Learning and adaptation can be time-consuming.
	Replicated Driving Behaviors	Generative Adversarial Imitation Learning [152]		
Personalized Qualitative Assessment	Driver Self-Evaluation	Preference Questionnaire [20], [44], Psychometric Tests [153], Driver Feedback [46], [154], Interviews [155]	• **Driver Engagement**: Directly involves drivers in the assessment, increasing engagement. • **Rich Insights**: Captures detailed insights from the driver's perspective that are not easily captured by quantitative data. • **Explainability**: Provides a clear and understandable overview of the studied driving behaviors.	• **Subjectivity**: The qualitative nature might introduce biases due to individual perceptions. • **Quantification Challenges**: Turning qualitative observations into actionable quantitative data can be difficult.
	Linguistic Insight Quantification	Rule-based Driving Scoring [12], [20], [27], [156] Fuzzy Logic-Based Methods [59], [71], [157]		

risk perception [140], aggression levels, and the probability distribution of accelerations [141]. These isolated attributes are studied to provide insights into specific aspects of driving behavior without considering their interaction or combined impact on overall driving style. He et al. [23] developed a personalized insurance pricing strategy based on the quantification of a driver's risk from trajectories. This method characterized drivers using their risk probabilities, mileage estimation, and their demographic information. Using aggressiveness index measured in energy spectral density (ESD) analysis was proposed by [28] to quantitatively evaluate driving style.

Analyzing the distribution of an independent attribute is straight straightforward approach to characterizing a driver. Kim et al. [142] personalized the acceleration behavior of an electric vehicle according to the driver's characteristics and quantified the performance by comparing each driver's driving data using Kernel Density Estimation. The analysis was conducted on five drivers to show how the kernel density function of acceleration of each driver differs from that of others. Likewise, Baek et al. [94] characterized a driver using a statistical model based on his or her time headway distribution and pedal control patterns. This approach allowed the model to adapt to the driver's changing preferences over time.

While a single, well-defined personal attribute can offer an intuitive depiction of a driver, it may fall short of comprehensively capturing the multifaceted nature of driving behaviors. Addressing this, researchers have gravitated towards multi-attribute models that yield more nuanced and holistic driver profiles. Das et al. [21] designed an LSTM-based Multi-Task Learning with Attention (MTLA) network to capture a driver's personality traits implicitly, where the attention mechanism acts as a feature selector and assigns weights on predefined traits for each individual. Similarly, Butakov et al. [91] examined drivers' willingness to balance time of arrival, fuel economy, comfort, and safety. This multi-attribute approach facilitated the resolution of optimization problems, helping drivers in navigating through signalized intersections.

C. Driver Labeling

This approach aims to identify and categorize drivers based on factors that affect their driving behaviors, e.g., sudden acceleration, hard braking, and other risky maneuvers. Meanwhile, explainable parameters (i.e., weights in the cost function) in Section IV-A and driver attributes in Section IV-B may also be used as the indexes for driver labeling. Driver clustering and classification are two main branches of driver labeling. While primarily designed for coarse-grained, group-based modeling, driver labeling also supports fine-tuning for individual-specific models as detailed in the taxonomy (Section II).

Driver clustering groups drivers based on similarities in their driving behavior without any pre-existing classes or categories. It is an efficient way to discover hidden patterns in the driver dataset through unsupervised methods. Commonly implemented algorithms for driver clustering include K-Means [2], [82], [83], [143], Gaussian Mixture Model (GMM) [76], [144], [145], Fuzzy C-Means [36], [68], and Polynomial Regression Mixture (PRM) [64]. A notable application of this approach is found in the work of Chen et al. [82], who developed a personalized path recommendation system for autonomous vehicles. In their system, driver clustering plays a crucial role in the initial phase by generating a preference weight vector, which lays the groundwork for tailoring path recommendations to individual driver preferences. The unsupervised nature of driver clustering is advantageous, as it minimizes the need for prior assumptions and naturally uncovers behavioral patterns within the data. This method not only facilitates effective feature extraction but also enriches data interpretation. By categorizing drivers into distinct groups, it adds layers of information, such as specific driver labels, which are essential for sophisticated downstream analysis and processing.

