

Human Driver Digital Twins: Definitions, Concepts, Use-Cases, and Engineering Challenges

Yannick Naudet

Luxembourg Institute of Science and
Technology
Esch/Alzette, Luxembourg
yannick.naudet@list.lu

Mirko A Ledda

The Goodyear Tire & Rubber
Company
Luxembourg, Luxembourg
mirko_ledda@goodyear.com

Klas Ihme

Institute of Transportation Systems
German Aerospace Center (DLR)
Braunschweig, Germany
klas.ihme@dlr.de

Mark Eilers

Humatects GmbH
Oldenburg, Germany
eilers@humatects.de

Fei Yan

Department of Human Factors
Ulm University
Ulm, Germany
fei.yan@uni-ulm.de

Christine E Boylan

The Goodyear Tire & Rubber
Company
Akron, Ohio, USA
christine_boylan@goodyear.com

Abstract

While the concept of the Human Digital Twin has been proposed within the automotive domain, a structured framework to define and operationalize it is currently lacking. This paper interrogates the concept of Human Driver Digital Twins (HDDTs), systematically distinguishing them from Human Driver Digital Models (HDDMs) and Human Driver Digital Shadows (HDDSs) based on data integration levels and bidirectional feedback loops. We examine a broad spectrum of automotive use cases to assess how the HDDT paradigm can enhance existing applications and where conventional driver modeling methodologies encounter functional limitations. Furthermore, we acknowledge engineering challenges, such as data sovereignty, standardized interaction protocols, and modular internal architectures. Ultimately, this work highlights how an HDDT framework allows systems to transcend the boundaries of static driver modeling, enabling persistent, adaptive, and personalized representations of the human driver.

CCS Concepts

• Applied computing → Transportation; • Computing methodologies → Modeling and simulation.

Keywords

Driver Model, Human Driver Digital Twin

ACM Reference Format:

Yannick Naudet, Mirko A Ledda, Klas Ihme, Mark Eilers, Fei Yan, and Christine E Boylan. 2026. Human Driver Digital Twins: Definitions, Concepts, Use-Cases, and Engineering Challenges. In *18th International Conference on Automotive User Interfaces and Interactive Vehicular Applications (AutomotiveUI Adjunct '26)*, September 20–23, 2026, Gothenburg, Sweden. ACM, New York, NY, USA, 6 pages. <https://doi.org/10.1145/3828158.3838234>



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AutomotiveUI Adjunct '26, Gothenburg, Sweden

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ACM ISBN 979-8-4007-2815-0/26/09

<https://doi.org/10.1145/3828158.3838234>

1 Introduction

The concept of Human Digital Twins has gained increasing attention as a means to represent, analyze, and interact with human behavior in complex socio-technical systems. Within the automotive domain, this paradigm offers new opportunities to formalize and operationalize models of human drivers that support simulation, prediction, and adaptive interaction. Building on the broader notion of Human Digital Twins, we introduce a structured conceptual framework for Human Driver Digital Twins (HDDTs), distinguishing different levels of representation and integration between drivers and computational models. Across these levels, the required degree of model complexity, synchronization fidelity, and operational integration depends crucially on the intended application.

In this work, we argue that HDDTs need not be understood as isomorphic replicas capable of perfectly reproducing human behavior, but instead as continuously updated computational hypotheses about driver state and behavior, constrained by ongoing observations and operational context of a particular use case. From this perspective, the usefulness of HDDTs lies less in replacing empirical data collection than in augmenting and extending it: enabling interpolation between sparse observations, exploring plausible counterfactuals, supporting personalization, and accelerating adaptation of the vehicle to the driver. The practical challenge is therefore how HDDTs can most effectively leverage limited real-world observations to produce simulations and predictions that are sufficiently faithful, transparent, and operationally useful for a given application domain. This framing exhorts us to distinguish more clearly the different levels of HDDT integration and capability, and motivates a more explicit discussion of validation, feedback loops, and operational embedding in automotive applications.

