



Review

Towards Transportation Metaverse: A Conceptual Perspective on Future Road, Railway, Maritime, and Aviation Systems

Masoud Khanmohamadi and Marco Guerrieri *

Department of Civil, Environmental and Mechanical Engineering (DICAM), University of Trento, Via Mesiano 77, 3812 Trento, Italy; masoud.khanmohamadi@unitn.it

* Correspondence: marco.guerrieri@unitn.it

Abstract

This perspective paper develops a system-level characterization of the transportation metaverse as a persistent, policy-aware digital environment integrating digital twins, real-time data, advanced analytics, and human-machine interaction into a unified operational framework. The study presents a cross-modal review of metaverse applications in road, rail, maritime, and aviation systems, identifying common opportunities, limitations, and research challenges. It further proposes a structured metaverse-based framework for smart roads as a reference case. The framework demonstrates how persistent virtualization, parallel future scenarios, embedded governance constraints, and human-in-the-loop decision support can improve uncertainty-aware planning, management, and operations. The paper positions the metaverse not as a deployable technology, but as an emerging paradigm for transportation governance. The study provides an architectural vision and research agenda for developing more resilient, transparent, and adaptive transportation systems. Potential applications include smart road management, multimodal traffic coordination, real-time operational control, infrastructure resilience planning, and decision support for policymakers under uncertain conditions.

Keywords: transportation metaverse; digital twins; smart roads and infrastructures; mobility governance

1. Introduction

As transport systems absorb rapid technological change (connected vehicles, automation, pervasive sensing, platform-based mobility) while still being judged by stringent time-based performance targets (e.g., travel time reliability, delays, and level of service), their future operating conditions will become simultaneously higher-demand and harder to predict. For example, the ITF Transport Outlook 2023 projects that by 2050, global passenger transport demand will increase by roughly 79% (Current Ambition scenario), and freight demand will approximately double, explicitly highlighting that policy pathways and external shocks create diverging trajectories and persistent uncertainty [1]. At the same time, real-world congestion indicators already show large, highly variable time losses (e.g., 43 h lost per driver on average in 2024 in the U.S., totalling about 4 billion hours and equivalent to \$74B in time costs), illustrating how small disruptions and network interactions scale into significant system-wide impacts [2]. This combination, rising demand, heterogeneous users/vehicles, dynamic control policies, and shock-prone environments, pushes transportation modeling beyond “stable-equilibrium” assumptions and toward