On the other hand, driver classification involves categorizing drivers into predefined classes based on their driving behavior for providing personalized services. Popular algorithms for driver classification include support vector machine (SVM) [2], [37], [68], tree-based classifier [64], [94], [140], LSTM time series classifier [21], probabilistic neural network (PNN) [83], and fuzzy inference classifier [71]. Typically employing supervised or semi-supervised learning approaches, driver classification relies on predefined driver types based on expert knowledge, facilitating easier implementation in real-world scenarios. The real-time driver classification system proposed by Bhumika et al. [21] is a notable example showing how the classification contributes to personalzation. Their system classifies drivers' behaviors into categories like 'normal', 'drowsy', or 'aggressive', and accordingly provides tailored recommendations for accepting or rejecting trip requests. Driver classification plays a key role in enhancing road safety and driver well-being by ensuring that driving assistance systems are closely aligned with the unique behaviors and needs of each driver.

Additionally, a key challenge in driver classification is the scarcity of true labels, which is crucial for model accuracy but often unavailable in real-world data due to the subjective interpretation of driving behaviors. For example, speeding could be seen either as an emergency action or reckless driving depending on the context. To combat this, researchers have turned to semi-supervised learning techniques to augment model accuracy using both labeled and unlabeled data. For instance, Guzman and Loui [146] applied a federated semi-supervised approach, initializing models with features extracted from unlabeled data, then refining them with labeled data. Chen et al. [147] employed a semi-supervised twin projection vector machine that enhances classification by using labeled data to establish the model's framework while utilizing unlabeled data to refine and validate its predictions. Similarly, Cheng et al. [148] implemented a teacher-student semi-supervised model for risky driving detection that uses a limited amount of labeled data to guide learning while extensively employing unlabeled data for model generalization. This approach enables the teacher to generate pseudo-labels from the unlabeled data, which are then used by the student for training, thus enhancing dataset size and detection accuracy without extensive manual labeling.

The driver labeling approach is popular due to its simplicity in categorizing and comparing different drivers. It can be implemented in both offline (to predict behaviors prior to driving) and online (to adapt recommendations in real time based on the driver's current state) manners. However, this method may sometimes oversimplify complex driving behaviors by fitting them into a limited number of categories.

D. Other Approaches

1) Personalized Driving Policy: Considering its ability to adapt to a driver's behavior over time, manage complex decision-making tasks, and adjust its actions based on different environmental states, personalized reinforcement learning (RL) is employed to create a highly responsive and personalized driving behavior model. Considering the driving aggressiveness and riskiness of each driver, researchers [149] designed an RL-based personalized driving system (i.e., vehicle controller) to recommend driving actions to the driver. Leveraging smartphone sensor data, Vlachogiannis et al. [150] utilized RL to develop a personalized driving behavior model that adapts to individual driving patterns and environmental states. The RL-based system analyzed critical driving metrics like aggressiveness and speeding to formulate personalized driving policies, which are delivered through a vehicle controller system, and recommended self-improvement strategies to drivers. Likewise, Uvarov and Ponomarev [151] presented an RL-based intervention strategy that trained a personalized policy to maintain the state (e.g., alertness) of a driver. Besides RL, generative adversarial imitation learning (GAIL) is getting famous for learning the complex driving policy of human driver [152], and it can be extended to discover the interaction policy between to multiple agents. Still, the limitations of these policy learning approaches cannot be neglected. It may require a large amount of data and computational resources to train the model effectively. The learning process can be slow and may require numerous iterations to converge.

2) Personalization by Qualitative Assessment: Besides the aforementioned objective behavior modeling approaches, incorporating qualitative assessment has emerged as a valuable strategy due to its explainability of driving behavior and its capacity to capture experience and preference from the driver's perspective. These qualitative assessment can be implemented by preference questionnaire [20], [44], psychometric tests [153], driver feedback [46], [154], and interviews [155].

Still, these intuitive and linguistic qualitative assessments require further quantification before they can be integrated into modeling frameworks. Consequently, rule-based methods have gained attention for effectively incorporating subjective judgments, often dictating the creation of rules or the formulation of scoring metrics [12], [20], [27], [156]. Within rule-based approaches, fuzzy logic-based methods have emerged as significant tools, as illustrated in works like [59] and [157]. These methods are especially adept at quantifying ambiguous linguistic concepts, offering a precise interpretation of subjective expressions, such as discerning the subjective boundaries of 'too close' in car following scenarios. However, these methods have their limitations, as they may introduce biases into the research and present challenges in achieving broad generalization. Typically, they are employed to complement objective methods, offering additional perspectives and enriching the analytical narrative.

V. Model Validation

The model validation process assesses the model's performance based on a set of benchmarks and indexes, measuring the model's accuracy, effectiveness, and generalizability. This step ensures the reliability and robustness of the model before deployment, enabling developers to observe its performance in real-world scenarios, pinpoint unexpected challenges, and fine-tune it as needed.

