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Review

Virtual Reality for Autonomous Vehicles: A Review of Safety, Training, and Human–Machine Interaction

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Abstract

Virtual Reality (VR) enables immersive, repeatable, and risk-free simulation of hazardous driving scenarios. VR is increasingly applied in autonomous vehicle (AV) research for safety evaluation, takeover training, and human–machine interaction (HMI) prototyping. This review synthesizes empirical work to assess the contributions of VR to takeover performance, training efficacy, ecological validity, and user acceptance. Evidence suggests that VR interventions can reduce takeover reaction times compared to conventional instruction, support iterative HMI design, and enhance user familiarity and calibrated trust in AV systems. Persistent limitations include simulator sickness, sample homogeneity, fidelity gaps between VR and on-road performance, and inconsistent reporting of scenario design. We recommend standardized reporting (PRISMA flow plus scenario metadata), longitudinal transfer studies, cross-cultural samples, and hybrid VR–AR validation methods to strengthen transferability and regulatory acceptance.

Keywords: Virtual Reality; Autonomous Vehicles; Human–Machine Interaction; Driver Training; Simulation

1. Introduction

The development of autonomous vehicles (AVs) represents one of the most transformative shifts in modern transportation, promising to enhance road safety, improve traffic efficiency, and expand mobility for populations traditionally underserved by conventional transport systems. Unlike traditional vehicles, AVs rely on advanced driver assistance systems (ADAS), artificial intelligence, and sensor-based decision-making to execute parts or the entirety of the driving task [1].

To standardize terminology and clarify expectations for automation, the Society of Automotive Engineers (SAE) International published the J3016 standard, which defines six levels of driving automation ranging from Level 0 (no driving automation) to Level 5 (full driving automation) [2]. This classification is based on two key dimensions: (1) the extent of the driver's involvement in the dynamic driving task, and (2) the technological performance and equipment of the vehicle. The framework aligns with the definitions of the German Federal Highway Research Institute (BASt) and corresponds, to some extent, with those established by the U.S. National Highway Traffic Safety Administration (NHTSA) [3].

As illustrated in Figure 1, SAE J3016 provides a globally recognized taxonomy that distinguishes between driver support features and fully automated driving.

At present, most commercially available vehicles operate at Levels 2–3, where drivers may engage in secondary tasks during automated driving but are still required to remain alert and respond promptly to a takeover request (TOR)

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when the automated driving system reaches its operational limits. Research indicates that inappropriate or delayed responses to TORs can compromise road safety and undermine public trust in AV technologies [4]. Traditional driver training and licensing methods are poorly equipped to prepare users for these novel demands. In particular, real-world training cannot safely reproduce high-risk scenarios such as sudden system failures, sensor malfunctions, or unpredictable road hazards.