Academic Editor: António Couto

Received: 13 April 2026

Revised: 19 May 2026

Accepted: 20 May 2026

Published: 22 May 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

probabilistic, data-driven, and hybrid (physics + learning) approaches. Recent transportation research has increasingly explored the growing spatiotemporal complexity of mobility systems and the limitations of purely deterministic modeling under dynamic and uncertain conditions. Several studies have therefore focused on uncertainty-aware traffic prediction, probabilistic forecasting and data-driven analytical models capable of capturing heterogeneous traffic dynamics under varying environmental and operational conditions. In parallel, advanced simulation and computational approaches have significantly expanded the analytical capabilities available for transportation-system modeling and optimization. Rowan et al. [3] systematically reviewed machine-learning-based microscopic traffic-flow models—covering car-following and lane-changing behaviors—and highlighted that such models can improve accuracy and flexibility but still need advances in transferability, heterogeneity capture and interpretability. Algherbal and Ratrouf [4] compared widely used microscopic, mesoscopic and macroscopic traffic-simulation platforms and showed that these software packages differ by scale (freeway versus intersection analysis), licensing status (open-source versus commercial) and degree of integration of intelligent transportation systems (ITS) and connected/autonomous vehicles. Kaddoura et al. [5] proposed an innovative hybrid micro-mesoscopic simulation approach for railway operations that bridges the gap between complex microscopic simulators and simplified planning tools; their approach provides scalable feasibility checks and conflict detection for train timetables and infrastructure. At the operational level, optimization and metaheuristic methods have been increasingly investigated for complex transportation planning and management problems. Bueno-Ferrer et al. [6] analyzed metaheuristic applications in transportation and found that such algorithms enhance system efficiency, optimization and adaptive management. Owais [7] offered a half-century review of transit network design research, identifying methodological trends and research gaps, while Mahmoudi et al. [8] critically reviewed analytical approaches for public bus transit planning and underscored the immaturity of existing methods, especially regarding sustainability and equity concerns. Li et al. [9] conducted a bibliometric review of the green vehicle routing problem and reported that research has proliferated since 2000, with emerging hotspots such as fuel consumption, electric vehicles and cold-chain logistics. Soto-Concha et al. [10] proposed mixed-integer optimization models for a vehicle-routing problem with release times and mobile-satellite reloading, showing their models reduce travel distance and fleet size while improving scalability. Chau and Gkiotsalitis [11] systematically reviewed metaheuristic optimization for multimodal transportation and discussed computational scalability and efficiency issues. Recent survey articles have also captured the rise in artificial intelligence methods. Zhang et al. [12] surveyed machine learning applications across air, marine, and land transport and found that these techniques improve predictive maintenance, energy management, and system optimization but still face challenges related to data quality, model complexity, and real-time implementation. Reviews of reinforcement learning by Michailidis et al. [13] and Lai et al. [14] emphasized the potential of RL for adaptive traffic control and transport decision-making yet noted that simulation-to-reality transfer, tailored control architectures and explainability remain open issues. Ali et al. [15] provided a comprehensive survey of deep-learning-based traffic-flow prediction models, comparing architectures such as DHST-Net, Att-DHSTNet and ASTMGCNet, and concluded that attention-based hybrid models outperform traditional approaches. Finally, Li et al. [16] conducted a bibliometric analysis of reinforcement-learning research in transportation, finding that RL has rapidly emerged as a promising method for smart mobility and categorizing publications by application domain while discussing future research directions. Taken together, these studies suggest the emergence of a broad, although heterogeneous, methodological toolbox, which gives clear motivation for an integrated approach to merge simulation, optimization, data, and

interaction into a single operational process. To address these constraints, the metaverse has emerged as a potential new paradigm for transportation systems, offering the possibility to integrate a physical transport network with a persistent, immersive, and data-oriented virtual environment. In this regard, the metaverse may enable real-time interaction among infrastructure, vehicles, users, and traffic control systems, integrating digital twins [17–19], IoT sensing [20,21], AI-driven analytics [22,23], and extended reality (XR) technologies within a shared virtual space [24]. Initial research shows that such environments contribute to greater fidelity in simulation, scenario exploration, human–system interaction, and decision-making under uncertainty, while enabling iterative integration of planning, operating, and control layers [25]. These characteristics suggest potential advantages over more fragmented analytical tools, particularly for representing complex system interactions, multi-actor dynamics, and policy-sensitive operational environments. This paper should be interpreted not as a conventional systematic review, but as a conceptual and cross-modal perspective on the emerging role of the metaverse in transportation systems. Rather than aiming to exhaustively catalog all existing studies, the article synthesizes representative and recent literature across road, railway, maritime, and aviation domains in order to identify common architectural principles, technological trends, operational opportunities, and governance-related challenges. The proposed smart road metaverse framework is therefore intended as an illustrative conceptual reference that integrates insights derived from the reviewed literature into a unified policy-aware and human-centered operational vision. In this regard, the paper combines literature synthesis with conceptual interpretation to support the development of future research agendas and interdisciplinary discussion surrounding metaverse-enabled transportation systems. In the subsequent sections, a detailed analysis of its architectures, applications and implications is offered. The remainder of this paper is organized as follows. Section 2 presents the methodological approach adopted in this study, including the literature-search strategy, selection criteria, and classification framework used for the reviewed studies. Section 3 introduces the metaverse paradigm, its fundamental concepts, and the enabling technologies supporting its development. Section 4 discusses current and emerging applications of the metaverse across different transportation systems, including road, railway, maritime, and aviation domains, with attention to both operational implementations and conceptual use cases. Section 5 examines the major opportunities, challenges, limitations, and open risks associated with metaverse-enabled transportation systems. Building on these insights, Section 6 proposes a conceptual metaverse-based framework for smart roads as an illustrative reference case for intelligent transportation applications. Section 7 discusses future research directions and broader implications for transportation planning, management, and operations. Finally, Section 8 concludes the paper by summarizing the principal findings, contributions, and wider relevance of this work.