A. Evaluation Stages

Similar to the validation of other personalized systems [158], the personalized driving behavior model can be evaluated through three sequential phases: Offline Playback, Driving Simulators, and Field Experiments. In the **Offline Playback**, the model takes in recorded data or uses an independent dataset distinct from the one used for model development to gauge its fidelity to real-world driving behavior. **Driving Simulation** are instrumental in assessing the model's performance against other benchmarks. The final phase, **Field Experiments**, necessitates testing the model in genuine traffic conditions. Progressing from a proof-of-concept phase to application-oriented studies, the current research landscape shows limited work that traverses all these stages. The majority focus primarily on the first phase, aiming to demonstrate the efficacy of their personalization algorithms.

Given that driving personalization models often deal with time series data, the resulting data sequences can be termed as 'trajectories.' In personalized driving, these trajectories encapsulate a series of actions or states over time, uniquely characterizing a driver's behavior patterns, ranging from pedal behavior and car-following distances to route selections. Additionally, driver labeling typically serves as an intermediary step in modeling. These models aim to categorize drivers based on their unique driving patterns and then feed into a trajectory-level personalization. Therefore, these clustering and classification models often adopt trajectory similarity measures for evaluation. Some studies with the primary focus on driver labeling compare selected features between driver classes, employing metrics such as confusion metrics for performance evaluation. For instance, Bhumika et al. [21] used Receiver Operating Characteristic (ROC) curves and F-scores to predict various driving behaviors, while Zahraoui et al. [143] applied False Discovery Rate (FDR) and Rate of Change (RoC) to assess the effectiveness of clusters formed from training and test trip data.

For validating the similarity of trajectories, metrics like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), or Root Mean Square Percentage Error (RMSPE) are frequently used [5], [31], [32]. Such metrics are apt for comparing trajectories with clear start and end points. Specifically, MSE offers a simple yet effective computation, RMSE ensures consistent unit measurements, and RMSPE ensures the metric remains insensitive to data scale. However,

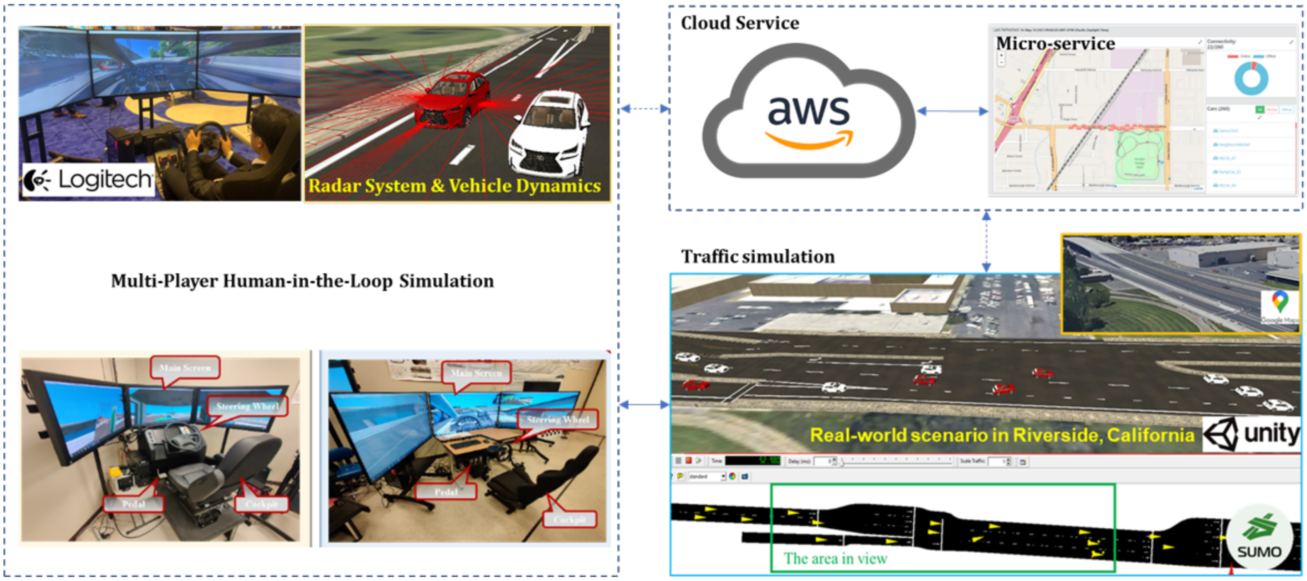

Fig. 4: Multi-driver co-simulation platform (adapted from [121], [123])