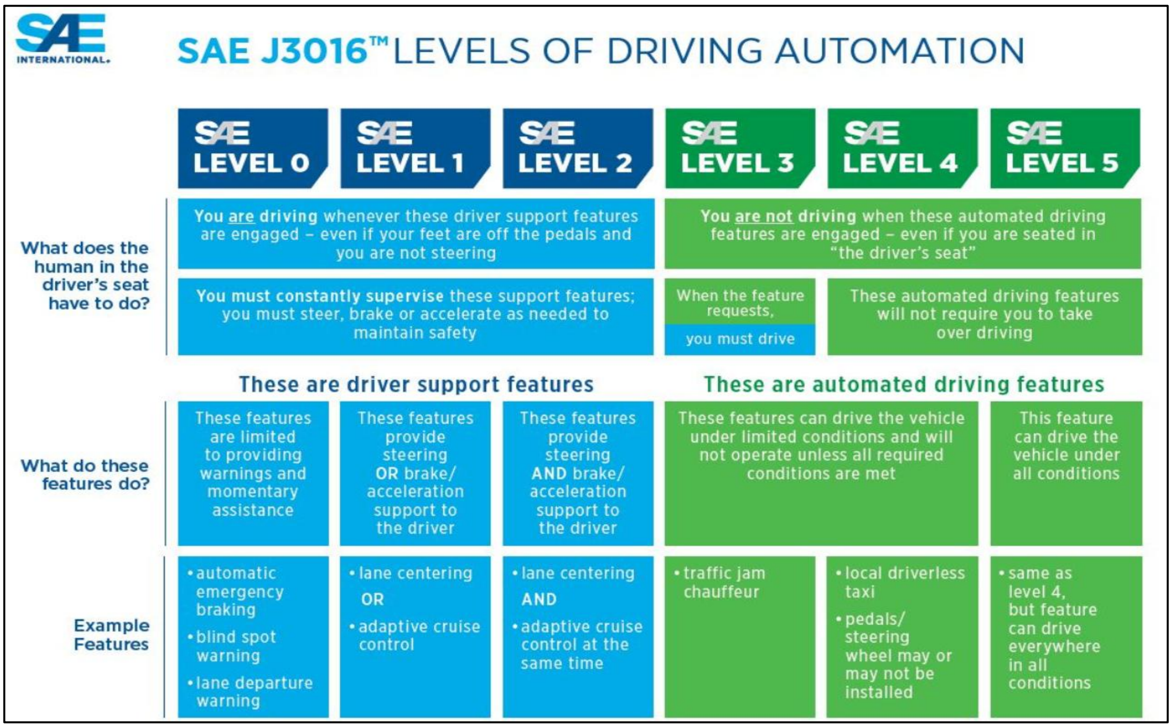

Figure 1. Levels of driving automation according to SAE J3016 [2].

VR offers a compelling alternative by enabling immersive, repeatable, and risk-free simulations of complex driving situations. VR environments allow drivers to practice takeover maneuvers, familiarize themselves with AV interfaces, and develop appropriate trust in automation without endangering themselves or others [5,6].

This paper reviews recent empirical studies on the application of VR in AV contexts, with a particular focus on driver training, takeover performance, and user acceptance. By synthesizing existing evidence, the review highlights both the potential and the limitations of VR as a supporting technology for AV deployment, while outlining directions for future research.

2. Methodology

This review followed a structured search and thematic synthesis approach. We searched Scopus, Web of Science, IEEE Xplore, and ScienceDirect for publications published between 2016 and 2025 using search strings such as "virtual reality, autonomous vehicles, and VR driver training." The initial search identified approximately 70 candidate studies. After screening titles and abstracts against predefined inclusion criteria (empirical focus on VR applications in AV safety, driver training, or human–machine interaction) and subsequent full-text review, 35 references were retained for synthesis. Extracted data included study objectives, experimental design, VR hardware/software, participant demographics, scenario descriptions, outcome measures, and principal findings. The synthesis is organized thematically into VR tools and infrastructure, safety validation and algorithm testing, takeover training and human factors, and limitations. A PRISMA-style flow diagram and an appendix table summarizing the 34 included studies (authors, year, n, VR setup, outcomes) are recommended for transparency and reproducibility.

3. VR Simulation Infrastructure (Hardware and Software)

3.1. Hardware platforms: HMDs, CAVEs, motion systems, sensors

The integration of VR into transportation engineering has become a critical tool for studying and developing AVs. VR simulators allow researchers to create controlled, safe, and cost-effective environments to test AV prototypes, evaluate human-AV interaction, and train AI systems without the risks associated with real-world testing [7,8]. These simulations, which can mimic complex scenarios like bad weather, traffic congestion, and pedestrian behavior, are essential for addressing the significant challenges of achieving full Level 5 autonomy [9]. The hardware and software used in these setups range from consumer-grade devices to highly specialized, custom-built systems.

VR Hardware

The hardware components of a VR-based AV simulation system are designed to immerse the user and capture their responses to the virtual environment.