2. Methodological Approach

In this study, a structured conceptual review methodology is used to examine the emerging topic of the metaverse's applicability to transportation systems. Instead of performing a fully systematic review aimed at capturing the entire body of available literature, an effort is made to identify representative interdisciplinary research and contributions published in recent years. Accordingly, the methodological approach extends beyond literature aggregation and aims to identify common principles, enabling technologies, operational implications, and research gaps associated with metaverse-enabled transportation systems. This methodology is appropriate given the exploratory nature of the topic, as conceptual work continues to outpace empirical studies at present. The bibliographic search was conducted across the main scientific databases, including Scopus, Web of Science,

IEEE Xplore, ScienceDirect, and Google Scholar, to identify, in the initial phase, as many relevant documents as possible for the present study. The review primarily focused on literature published between 2018 and 2026 to capture recent developments across several innovative topics, including digital twins, immersive environments, artificial intelligence, cyber–physical systems, and metaverse-based transportation solutions. Relevant keywords used in searches included: “transportation metaverse”, “mobility metaverse”, “digital twins in transportation”, “smart roads”, “railway digital twins”, “maritime metaverse”, “aviation metaverse”, “immersive transportation systems”, “XR in mobility systems”, and “AI-enabled transportation environments”. In terms of inclusion criteria, preference was given to peer-reviewed journal articles, highly relevant conference papers, recent technical reports, and conceptual studies related to applications of immersive digital environments, digital twins, intelligent infrastructure, and human–machine interaction systems to transportation systems.

On the other hand, studies focusing solely on virtual worlds for entertainment or other metaverse applications were generally not included. Priority was given to publications providing operational, technological, governance-related, or system-level insights relevant to transportation metaverse applications. The reviewed papers were evaluated along several complementary dimensions: transportation modes (road, railway, maritime, and aviation), technological components, operational applications, governance implications, and implementation level. Finally, the literature was classified by implementation stage:

- conceptual studies
- simulation-based studies
- prototype developments
- pilot implementations
- operational applications

This classification framework supported the comparative analysis presented throughout the manuscript and facilitated the identification of common opportunities, limitations, and future research directions across transportation domains.

3. Metaverse: Concepts and Enabling Technologies

The historical evolution of the metaverse can be interpreted as a progressive convergence of technological, computational, and virtual-interaction paradigms that gradually enabled persistent, immersive, and data-integrated digital environments. As illustrated in Figure 1, the development of the metaverse did not emerge from a single technological breakthrough, but rather evolved through multiple interconnected stages involving networked virtual worlds, simulation technologies, immersive visualization systems, cloud-based infrastructures, and intelligent cyber–physical integration. Mystakidis [26] defines the metaverse as a persistent, socially interconnected virtual environment, while Dionisio et al. [27] identify critical technological characteristics, including real-time interaction, persistence, interoperability, and user-generated content. During the late 1990s and early 2000s, advances in game-engine technologies and large-scale collaborative virtual environments significantly improved the realism and scalability of virtual worlds. Andrade [28] reviewed the evolution of game-engine architectures and their capability to support complex interactive environments, whereas Trenholme and Smith [29] demonstrated the role of game engines in constructing first-person virtual environments with enhanced real-time rendering capabilities. Chia [30] further argued that modern game engines evolved beyond entertainment platforms and became important infrastructures for automation and virtual-system development. In parallel, Greenhalgh and Benford [31] investigated communication mechanisms in large-scale collaborative virtual environments, while Moghaddam and Moghaddam [32] highlighted the importance of broadband infras-

structure for supporting sustainable, data-intensive immersive systems. Wang et al. [33] additionally proposed a human–computer interaction framework for three-dimensional virtual worlds, emphasizing the importance of interactive digital interfaces within emerging metaverse environments. As shown in Figure 1, the following developmental stage was characterized by major advances in simulation, visualization, and immersive technologies.