2 Origins of Digital Twin

The original goal of the Digital Twin (DT) was to monitor, predict, and simulate a remote physical system in real time in order to anticipate failures, mitigate risks, and support timely adaptation and control. To achieve this goal, researchers proposed a digital representation that mirrors the physical system as closely as possible through an integrated set of models capturing its structure, properties, states, and dynamics. A DT thus consists of a model of

a physical system that remains continuously synchronized with the real system through ongoing updates from data describing its states and behavior, while also providing feedback and analytical insight to support system operation. This continuous synchronization enables the DT to maintain an accurate representation of the system at any given time and support intervention when necessary. Given this tight coupling, the most common applications of DTs include predictive maintenance and simulation of counterfactuals.

The DT concept originated in Product Lifecycle Management (2003) as a term for a digital equivalent of a physical product that receives data from the product itself [3]. Early implementations combined digital models of products and factories with integrated 3D representations at design time and sensor observations at run-time in order to provide a real-time view of physical reality. Researchers later extended the concept to broader classes of systems, with NASA offering one of the first definitions through its effort to create digital equivalents of space vehicles [18]. Today, DTs appear primarily in manufacturing and smart cities, although the growing number of competing definitions has created confusion about the precise nature of the concept.

An analysis of existing definitions led researchers to define a DT as “a set of adaptive models that emulate the behavior of a physical system in a virtual system getting real time data to update itself along its life cycle” [17]. Researchers further identified the goal of a DT as “replicating the physical system to predict failures and opportunities for changing, to prescribe real time actions for optimizing and/or mitigating unexpected events observing and evaluating the operating profile system”.

A mismatch nevertheless remains between classical digital models and digital twins, although a classification scheme based on levels of data integration between the physical system and its digital counterpart can resolve this discrepancy [7]. Under this scheme, a *digital model*, whatever its kind, may incorporate observational data from a physical object, but a human operator must update the model manually. Once the system receives automated data feeds, the model becomes a *digital shadow*. When changes in the digital object also induce changes in the physical object, the system becomes a *digital twin*.

3 Human Driver Digital Twin: definitions and state of the art

Human Digital Twins (HDTs) are digital twins of human individuals. The concept is a relatively recent development, with applications emerging particularly in healthcare and manufacturing. Based on a systematic literature review, Gaffinet et al. define an HDT as: “a class of Digital Twin whose twinned entity is a human individual. It is a digital representation of the twinned human, emulating their state and dynamics. It automatically receives data, with optional manual entries, and provides automatic feedback directly to the twinned human” [1].

Hu et al. [5] appear to have introduced the term Driver Digital Twin (DDT) in the context of intelligent vehicles. The authors argued that autonomous vehicles require a digital version of the human driver in order to adapt not only to the environment but also to the driver, thereby ensuring harmonious vehicle-driver collaboration [5]. The DDT updates models of driver behavior and cognition with real-time observed data, while also providing feedback to the

driver. The DDT is thus positioned as an evolution of existing Driver Monitoring Systems (DMSs) extending beyond observable driving behavior to include underlying dimensions such as cognition, emotion, attention, intentions, personality, preferences, physiological state, and capabilities. Proponents further identify key functions for a DDT, including attention estimation, distraction and fatigue detection, workload and stress estimation, intention prediction, emotional-state monitoring, trust monitoring, and personalized behavior modeling. More broadly, researchers envision DDTs coupled with vehicle DTs as core elements of future transportation systems supporting prediction, adaptation, and personalized interaction between autonomous and human-driven vehicles [4].