- Head-Mounted Displays (HMDs): These are the most common and accessible pieces of VR hardware. HMDs such as the HTC Vive, Valve Index, and Meta Quest provide high-fidelity visual experiences, wide fields of view, and motion tracking that increase immersion. Researchers frequently prefer tethered, research-grade HMDs over mobile, phone-based solutions because of their superior tracking precision, lower latency, and support for room-scale experiences, attributes that materially affect experimental control and the quality of behavioral and sensor data collected in AV studies [10][10]. Figure 2 illustrates commonly used HMD models and typical headset configurations; differences in tracking fidelity, field-of-view, and tethering are important considerations when selecting an HMD for experimental protocols.

Figure 2. Popular models of Head Mounted Displays for VR.

- VR CAVE Systems: For multi-user or collaborative studies requiring external visual context, CAVE (Cave Automatic Virtual Environment) systems provide an alternative to single-user HMDs. A CAVE projects imagery onto multiple surfaces (walls, floor, ceiling) to create an enveloping virtual environment that multiple participants can enter and observe simultaneously. CAVE installations are especially useful for studying interactions that involve both vehicle occupants and external road users, and for prototyping external human–machine interfaces (eHMI) in socially shared spaces. A representative CAVE installation is shown in Figure 3; the figure emphasizes the multi-surface projection architecture and the potential for synchronous multi-participant observation and interaction.

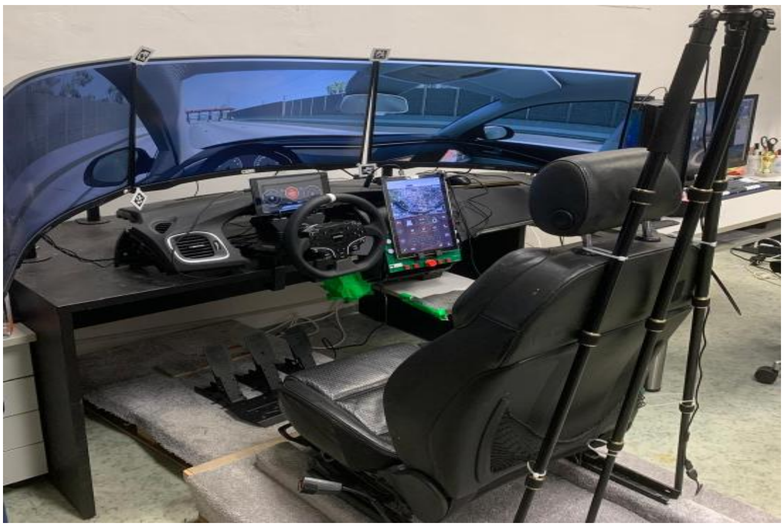

Figure 3. VR CAVE Systems

- Motion Platforms and Haptic Feedback: To increase the realism and ecological validity of the simulation, researchers often integrate motion platforms and haptic devices. Motion platforms reproduce kinesthetic cues associated with acceleration, braking, and turning, while haptic devices (for example, vibrating seats or force-feedback steering wheels) convey tactile road information and in-vehicle alerts. These forms of sensory augmentation help reduce simulator sickness and strengthen the sense of presence. Examples of instrumented driving hardware used to assess control-input fidelity, such as racing-simulator chassis and pedal assemblies, are provided in Figure 4.

Figure 4: Racing-simulator chassis and pedal assembly for control-input fidelity assessments.

- Physiological Data Capture: To get a deeper understanding of a user's response to the simulation, researchers may use additional sensors to capture physiological data. Devices for measuring heart rate, skin conductance, and electroencephalogram (EEG) data can infer a user's mental state, such as stress, anxiety, or arousal, providing valuable quantitative data for human-factors studies.

3.2. Software stacks: Open-source, engines, and proprietary tools

The software is the backbone of the simulation, providing the virtual world and the logic for the AV and its environment.