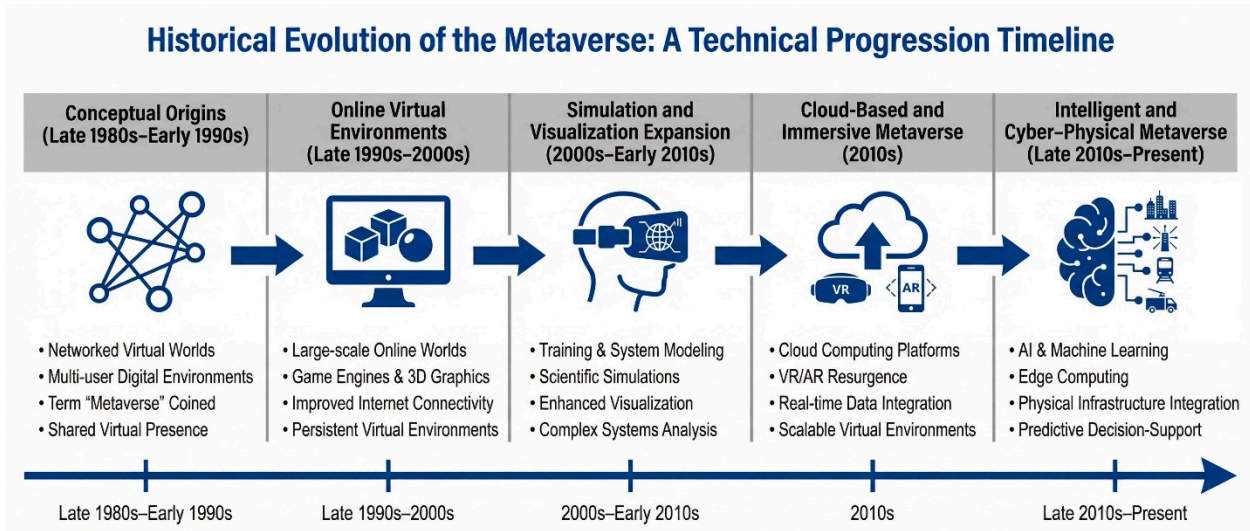


Figure 1. Historical evolution of the metaverse from early virtual worlds to intelligent cyber-physical systems.

Wiederhold [34] reviewed lessons from early virtual reality systems and highlighted both their technical limitations and their long-term potential for immersive interaction. Korkut and Surer [35] later conducted a systematic review of visualization techniques in virtual reality and demonstrated how advances in rendering, interaction fidelity, and spatial representation improved user immersion and analytical capability. Lee et al. [36] applied virtual reality metaverse technologies to aircraft maintenance simulation and demonstrated their usefulness for remote education and training applications in complex operational environments. During the 2010s, cloud computing, blockchain integration, and large-scale data infrastructure further transformed the metaverse into a scalable, continuously connected environment. Mandala et al. [37] discussed the integration of blockchain and cloud-computing technologies within multidisciplinary metaverse architectures, while Zhang et al. [38] reviewed the role of big-data technologies in supporting real-time metaverse analytics and distributed data processing. Schlichting et al. [39] investigated virtual and augmented reality presence and emphasized the importance of immersive perception in metaverse interaction systems. More recently, Hatami et al. [40] analyzed the challenges associated with real-time metaverse synchronization, latency, and scalability. The most recent stage of metaverse evolution, also illustrated in Figure 1, involves the integration of artificial intelligence, edge computing, immersive interfaces, and cyber–physical systems into intelligent operational environments. Huynh-The et al. [41] comprehensively surveyed artificial intelligence applications in the metaverse and highlighted the growing role of machine learning, reinforcement learning, and intelligent agents in adaptive virtual environments. Baidya and Moh [42] reviewed resource-allocation mechanisms for edge-computing-enabled metaverse systems and demonstrated the importance of low-latency distributed computation for real-time interaction. Murala and Panda [43] analyzed immersive technologies, including augmented reality, virtual reality, and extended reality, emphasizing their role in enhancing multisensory interaction within metaverse ecosystems. Lee and Kundu [44] further introduced integrated cyber–physical systems