complexities arise with varied data lengths, different start and end times, or noise. Hence, alternative validation metrics have been explored. For instance, Wang et al. [31] also employed the Log Predictive-Density error (LPD) which considers the entire prediction distribution, penalizing overconfident predictions more than acknowledged poor predictions. On a similar note, Toohey et al. [159] introduce and compare four trajectory similarity measures: Longest Common Subsequence (LCSS), Fréchet Distance, Dynamic Time Warping (DTW), and Edit Distance. LCSS is efficient against noise and outliers but can be sensitive to minuscule trajectory alterations and might not be suitable for varied trajectory lengths. Fréchet Distance is robust against noise and manages different trajectory lengths but can be computationally intensive for larger datasets. DTW is appropriate for varied trajectory lengths and time distortions but can be noise-sensitive and resource-intensive. Edit Distance is effective for diverse trajectory lengths and time distortions and is scalable for larger datasets but may be noise-sensitive. Expanding on the LCSS metric, Huang et al. [35] proposed a similarity function (SF) to compare two trajectories. Beyond trajectory comparisons, contrasting the distribution of key indices from model-generated data is also prevalent. For instance, Baek et al. [94] validated a personalized speed planning algorithm using Time Headway (THW) as an index and used Kolmogorov-Smirnov (K-S) distance and Kullback-Leibler (K-L) divergence to measure the resemblance between the driving styles of their algorithm and human drivers. Also, Wang et al [138] compared the observed frequency of variables in the collected datasets with the expected frequency of samples from the learned model by the goodness-of-fit (GoF) statistic value.

While offline playback offers clarity, critics argue that the abstract nature of personalization might not be fully reflected by mere time series or distribution matches. Overemphasis could lead to overfitting. Therefore, real-time validations are essential, enabling instantaneous driver feedback on new systems as a representation of personalization performance. Despite the rising use of driving simulators and Human-in-the-loop simulators for the design and validation of autonomous vehicle systems, leveraging real-time driver feedback for validating personalization remains relatively uncharted. An exception is the work of Zhao et al. [32], [80], [81], who, in their validation of a personalized Adaptive Cruise Control (ACC) system, focused on driver interventions. They introduced metrics like the Percentage of Interruption (PoI) which denotes the fraction of time the driver intervenes with the acceleration or brake pedals, and the Number of Interruption-per-Minute (NIM), indicating the frequency of such interventions.

Beyond measures of trajectory similarity and real-time feedback, questionnaires emerge as an instrumental approach to validate personalized driving behavior. They enable a direct capture of drivers' subjective evaluations, adding depth to objective metrics. For example, Panou et al. [10] used multi-phase trials to assess a personalized collision avoidance system (P-CAS) by measuring driver reaction times. After the trials, participants completed questionnaires that focused on their opinions about different warning settings. Similarly, Amado et al. [160] utilized questionnaires but uniquely incorporated an expert observer. This expert compared drivers' self-assessments against an objective evaluation, aiming for a balanced understanding of the evaluated skills and performances.

In the quest to quantify a driver's satisfaction and trust in personalized systems, researchers have looked beyond just indirect metrics. A growing trend is to incorporate physiological sensors to measure a driver's bodily responses during interactions with these systems. For instance, Nacpil et al. [161] elaborated on how biosignals, obtained via tools like smartwatch sensors for electrocardiography (ECG) and headsets for electroencephalography (EEG), can be harnessed. Originally intended for clinical applications, like EEG for diagnosing epilepsy or discerning emotions, these tools are now being repurposed. Furthermore, methodologies such as eye tracking, impedance cardiography (ICG), and photoplethysmography (PPG) are also employed, enriching the range of data available to analyze a driver's interaction with the personalized system.

In contrast to driving simulators, field experiments offer enhanced validation by reflecting real-world driving conditions. However, they encounter issues such as safety concerns, regulatory constraints, and the complexities of system design, which can limit the extent of their validation. Still, some researchers choose on-road experiments for direct validation. For example, Panou et al. [10] used multi-phase trials to assess a personalized collision avoidance system (P-CAS) by measuring driver reaction times. After the trials, participants completed questionnaires that focused on their opinions about different warning settings. Similarly, Amado et al. [160] utilized questionnaires but uniquely incorporated an expert observer. This expert compared drivers' self-assessments against an objective evaluation, aiming for a balanced understanding of the evaluated skills and performances.