- Open-Source Simulators: Open-source platforms have become indispensable for academic research due to their flexibility and accessibility. CARLA Simulator, developed expressly for autonomous driving research, is among the most widely adopted. CARLA provides a robust API that allows researchers to control dynamic entities such as traffic flow, pedestrian behavior, weather, and sensor inputs. Its customizable sensor suites (e.g., LiDAR, radar, monocular and stereo cameras) and built-in traffic manager for non-player characters make it highly versatile for both benchmarking and reinforcement learning. Another example is VSim-AV, which leverages the Unity engine to provide a modifiable platform for scenario design and AV performance evaluation [11]. The open-source model promotes transparency, community contributions, and rapid prototyping, albeit with potential limitations in fidelity compared to commercial solutions.
- Game Engines: Commercial game engines such as Unity and Unreal Engine are increasingly integrated into AV research workflows because of their photorealistic rendering, physics engines, and modular scene-building capabilities. These platforms enable the creation of complex urban and rural driving environments with high graphical fidelity. Their extensibility allows integration of custom physics models and AI agents, making them suitable for both closed-loop driver-in-the-loop experiments and large-scale dataset generation for machine learning [11]. Compared to open-source options, game engines offer enhanced realism and professional toolchains, though licensing and performance optimization can present barriers.
- Customs and Proprietary Software. In parallel, several research and industrial teams rely on proprietary software coupled with dedicated hardware to build domain-specific simulators. These systems are designed for specialized applications, such as testing human–vehicle interactions (HVI), evaluating external human–machine interfaces (eHMI), or validating advanced driver-assistance systems. Proprietary platforms typically provide high-fidelity

vehicle dynamics, validated physical models, and seamless integration with hardware-in-the-loop (HIL) architectures, though at considerably higher cost. Such configurations are particularly suited for late-stage industrial validation and certification processes.

- Cost and Fidelity Comparisons. To provide a comparative overview of commonly used VR simulation software and associated hardware, Table 1 presents representative tools with indicative cost ranges and fidelity levels. This summary highlights the scalability of open-source simulators, the realism afforded by professional game engines, and the comprehensive fidelity achieved through custom industrial platforms.

Table 1. VR Simulation Tools, Costs, and Fidelity Levels

Tool/Equipment	Approx. Cost Range (USD)	Fidelity Level
CARLA (Open-source software)	Free	Software-based, scenario generation, low-cost, scalable
Simcenter PreScan	$20,000 - $50,000	High fidelity, physics-based, industry standard
VI-grade VTD	$50,000+	High fidelity, full-stack vehicle dynamics + VR
Consumer VR HMD (HTC Vive/Meta Quest)	$400 - $1,500	Medium fidelity, visual immersion
Research-grade driving cabin + motion system	$100,000 - $500,000+	High fidelity, kinesthetic realism
dSPACE HIL + SCALEXIO	$50,000 - $200,000+	High fidelity, hardware-in-the-loop integration
Tobii Pro Eye Tracker	$5,000 - $20,000	High fidelity gaze/attention measurement

4. Applications for AV Development and Safety Validation

4.1 Safety validation, scenario generation, and edge-case testing

The automotive industry has traditionally relied on physical prototypes and extensive road testing for vehicle design and validation. However, the integration of VR has introduced a transformative paradigm for accelerating development and improving safety validation [12]. VR enables the creation of detailed, interactive virtual representations of vehicles and manufacturing environments, allowing for real-time simulation, iterative testing, and optimization in a risk-free digital space [12–14].

One of the most significant advantages of VR platforms is their ability to replicate complex and hazardous driving conditions that are difficult or impossible to reproduce in real-world testing. For example, VR can simulate edge-case scenarios such as sudden pedestrian crossings, adverse weather conditions, and sensor malfunctions, thereby improving the robustness of AV systems [15]. This approach enables a more comprehensive assessment of vehicle performance across diverse contexts, ultimately contributing to the development of safer and more reliable self-driving systems [16].