and industrial metaverse architectures that link physical infrastructure with intelligent virtual environments. Consequently, the metaverse can increasingly be interpreted as a potential operational framework for predictive analysis, intelligent coordination, and human-centered decision support. Park and Kim [45] develop a taxonomy of metaverse components that includes persistent virtual spaces, avatars, digital assets and social systems. Their framework emphasizes that metaverse platforms must maintain world state over long durations, support synchronous and asynchronous user interactions, and provide continuity across sessions. Wang et al. [46] extend this perspective in their survey of metaverse technologies, applications and challenges, highlighting key enabling technologies such as IoT, AI, blockchain and advanced networking. Lv, Shang and Guizani [47] examine how digital twins and metaverse frameworks influence urban development, describing how high-fidelity virtual replicas of cities support planning and infrastructure management. Wang et al. [48] introduce the concept of an “Engineering Brain,” proposing that the metaverse serves as a collective intelligence platform for engineering design and operations. Akbar and Ali [49] apply digital twins and fuzzy multi-criteria decision-making to predictive traffic management in Malaysian smart cities, demonstrating how real-time virtual representations and analytics improve transport operations. Zheng and Yuan [50] review progress in quality-of-experience research for the metaverse, identifying factors such as latency, jitter and visual fidelity that influence user satisfaction. Porcu et al. [51] provide an initial analysis of QoE dimensions for the metaverse and propose measurement frameworks tailored to immersive environments. Deveci et al. [52] present a decision-support system that prioritizes sustainable urban transportation options within a metaverse context, showing how fuzzy logic and multi-criteria analysis aid urban planners. Huynh-The et al. [41] note that AI algorithms enable autonomous control and predictive analytics, while reinforcement learning allows dynamic adaptation to user behavior and environmental changes. Zhu et al. [53] survey brain-computer interfaces (BCIs) for human-centric metaverse applications, suggesting that future interfaces could translate neural signals directly into avatar actions. Khanna et al. [54] discuss challenges in implementing the metaverse in industrial contexts, focusing on human-system interaction and usability. Both works emphasize the need for intuitive input devices and multimodal feedback to improve adoption. Allam et al. [55] conceptualize the metaverse as a virtual form of smart cities and analyze its environmental, economic, and social sustainability implications. They argue that virtual modeling and simulation can improve urban planning, reduce waste and engage citizens in co-designing future cityscapes. Yang et al. [56] review interoperability from a digital-ecosystem perspective and stress that seamless data and asset exchange across platforms is essential for a functional metaverse. Jung [57] proposes an architecture for interoperability between heterogeneous metaverse platforms, introducing standard interfaces and middleware layers. Perey [58] further argues that open interoperability is a fundamental requirement for a truly open metaverse ecosystem, cautioning against vendor lock-in. Uzun [59] provides a comprehensive overview of metaverse governance, covering aspects of data privacy, digital identity, intellectual property rights, and legal jurisdiction. Goldberg and Schär [60] conduct an empirical analysis of voting within decentralized autonomous organizations (DAOs) and suggest that decentralized governance structures could support fair and transparent decision-making in metaverse projects. These works stress that ethical oversight, transparency and accountability mechanisms must be embedded into metaverse architectures.

4. Metaverse in Transportation Systems

Recently, the metaverse has attracted increasing attention as a new digital architecture capable of extending traditional modeling and decision-support methods within trans-

portation systems. The metaverse allows virtual environments to be persistent, interactive, and data-synchronized so physical transport infrastructure, vehicles, users, and control mechanisms can have tighter integration. This paradigm can support continuous interaction among diverse actors, real-time data streams, and adaptive system behaviors in a unified virtual space instead of isolated simulation or optimization tools. These are especially important for the transportation system, where spatiotemporal dynamics, uncertainty, and multi-actor decision-making are dominant at the planning, operations, and management levels. In that respect, the metaverse could be considered an evolution of digital representation and control concepts in the digital era, encompassing digital twins, artificial intelligence, immersive interfaces, and advanced communication technologies. This section presents the metaverse paradigm in transport and its applications across various transport modes.