B. *Validation Tools*

The aforementioned three phases for model evaluation phases mainly rely on human-in-the-loop (HuiL) driving simulators and field experiment testbeds. Developing these tools becomes essential in validating the model, ensuring that it not only meets the designated benchmarks but is also robust and reliable in real-world applications.

1) Simulation Platform: Evaluation of HuiL driving simulator demands a high standard for vehicle model, user interface, and traffic environment. Much research has been carried out to construct open-platform game engine-based simulators, such as NVIDIA DRIVE Sim [162] based on Omniverse [163], CARLA [164] based on Unreal Engine 4 (UE4) [165] and SVL [166] based on Unity [167]. These simulators are equipped with high-fidelity physical engines, sophisticated UI designs, and adaptable road environments that incorporate various weather and road conditions, facilitating comprehensive autonomous driving simulations. Additionally, they offer extensive customization options for onboard sensors, including radar, LiDAR, camera, and GPS, ensuring a versatile and realistic simulation environment. While game-engine simulators are adept at providing intricate simulations for individual vehicles, they face challenges in terms of the computational load and in effectively replicating complex, dynamic traffic environments. In contrast, tools like PTV VISSIM [168], a commercial microscopic traffic simulation platform, as well as SUMO [169], an open-source alternative, excel in creating realistic traffic environments. However, these microscopic traffic simulators ignore the complex interaction between drivers and may not be good at simulating individual vehicles. Therefore, fusing the game engine-based simulator and traffic simulator [170], [171] becomes the solution to provide a simulation platform for personalized driving behavior evaluation.

A multi-human-in-the-loop (MHuiL) platform, developed by Zhao et al. [121], [123], seamlessly integrates the features of Unity and SUMO, enhanced by the computing power and personalized data storage facilitated by Amazon Web Services (AWS). This platform is designed for driving behavior data collection, algorithm development, and model evaluation. As shown in Fig. 4, the platform is equipped with two sets of driving cockpits, enabling two drivers to simultaneously participate in a single simulation, marking a significant advancement in interactive behavior modeling.

This MHuiL platform stands out in driving behavior model evaluation, primarily due to its high-fidelity driving environment, building on a replication of a real-world on/off-ramp scenario in Riverside, California. Also, for a fair evaluation, its scenario replay feature ensures identical environmental settings for comprehensive analyses. This intricate simulation is made possible and robust by the Edge-Gateway, a pivotal element that bridges the integration and synchronization of data and functionalities between Unity, SUMO, and AWS. It ensures not only seamless interoperability within the platform but also extends compatibility, facilitating the integration of other simulators, software, and real-world end devices for a comprehensive simulation experience.

Besides model evaluation, this tool enables the personalized dataset collection for each driver at a low cost and addresses the long tail problem by replicating rare scenarios. It underscores the platform's adaptability in data collection, enhancing the dataset's diversity. Moreover, the multi-player setup amplifies the focus on interaction behavior, capturing nuanced decisions and reactions from both drivers' perspectives. This rich dataset is further enriched by AWS's real-time support for services like trajectory prediction, driving scoring, and fuel consumption analysis, facilitating deeper, more insightful analyses.

2) Real-World Testbed: While HuiL simulations are invaluable for initial testing and iterations, the complexity of real-world conditions necessitates comprehensive evaluations through real-world test beds. These testbeds evaluate the model's adaptability and performance under practical challenges such as communication delays, signal loss, sensor accuracy, and computational limits, offering a thorough assessment beyond the controlled environments of simulations. However, constructing a large-scale real-world testbed (e.g., Mcity [172]) is both time-intensive and resource-heavy. As stated in [173], a naturalistic-FOT (N-FOT) experiment "cannot be conducted for less than $10,000,000", and hence researchers search for more cost-effective alternatives like scenario-based testbeds and mini-cities [174]–[176], which offer a practical environment for proof-of-concept development and algorithm evaluation.

To study personalized driving behavior (model development and evaluation), a vehicle-edge-cloud digital twin testbed was built by Liao et al. [66]. This real-world testbed involves three passenger vehicles, an edge server, and AWS, as presented in Fig. 5, which was used to collect a personalized dataset and evaluate the performance of the proposed personalized lane change behavior prediction system.