Moreover, VR accelerates the development cycle by allowing rapid iteration and testing of design modifications, reducing the time and costs associated with physical prototyping [14]. Applications extend beyond design, encompassing the validation of sensor performance, algorithm efficiency, and human–machine interface (HMI) elements, ensuring that autonomous systems function effectively before deployment [17]. A schematic overview of these application domains is provided in Figure 5, which illustrates the role of VR in safety validation, scenario generation, and system-level testing for autonomous vehicles.

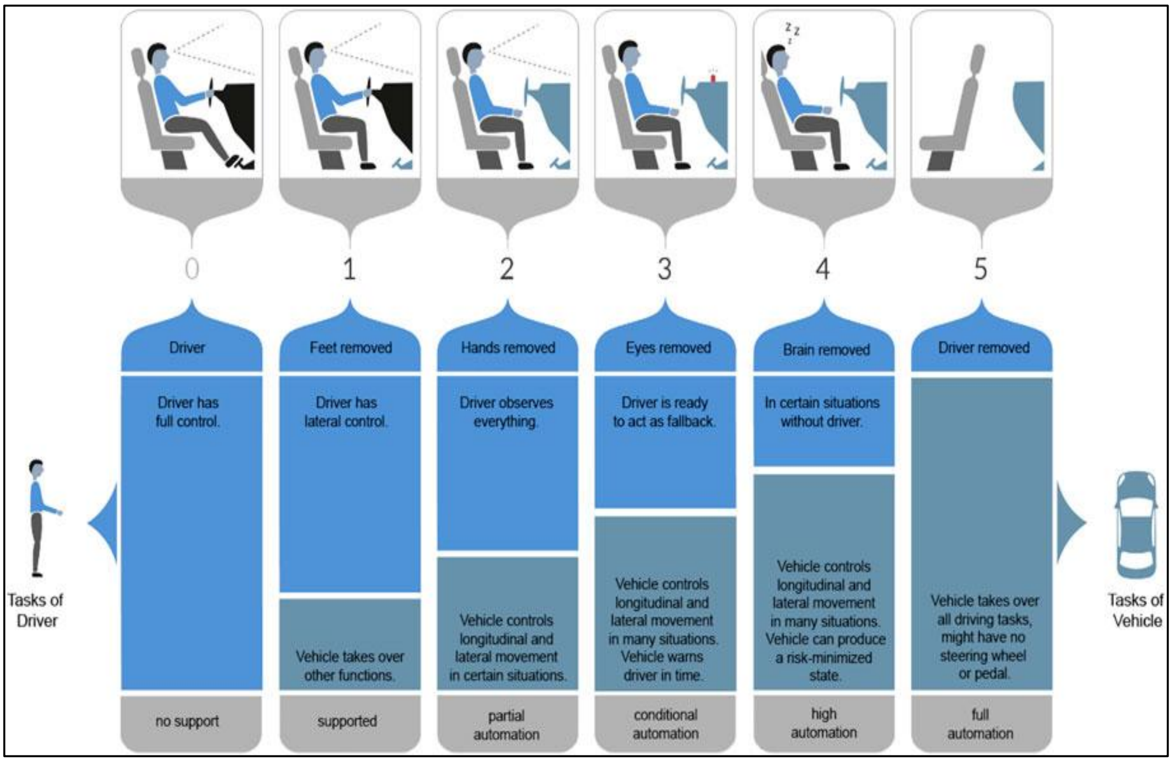

Figure 5. Diagram of VR Applications in Automotive Development (adapted from [18])

4.2 Algorithmic testing, sensor anomaly injection, and performance benchmarking

Safety validation remains one of the most pressing challenges for AV deployment. VR simulations provide a risk-free environment for evaluating key safety dimensions such as sensor fusion, AI-based navigation, and decision-making under uncertainty [19]. These virtual environments allow researchers to examine system responses to critical hazard blocked road markings, erratic driver behavior, or system failures—without exposing participants to real danger [20].