4.1. Metaverse for Smart Roads

The evolution of intelligent transportation systems (ITS) reflects a progressive redistribution of intelligence across road transport networks. As summarized in Figure 2, early traffic-management systems in the 1980s and early 1990s relied primarily on fixed-time signals, inductive loop detectors, centralized traffic-control centers, and rule-based optimization. Yan et al. [61] describe this early ITS phase as an infrastructure-centered approach focused on congestion mitigation, signal coordination, and incident detection. In the following stage, corresponding to the late 1990s and 2000s in Figure 2, ITS expanded toward advanced traffic management and traveler information systems. Gamboa-Rosales et al. [62] show, through a systematic mapping of ITS research themes, that GPS, variable-message signs, network monitoring, and adaptive signal-control systems became increasingly central to road-network coordination. Avcı and Koca [63] review the main technologies and security challenges of ITS, emphasizing the growing role of communication infrastructure and cybersecure data exchange. Walch et al. [64] specifically focus on cooperative ITS and show that C-ITS assessment increasingly concerns vehicle–infrastructure cooperation, deployment impacts, and system-level evaluation. Abdelkader et al. [65] review connected-vehicle technologies and identify V2V and V2I communication as key enablers of localized and vehicle-centric decision-making. More recently, the final stage shown in Figure 2 reflects the transition toward data-driven and intelligent ITS. Zhang et al. [66] provide an early survey of data-driven ITS and highlight the role of large-scale sensing, data mining, and predictive models in traffic analysis. Machin et al. [67] review artificial intelligence techniques in ITS and discuss their use in adaptive control and traffic management applications. Guerrieri [68] extends this technological transition to smart road geometric design and capacity estimation under AV and CAV conditions. Khanmohamadi and Guerrieri [69] review advanced sensor technologies for CAV road-condition monitoring, demonstrating how vehicle-based sensing can contribute to infrastructure intelligence. Guerrieri and Khanmohamadi [70] further illustrate this transition through the COM-Roundabout concept, which proposes dynamic infrastructure configuration as a smart, self-regulating road system application.

As road transport systems become more interconnected, intelligence confined to individual components becomes insufficient for representing cross-scale interactions among infrastructure, users, vehicles, control strategies, and governance mechanisms. Dey et al. [71] conceptualize transportation cyber–physical systems as integrated environments where infrastructure, digital systems, and users interact within smart-city and regional mobility contexts. Neirotti et al. [72] show that smart-city initiatives depend not only on technology but also on institutional coordination, data integration, and service-oriented urban governance. Docherty et al. [73] argue that smart mobility requires new governance structures