Recent work using the term DDT has primarily focused on data-driven driver models for narrow use-cases, often without a clear feedback loop to the driver. Nevertheless, these studies demonstrate the value of incorporating driver profiles into vehicle personalization and predictive systems. For example, researchers have used DDTs to predict lane-change behavior in human-driven vehicles so that automated vehicles can adapt accordingly [8]. In this case, the DDT is reduced to a driver behavior model based solely on trajectory data, although personalization improves both lane-change intention and trajectory prediction relative to non-personalized approaches. In [9], the same research team later applied DDTs to driver-distraction detection using video-based emotion and action recognition with temporal localization of driver behaviors. Yet, up to the present day, a common definition for human digital twins in the context of driving is lacking and has not been provided by earlier work [4, 5, 8, 9]. We define the Human Driver Digital Twin (HDDT) as *an HDT of a human in its specific role of vehicle driver*, i.e., the twinned system comprises a person driving a vehicle. Building on the DT classification scheme proposed in [7] and adapted to HDTs in [1], we distinguish among those models of an individual driver that are Human Driver Digital Model (HDDM), Digital Shadow (HDDS) and Digital Twin (HDDT), according to the nature of the data feeds between the twin and the human:

- (1) A **Human Driver Digital Model (HDDM)** models an individual human driver without automated data exchange. Driver models used in simulation typically fall into this category, as do artificial agents that incorporate driver models but operate without automated interaction with the driver.
- (2) A **Human Driver Digital Shadow (HDDS)** is a human driver model that updates from automated data streams it receives about the human driver. Data sources here can be sensors embedded in the vehicle (e.g. cameras, eye trackers, or electrocardiogram in steering wheel), sensors installed on the driver (e.g. wearable fitness trackers or physiological sensors), the vehicle’s CAN bus (e.g. steering movements, gas or brake pedal position) and/or driver interaction with the navigation or infotainment system of the car that may reflect goals or preferences. Although the shadow may analyze, simulate, or predict driver behavior, it does not automatically communicate changes in its state back to the driver.
- (3) A **Human Driver Digital Twin (HDDT)** has integrated and automated bidirectional data flows, supplemented by manual driver input. Changes at the twin level can therefore generate feedback to the driver when appropriate. Like other DTs and

HDTs, an HDDT can support prediction and simulation while also emulating driver behavior.

Today, DMSs exploit real-time sensor observations of driver behavior and vehicle control inputs to detect specific behaviors and generate warnings. These systems rely on predefined driver models tailored to the situations they monitor and, in that limited sense, resemble a form of HDDT. However, they are so far limited to monitoring, problem detection, and situation identification, while a more complete HDDT would also support prediction and simulation. Moreover, current DMSs aim primarily to detect problematic situations rather than to maintain a comprehensive and reliable driver model. Following [5], we therefore view HDDTs as a potential next generation of DMS, capable of offering both broader and more personalized services.

4 Driver Models and how they connect to HDDT

Long before the hype on digital twins, the modeling of human driving behavior has been an extensive area of research in the transportation systems domain since 1938 [2]. Different types of models emphasize different aspects of driving behaviors. A first distinction can be made among *performance*, *normative*, and *behavior* driver models. *Performance* driver models target what the most capable drivers can do in a given situation [13][11]. *Normative* models address what a driver *should* do [14]. Lastly, *behavior* driving models concern what drivers actually do in a given situation. Such models are often descriptive because they can predict behavior but cannot explain it [6]. These three model types differ in their potential contribution to an HDDT. A performance model may define the limits of what a driver can still safely perform under certain conditions, e.g. during a transition of control from automation to the human driver. A normative model may provide a reference against which observed driver behavior can be compared, for example in driver training. A behavioral model may describe or predict the veridical actions of a driver, even down to gaze allocation [9]. However, existing applications rarely combine the three HDDT-defining properties: individual-level modeling, continuous real-time updating, and a bidirectional feedback loop to the driver [5].

Michon [10] further described behavior driver models along with a two-way classification, firstly distinguishing between *taxonomic* and *functional*, and secondly between *input-output (behavioral)* and *internal state (psychological)* driver models. Taxonomic models can be seen as inventories of isolated facts, e.g., task models [15]. In contrast, functional models specify components of driver behavior and their dynamic relations, which are executable and can be used in simulations and/or potentially real-world environments. Input-output models can support prediction of behavior, like lane-change decisions [8], but provide limited access to latent psychological mechanisms. Internal-state models, by contrast, attempt to represent psychological constructs such as attention, fatigue, workload, situation awareness, or trust. These models are especially relevant for HDDTs, which require interpretable representations of driver state beyond observable behavior to enable and explain adaptive interaction [5].