Furthermore, VR facilitates standardized testing protocols by offering repeatable and reproducible simulations of high-risk conditions. This strengthens safety benchmarks across the AV industry and builds public trust in automation [21]. By exposing vehicles to photorealistic representations of varied lighting, weather, and traffic densities, VR testing supports comprehensive validation of perception systems, which are crucial for ensuring reliable sensor performance.

The literature highlights how VR contributes directly to addressing core safety challenges: immersive training improves takeover request (TOR) response times [4]; rare and dangerous hazards such as sudden pedestrian incursions can be simulated for robust system evaluation [15]; and sensor malfunction scenarios can be replicated to train emergency maneuvers [22]. Equally important, VR familiarization tours help calibrate trust in automation, preventing both over-reliance and underuse [23], while HMI prototypes can be iteratively tested to reduce user confusion [5,17].

Table 2. Safety challenges in AVs and VR contributions

Safety Challenge in AVs	VR Contribution	Key References
Takeover Request (TOR) delays	Immersive TOR training scenarios improve driver readiness and response time	Sportillo et al. (2018). [4]
Unpredictable road hazards (e.g., pedestrians, cyclists, sudden stops)	VR replicates rare or dangerous edge-case scenarios in safe environments	Candela et al. (2021); Chen et al. (2025). [15,19]
Sensor or system malfunctions	VR allows simulation of sensor failures, enabling drivers to practice emergency maneuvers	Mirzarazi et al. (2024). [22]
Overtrust or mistrust in automation	VR familiarization tours calibrate driver trust and improve understanding of system limits	Ebnali et al. (2021). [23]
Human–Machine Interface (HMI) confusion	VR enables iterative testing of dashboard layouts and alerts before real-world trials	Zou et al. (2021); Riedmaier et al. (2020). [5,17]

5. Human Factors

5.1 Takeover requests and training efficacy

A core human-factors challenge for conditionally automated vehicles is ensuring timely and appropriate takeover responses. VR permits repeated exposure to TOR scenarios, unexpected system limits, sensor failures, or complex traffic contexts, allowing subjects to practice and refine response strategies. Empirical studies report that VR-based training reduces takeover reaction times and improves procedural accuracy compared to conventional instruction alone. [4] VR training can therefore be an effective tool to increase immediate takeover preparedness.

5.2 HMI prototyping and calibration of trust

VR's rapid-prototyping capability supports iterative testing of in-vehicle HMIs (dashboard alerts, eHMI for external intent signalling) and can reveal design features that reduce user confusion or ambiguity. [5], [17] Familiarization tours in VR help calibrate expectations, mitigating both overtrust and underuse of automation by allowing users to experience system limits in a controlled environment. [23] However, long-term transfer of training gains from VR to on-road behavior remains under-investigated and is a priority for future longitudinal studies.

5.3 Public education and acceptance

Beyond driver training, VR can be deployed for public demonstrations to increase awareness and acceptance of AV capabilities and limitations. Immersive experiences can align user expectations with actual system behaviors and thereby influence adoption trajectories. [23]

6. Perception, Decision-making, and Explainability

VR environments provide a robust platform for refining the perception and decision-making capabilities of autonomous vehicles by enabling the generation of highly realistic and customizable sensor inputs [24]. This allows for the systematic injection of various sensor anomalies, occlusions, and adversarial conditions to evaluate the robustness of perception algorithms without risking real-world incidents [25] Furthermore, VR facilitates the development of sophisticated decision-making models by simulating rare and high-risk scenarios, such as sudden obstacle appearances or complex multi-agent interactions, which are crucial for training robust AI systems [26]. This rigorous simulation helps refine the vehicle's ability to interpret complex, dynamic environments through diverse data sources, including video streams, sensor measurements, and contextual textual information, while ensuring transparency in AI-driven decisions [27]. The capacity to meticulously analyze and refine these intricate decision pathways within a simulated environment is instrumental for developing explainable artificial intelligence for AVs, a critical factor for regulatory compliance and public acceptance [28]. Moreover, VR enables the testing of human-machine interaction elements, allowing developers to optimize how the AV communicates its intentions and decisions to occupants and external road users, thereby improving overall system safety and user trust.