The architecture of this testbed maximizes the computational prowess of the cloud server. It crafts a unique digital twin for each driver, extrapolated from their personalized driving model. This facilitates real-time simulations and analyses within a virtual environment and can connected to the simu-

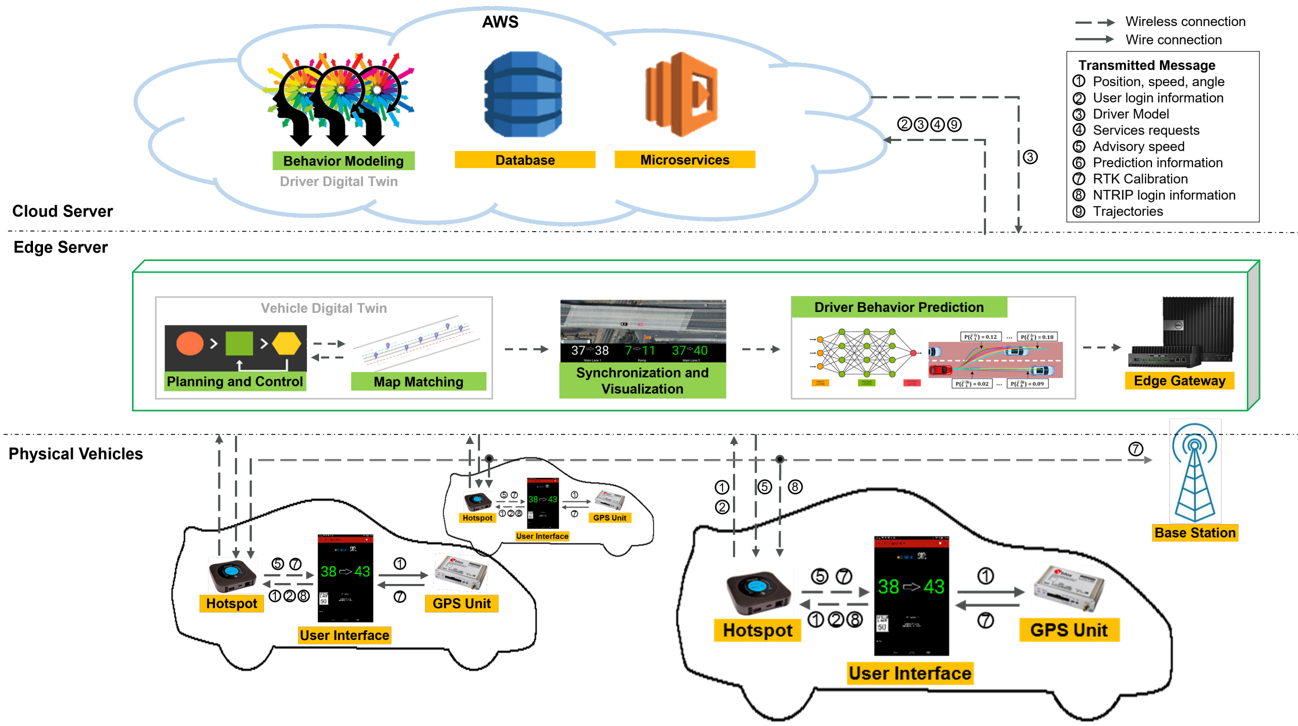

Fig. 5: Vehicle-edge-cloud digital twin platform for personalized dataset collection and algorithm validation [66]

lation platform. With AWS's data storage and computational power, each driver's digital twin is dynamic, evolving, and adapting through the continuous intake of real-world driving data.

The integration of an Edge-Gateway on the edge server mitigates the challenge of communication latency between the cloud and vehicles, ensuring seamless data exchange and real-time service delivery to vehicles. The portability of this testbed, necessitating only a tablet and GPS unit per vehicle, enhances its applicability. It can be effortlessly deployed in any area with signal coverage and is adaptable to various scenarios. Further, the model evaluation is enhanced by the edge server's capability to replicate specific scenarios and direct each vehicle to predetermined locations at targeted speeds. This level of control ensures an environment of consistency, enabling accurate assessment and comparison of model performances under identical conditions.

VI. Gaps and Opportunities

Despite considerable advancements in driving behavior personalization, unexplored areas and unanswered questions persist, offering potential opportunities for research and innovation. This section illuminates these opportunities, pinpointing specific gaps in the existing body of literature and proposing pathways for future exploration to enrich our collective understanding and knowledge.

A. Personalized Dataset and Validation

The first impediment in personalized driving behavior studies is the notable absence of open-source datasets that are tailored to individualized driving patterns. Such datasets are instrumental for benchmarking and cross-validation in the development of more precise and adaptive models.

Next, a personalized driving dataset in mixed traffic is significant. In the foreseeable future, human-driven and intelligent vehicles are anticipated to coexist on the roads, and understanding the dynamics of their interactions becomes paramount. Although datasets like Drive&Act [105] have provided benchmarks for action recognition in automated vehicles, there is a pronounced need for personalized datasets in mixed traffic that capture the intricacies of human driving behaviors in mixed traffic environments. Answers to 1) how human drivers will interact with other intelligent vehicles, and 2) how they will behave in an intelligent vehicle, are worth studying.