For the purpose of relating existing driver models to HDDTs, four additional dimensions are particularly relevant. First, driver models may represent either a *population-level* or *generic driver*, a

specific driver group, or an *individual driver*. Many classical models are formulated at the population level, whereas personalized models attempt to capture the stable or dynamically changing characteristics of a specific individual. Second, driver models differ in whether they are updated offline from previously collected data or continuously fed by real-time observations during driving. Third, models differ in their operational embedding: some are used only in simulation or analysis, whereas others may be integrated into in-vehicle systems such as DMSs. Fourth, models differ in whether their outputs remain internal to the technical system or are translated into feedback communicated directly to the driver.

Existing driver models are necessary but not sufficient for HDDTs. Unlike a conventional model, which may lack individualization, real-time updating, system embedding, and driver feedback [5, 7], an HDDT integrates such models into a dynamically updated, individually coupled architecture that closes the loop back to the driver. A future HDDT could thus be realized by aggregating and coordinating existing model types within such a framework.

5 Driver-centric (personalized) aspirational applications in the automotive sector and how they classify

Table 1 summarizes representative use cases for HDDTs, spanning safety-critical interventions, personalization of vehicle behavior and interfaces, driver training, operational risk monitoring, and broader connected mobility applications. HDDTs enable short-term, individual-centric adaptations, such as dynamically adjusting distraction thresholds, interpreting driver emotional state in context, and optimizing takeover timing in semi-automated driving. These applications rely on real-time sensing and inference to tailor system responses to the current driver state, improving both safety and user experience relative to static, one-size-fits-all baselines. Closely related are adaptive control and HMI personalization use cases, where HDDTs could continuously refine ADAS behavior and cockpit ergonomics based not only on currently observed driver preferences and behavior but also on accumulated knowledge about the individual.

Beyond these immediate adaptations, Table 1 also highlights longer-term and population-informed applications of HDDTs. Over extended time horizons, digital twins support persistent modeling of driver skill, behavior, and physiological baselines, enabling personalized training for both novice and experienced drivers, proactive detection of health or safety risks, and nuanced insurance and fleet analytics that disentangle intent from raw kinematics. At the population level, aggregations of driver models inform traffic simulation and forecasting, enabling more realistic multi-agent interactions and cooperative planning in complex environments. Taken together, these use cases can be understood along an implicit two-dimensional design space: short- versus long-term temporal scope, and individual- versus population-level modeling. HDDTs derive much of their value from operating across these axes, leveraging population-level insights to initialize and inform individual models, while continuously updating those models through short-term observations that accumulate into long-term behavioral understanding.