7. VR in Transport Research

The use of VR in transport research is not new; early applications date back to aviation simulators and traffic psychology studies. In recent decades, however, advancements in VR hardware (e.g., head-mounted displays, haptic steering wheels) and software (e.g., Unity, Unreal Engine) have significantly increased simulation fidelity and realism [29,30].

In automotive contexts, VR enables risk-free exposure to dangerous conditions, precise control over experimental variables, and repeatability of scenarios that are infeasible in on-road trials [31]. Importantly, VR allows for large-scale stress-testing of AV algorithms under diverse traffic and environmental conditions, which would be prohibitively expensive using traditional physical testing [32]. By generating statistically significant datasets of rare and challenging scenarios, VR enhances the reliability of safety assessments and provides regulators with stronger evidence of AV readiness.

8. Limitations, Methodological Gaps, and Ethical Considerations

8.1 Simulator sickness and sensory fidelity

Simulator sickness from visual–vestibular mismatch reduces usable session lengths and excludes a subset of participants. [5] Sensory fidelity, particularly vestibular and tactile realism, remains a principal limit on ecological validity for certain behaviors. [33] Where kinesthetic feedback matters (e.g., fine control during steering recovery), VR-only setups can under-represent real-world dynamics.

8.2 Sample heterogeneity and generalizability

Many primary studies rely on small, convenience samples (often students), which restricts generalizability across demographic and cross-cultural populations [34]. The field needs larger, more representative samples and multi-site studies to validate findings robustly.

8.3 Incomplete reporting and reproducibility

A recurrent issue is inconsistent reporting: scenario parameters, hardware/software versions, sensor models, and validation metrics are often absent or insufficiently detailed. This inhibits reproducibility and comparative synthesis. The manuscript recommends standardized reporting templates (scenario metadata + outcome definitions) and the inclusion of a PRISMA-style flow and appendix table to improve transparency.

8.4 Ethical and regulatory considerations

Simulating hazardous events can raise ethical questions if users experience high stress. Institutional review and informed consent processes should explicitly outline simulated stressors and exit protocols. Regulatory uptake of VR-derived evidence requires standardized validation procedures and transparent linkage between simulated outcomes and field performance [34].

9. Recommendations and Future Directions

1. Standardize reporting: Adopt a minimum reporting dataset (PRISMA flow + scenario metadata, hardware/software versions, sensor models, subject demographics) to improve comparability and reproducibility.
2. Longitudinal transfer studies: Assess retention and real-world transfer of VR-trained takeover skills through longitudinal designs and field validation.
3. Hybrid validation methods: Combine VR with AR, motion platforms, or controlled-track validation to bridge sensorial gaps and enhance external validity.
4. Cross-cultural and representative sampling: Prioritize diverse participant pools to examine cultural and demographic moderators of trust and HMI interpretation.
5. Integration with explainable AI: Use VR to test interfaces that communicate AV decisions to humans and to evaluate the effect on trust calibration.

10. Conclusions

VR is a promising platform for accelerating AV safety validation, HMI prototyping, and takeover training in controlled, repeatable settings. Empirical evidence supports VR's role in improving immediate takeover performance and facilitating rapid HMI iteration; however, the field must address ecological validity, simulator sickness, small/homogeneous samples, and inconsistent reporting. Standardized methods, hybrid validation designs, and longitudinal transfer studies are the necessary next steps to make VR-derived evidence actionable for regulators and industry.

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