Furthermore, the complexity of driving behaviors necessitates a longitudinal approach to data collection. A brief segment of trajectory or short-term data is often insufficient to encapsulate the detailed and recurrent patterns of individual drivers since factors like emotion, weather, and traffic conditions can introduce variability. Long-term data collection emerges as a pivotal element in distilling consistent and recurring driving patterns amidst the noise of occasional and situational variations.

The validation of personalized models poses another challenge. The current paradigm often relies on post-implementation assessment, gauging whether drivers are satisfied with the product outcomes determined by the models. This approach underscores the necessity of incorporating drivers' feedback more integrally in the model evaluation and evolution processes. Another future research could explore the thresholds and triggers for model updates, ensuring the models remain adaptive and reflective of the drivers' evolving behaviors and preferences.

The integration of digital twins in the driving behavior personalization has been identified as a promising avenue, although it is yet to be fully explored and optimized. One of the cardinal advantages of employing digital twins lies in their potential for extensive data collection, which is pivotal for honing the accuracy and adaptability of driving behavior models. The support of the cloud (e.g., AWS and similar cloud service) facilitate the long-term recording and analysis of individual driving data. With the continuous influx of new data, the adaptability of the model over time ensures that the model dynamically reflects the evolving patterns, behaviors, and preferences of individual drivers.

B. Personalized Perception Behavior

One significant gap in the current research is the sparse discussion on personalized perception behavior, even within the broader context of general perception behavior. Perception behavior forms the foundational layer in the driving behavior model, dictating how drivers assimilate information from their surroundings. It is crucial to acknowledge that the information processed by each driver can vary significantly, due to various factors including individual perception behaviors, prior experiences, and situational awareness. A comprehensive understanding of the types of information absorbed by drivers is essential to accurately analyze the subsequent, distinct cognition and actuation behavior.

The deficiency in personalized perception behavior study is manifested in certain shortcomings. For instance, research tends to analyze car-following behavior with a narrow focus, predominantly scrutinizing the driver's reactions to the vehicle directly in front. However, in reality, drivers engage in a much more complex perceptual process, continuously monitoring their surroundings, including utilizing rear mirrors to gauge the actions of the vehicles behind them and potentially adjusting their strategies accordingly, especially when they perceive they are being tailgated. Furthermore, individual drivers exhibit unique habits and preferences when it comes to observing the road environment. For instance, while some carefully check over their shoulder to gauge the traffic behind or in the blind spot, others may only give a glance, relying more on mirrors or other cues. An analysis of head positions [84], [177] could serve as a rich data source, offering insights into how drivers perceive side-lane traffic and enhancing the accuracy of lane change predictions.

Further research in this domain could potentially shed light on how personalized perception behavior intertwines with cognition and actuation phases. Therefore, highlighting the pivotal role of perception behavior and advocating for more extensive research in this area stands as a pressing need in the field, poised to potentially revolutionize our understanding of driving behavior from a more personalized and insightful vantage point.

C. Personalized Interaction Behavior

The study of personalized interaction behavior, while having gained attention, is still an evolving field with marked gaps and untapped opportunities. The complexity of interaction behavior is woven by not only the individual driver's habits, skills, and responses but is also significantly influenced by the dynamic interplay of multiple actors within the traffic system. Each driver's opinion on the interaction is different, and to model their personalized interaction behavior, there is a noted absence of comprehensive research addressing intricate questions: When and under what circumstances does interaction occur? Who initiates and who responds? What are the tangible and intangible impacts of these interactions? Furthermore, the extent to which drivers consciously aim to influence their environment and respond to the perceived intentions of others is uncharted territory. This raises other pivotal questions: Can we quantify the intensity of interactions? Can we map the trajectory of actions and reactions in real-time driving scenarios, offering insights into the fluid, adaptive nature of driving behaviors?

Addressing these gaps requires innovative methodologies and tools capable of capturing and analyzing the multi-modal driver interactions. Still, current interaction research [86] focuses more on general multi-agent interaction and has barely scratched the surface of understanding how a driver's actions are influenced by personalized driving patterns, incite reactions from surrounding drivers, and vice versa. One of the profound fields is the application of causality and circular causality analyses [6], [178] in the study of interaction driving behaviors.