Table 1: Non-Exhaustive Example Use Cases for Human Drivers Digital Twins

Category	Example Use Cases	Traditional Baseline	Digital Twin Value-Add
Active Safety	Detection of visual distraction	Real-time head/eye tracking mapped to fixed bounding boxes. Triggers alerts using static time-off-road thresholds (e.g., > 2 seconds).	Adapts thresholds dynamically by modeling individual baseline scanning patterns, cognitive load, and unique physical edge cases (e.g., prosthetic eye), minimizing false positives.
	Recognition of driver emotions	Computer vision tracking facial expressions to classify instantaneous emotional states (e.g., anger).	Contextualizes ephemeral facial shifts with long-term personality traits, current trip goals, and environmental context to allow subtle, non-intrusive cabin adjustments.
	Transition of Control (Take-over optimization)	Fixed time-budget countdowns (e.g., 5 seconds) for transition of control requests in L2/L3 automation, regardless of current human state.	Dynamically calculates optimal take-over time windows and HMI modality based on the driver's real-time cognitive readiness, physical posture, and historical secondary-task engagement patterns.
	Health and medical incident monitoring	Reactive detection systems (e.g., hands-off-wheel torque sensors triggering emergency stopping routines after a prolonged delay).	Proactively monitors subtle deviations from the driver's physiological baseline (e.g., anomalies in micro-steering inputs or heart-rate variability), combined with chronic health patterns, to predict and mitigate sudden medical incapacitation before total loss of vehicle control or to enable early safe-stop maneuvers.
Personalized HMI	Personalization of ADAS functionality	Driver manually selects discrete, static performance presets (e.g., Comfort, Sport, Eco modes for Adaptive Cruise Control).	System learns implicit driving comfort thresholds to dynamically micro-adjust ADAS actuation (e.g., customized braking profiles and time headway), actively stabilizing user trust in autonomy.
Driver Training	Personalization of ergonomics (interior & HMI)	Static look-up tables based on raw weight/height sensors or manual memory buttons for seating and HUD/instrument cluster configuration.	Tracks long-term behavioral changes, evolving physical fatigue, and cognitive load to proactively adapt seating contours, steering wheel position, climate, and information displays (HUD/infotainment) for safer information consumption while driving.
	Training of novice drivers	Standardized initial training curricula culminating in a one-time, static examination (theoretical and practical) for licensing; skill tracking and training strategy mostly based on subjective impressions of driving instructor	Maintains a persistent, long-term profile of student skill evolution and cognitive load, tailoring simulator scenarios or feedback loops to specific sub-skill deficiencies (e.g., merge timing, speed control in curves) with graduated licensing milestones.
	Training of experienced drivers	Static user manuals or generic on-screen onboarding tutorials for advanced, automated vehicular features.	Identifies long-term behavioral gaps or skill degradation when interacting with complex vehicle automation, enabling targeted skill maintenance and continuous performance optimization.
Operational Risks	Telemetry for insurance and fleets	Usage-Based Insurance (UBI) metrics calculated purely from raw vehicle kinematics.	Disentangles human intent from raw vehicle kinematics, gaze data, and interaction patterns; determine whether incident resulted from inattention, misjudgment, or unavoidable circumstances.
Connected Mobility	Traffic simulation	Multi-agent microscopic simulations based on parameterized behavioral heuristics (e.g., Intelligent Driver Model) or macroscopic flow models derived from aggregate GPS data.	While high-fidelity behavioral agent models provide richer simulation swarm dynamics, the lack of an active, bi-directional feedback loop to an individual operational vehicle yields low marginal utility for a personalized HDDT architecture.
	Active traffic forecasting	Short-term trajectory and intent prediction of surrounding vehicles using generic kinematic or physics-based models.	Co-simulates the localized intentions and behavioral characteristics of both the host driver and surrounding agents, allowing proactive cooperative planning (e.g., adaptive merging or intersection negotiation).

6 Discussion and perspectives

While the HDDT could be conceived as an integral part of a specific system with a specific purpose, the general concept of a persistent digital entity owned and controlled by the individual driver opens new avenues for what could constitute the future of driving. However, the long-term value of such a construct would depend on two main requirements: (1) *interoperability*, enabling bi-directional interactions with heterogeneous applications that each maintain consistency and trustworthiness, and (2) *extensibility*, where the HDDT itself must be able to integrate new concepts and scientific breakthroughs over time. From this perspective, HDDTs should not necessarily be understood as monolithic, application-specific models, but rather as standardized interfaces to structured representations of human driving behavior and state. Vehicles, simulators, training systems, or mobility services would interact with the HDDT through well-defined protocols, enabling them to query driver-relevant states, contribute new observations, or request predictions under specified conditions. Such protocol-level standardization is a prerequisite for interoperability across manufacturers, automation stacks, and deployment contexts. Equally important is the internal logical architecture of the HDDT. To support long-term evolution, the internal structure should be explicitly modular, allowing distinct sub-models, such as fatigue estimation, trust in automation, or skill evolution to be added, replaced, or refined without disrupting external interfaces. A clear separation between data ingestion, state estimation, behavioral modeling, and learning components would allow the HDDT to accommodate continuous enhancement while preserving backward compatibility.