The pursuit of uncovering the secrets of personalized interaction behaviors, their triggers, dynamics, and impacts, is not just an academic endeavor but a critical pathway to making our roads safer, more efficient, and harmonious spaces where technology and humanity intersect seamlessly.

D. The Rise of Large Language Models

The incorporation of Language Learning Models (LLMs) is emerging as a pivotal evolution in the domain of personalized driving behavior modeling. The complex narratives of driving, encompassing diverse scenarios and driver responses, can be intricately mapped and communicated through the advanced linguistic capabilities of LLMs. For example, LINGO-1 developed by Wayve [179] employing LLM-based vision-language-action model (VLAM) for interpreting driving scenarios has demonstrated a promising research direction. A LINGO-1-empowered vehicle can inform the driver that it stopped because of pedestrians crossing the road. The capacity to explain the rationale behind each vehicular movement in comprehensible language not only enriches the driver's situational awareness but also fortifies the trust dynamics between the driver, the vehicle, and the embedded AI systems.

The prospect of leveraging LLMs to model personalized driving behaviors presents a compelling advancement in the field of AI-assisted driving. Envision AI systems, augmented by the advanced capabilities of LLMs, meticulously tailored to resonate with each driver's unique style and reactions. Different from transcends traditional and generalized solutions, this approach introduce a sophisticated AI co-pilot, which is designed to not only interpret and forecast driving scenarios in real-time, but also to do so through a lens that is distinctly tailored to each driver. By elucidating decisions and maneuvers with remarkable clarity, it demonstrates an intricate understanding of individual drivers' preferences and patterns, thereby personalizing the driving experience to an unprecedented degree.

But the potential of LLMs extends even further. They offer a transparent view of the reasoning behind each driving decision. Drivers are not just passive recipients of information but are engaged participants, gaining insights into their behaviors and habits. If the AI's interpretation is not quite right, drivers can offer feedback, creating a dynamic learning environment where both the AI and driver evolve together. This synergy promises not just a customized driving experience but also one that's safer and grounded in mutual understanding and trust. It's a scenario where technology and humanity intersect, each enhancing the other, leading to a new era of intelligent, personalized, and explainable driving.

E. Discussion

As we navigated the methodologies of personalization in driving behavior and analyzed the pros/cons of each type of approach, it is crucial to consider three key points:

Personalization vs. Generalization. While personalization enhances the driving experience, over-personalization might constrain system flexibility and potentially induce over-reliance that could compromise safety and negatively impact overall traffic efficiency. The appropriate level of personalization is driver-specific and calls for continued research and feedback.

Model Robustness. Personalized models need to handle diverse driving scenarios effectively, but overfitting can pose challenges. Robustness needs training on various scenarios, using strategies to avoid overfitting, and regular model validation and updates based on real-world performance.

Ethical and Privacy Concerns. As we collect and process extensive amounts of sensitive personal data, this raises critical questions regarding data security, privacy, consent, and ownership. Balancing the creation of highly personalized driving models with ethical imperatives and legal frameworks is essential. Safeguards need to be established to ensure data privacy and security while enabling the beneficial aspects of personalization (e.g., blockchain technology and federal learning [180]).

Constraints. Even though this review covers many aspects of personalization in driving behavior, there are still some advanced technologies, such as Virtual Reality (VR), Augmented Reality (AR), and other wearable devices, that remain unexplored. Integrating these technologies into data collection—whether in simulation environments, NDS, or FOT—presents an unexplored frontier that could significantly enhance the granularity and accuracy of behavioral data for better personalization.

VII. Conclusions

In this paper, we proposed a comprehensive taxonomy for personalized driving behavior, based on a thorough literature review. This taxonomy is structured along the span of time, driving behavioral response pipeline, granularity, and interaction. We explained the process of driving behavior personalization in detail, focusing specifically on the development of personalized behavior models. We elaborated on common personalization approaches, providing detailed explanations supported by extensive literature. This work serves as a valuable resource for future research and development in the field of personalization in driving behavior.

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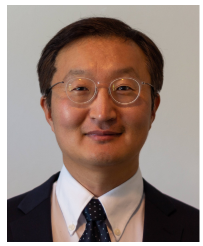

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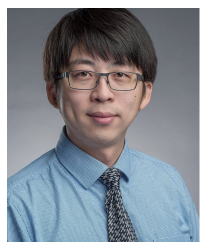

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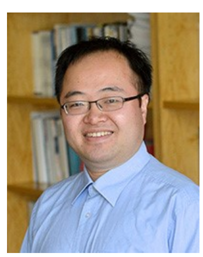

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