More fundamentally, the usefulness of an HDDT should not be conflated with the completeness of its representation. An operational HDDT need only model aspects of a human that are relevant to the use case it supports. However, this observation does not eliminate the challenge of data availability, as implementation of HDDTs depends on collecting relevant observations across varying temporal and contextual conditions. While numerous approaches from machine learning [20] may help alleviate data scarcity, evaluating them falls outside the scope of this paper. Determining the data required to achieve trustworthy prediction and adaptation remains an essential topic in HDDT research.

While standardized protocols and modular internal architectures would support portability, longevity, and cumulative scientific improvement through compatible extensions, as mentioned in [5], clear governance is required to define access rights, consent, and control over read/write to the HDDT, ensuring that human agency and trust are preserved. These points have already been emphasized for HDT in general, with the important property of "personal data keeper" [12][16], assuming all data records are GDPR compliant (for Europe, [19]). With this feature, an HDT is expected not only to store personal data about a twinned human, but to control sharing and access by third parties.

It is worth pointing out that the relevance of the HDDT does not necessarily diminish as we progress through SAE levels of vehicular automation; rather, its role shifts from feeding an active co-pilot to shepherding a context-aware passenger. At Levels 1 to 3, the HDDT has great potential in managing handovers and calibrating ADAS interventions to match driver states. However, even at elevated

automation levels (level 4 and 5), where the driver is functionally a passenger, the HDDT remains an interesting concept; for example, adapting trajectory planning to ensure the cabin environment aligns with occupants' current states and preferences.

Despite the clear benefits, the path to a universal HDDT is fraught with engineering challenges. Introducing a centralized, standardized twin significantly increases system complexity, particularly when standards are non-uniformly adopted or lag behind technological breakthroughs. There is a risk of architectural ossification, where early design choices for the HDDT might not accommodate future use-cases. If an HDDT architecture is not designed for a specific use-case ten years hence, the industry faces a choice: maintain legacy support, which bloats the code and increases the attack surface, or break compatibility, which risks orphaning millions of existing driver profiles. Managing this versioning requires a design that prioritizes graceful degradation, where newer systems can still extract basic behavioral primitives from older twin versions while ignoring unsupported, high-fidelity features.

Last, according to our definition, the HDDT can be viewed as a special case of HDT. While focusing strictly on the driving task provides a manageable scope for automotive engineers, it ignores the reality that a driver's behavior is influenced by their life outside the car; for example, stress from work or general health. Tying the HDDT to a more task-agnostic HDT offers the benefit of a seamless life-to-vehicle transition, where the car "knows" you are exhausted before you even touch the door handle. However, this integration likely introduces significant drawbacks in terms of data privacy and scope creep. The challenge here lies in maintaining a task-specific lens for driving while allowing the twin to ingest relevant external context when it serves safety and personalization.

Crucially, the HDT's role as "personal data keeper" may mitigate this very challenge. In this case, the HDDT would itself be the specific interface offered to the vehicle, and the means by which specific access rights to personal data are granted explicitly by the driver.

To conclude, this work provided an explicit and operationalizable definition of the concept of a Human Driver Digital Twin along with the related concepts Human Driver Digital Shadow and Human Driver Digital Model, which was lacking thus far in the literature. In doing so, the scientific community now possesses a shared terminology to discuss HDDTs and to systematically investigate their potential applications across the automotive domain. By addressing the critical engineering challenges associated with real-world deployment, we provide a structured foundation for future research. Ultimately, this framework suggests that the HDDT construct is a necessary evolution for the next generation of human-centric transportation and mobility services, shifting the paradigm from static, reactive modeling toward persistent, bidirectionally coupled representations that anticipate and adapt to human behavior across driving contexts.

Acknowledgments

The work has benefited from Dagstuhl Seminar 26132 "Driver State Modelling: Cognitive and Computational Challenges".

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