that connect transport operations with land-use planning, digital platforms, and public policy. Within this context, smart roads represent a shift from vehicle-centric intelligence toward infrastructure-centered and system-level decision support. Goumiri et al. [74] identify smart mobility challenges related to heterogeneous data, multimodal coordination, cybersecurity, and real-time decision-making. Almatar [75] discusses smart-transportation planning challenges, emphasizing implementation barriers, planning uncertainty, and institutional readiness. Chen et al. [76] specifically frame smart roads around roadside perception, vehicle–road cooperation, and emerging business models, showing that infrastructure must become an active participant in sensing, communication, and control rather than a passive physical carrier of traffic. Figure 2 should therefore be interpreted as more than a historical timeline. It summarizes the conceptual transition from reactive and infrastructure-based traffic management toward connected, data-driven, and AI-supported road intelligence. However, despite these advances, conventional ITS and smart road systems often remain episodic, component-based, and bounded by predefined modeling assumptions. They are strong in sensing, prediction, and local optimization, but weaker in representing long-term system evolution, governance constraints, policy feedback, and multiple uncertain futures before real-world deployment. Within this gap, the metaverse may provide an integrative framework for smart road planning and management. Figure 3 presents the smart road metaverse as a unified decision environment linking persistent simulation, parallel futures, adaptive control, proactive safety assessment, policy testing, and socio-technical planning. Njoku et al. [77] review metaverse applications in data-driven ITS and identify real-time data fusion, interoperability, cyber–physical integration, and privacy as major implementation challenges. Zhang et al. [78] further demonstrate how multimodal artificial intelligence and semantic graph learning can support intelligent vehicle retrieval and traffic surveillance within ITS environments. Their MAGAE framework integrates large language models, graph attention mechanisms, and cross-modal semantic alignment to bridge visual and textual representations of vehicles, enabling more accurate retrieval of target vehicles from urban surveillance systems. The study further highlights the growing role of AI-driven semantic understanding and multimodal data fusion in future intelligent transportation infrastructures. Zhang et al. [79] introduce “parallel vision” for ITS in the metaverse, explaining how real-world transportation systems and virtual environments can operate together to support predictive analysis and parallel control. Guerrieri et al. [80] proposed an image-processing-based framework for automatically detecting vehicles, estimating speeds, reconstructing trajectories, and evaluating traffic-related pollutant emissions using video surveillance data. Their methodology demonstrates how computer vision and traffic analytics can support real-time environmental monitoring and intelligent transportation management within smart road infrastructures. Papadopoulos et al. [81] develop a geospatial metaverse architecture that integrates spatial computing, digital twins, and virtual worlds, which is directly relevant to road systems because spatial consistency is essential for traffic-state interpretation and infrastructure representation. Reddy et al. [82] address governance and policy issues for a green metaverse, emphasizing sustainability-oriented rules and institutional safeguards. Yang [83] argues that metaverse governance should be supported by technical standards, because interoperability, accountability, and trustworthy system operation cannot be achieved through isolated platforms.

In a smart road context, the metaverse should not be viewed as a replacement for existing ITS tools, but as an overarching environment that reorganizes them into a persistent and policy-aware system. Weinberger [84] defines the metaverse through qualitative meta-synthesis and emphasizes persistence, interoperability, embodiment, and interaction as core conceptual features. Schöbel and Tinglehoff [85] analyze how metaverse platforms create value and identify implementation challenges related to platform design, adoption,

and stakeholder engagement. Lv et al. [86] explain how digital twins can be constructed across scales, states, and relations, which supports the idea that road assets, traffic flows, users, and policies can be represented simultaneously in a multi-layer virtual environment. In this way, the components shown in Figure 3 should be understood as interconnected layers rather than isolated applications.

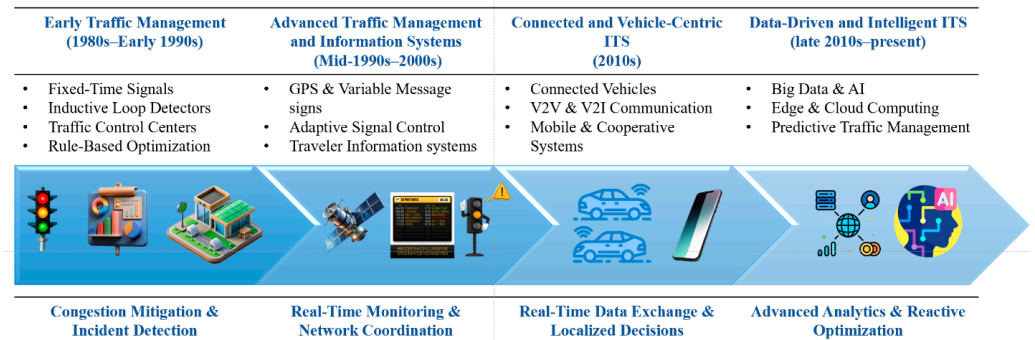


Figure 2. Historical evolution of intelligent transportation systems (ITS).



Figure 3. Conceptual representation of the metaverse as an integrative environment for smart road systems.

One major application domain is predictive analysis of traffic and infrastructure performance. Akbar and Ali [49] propose a digital-twin- and metaverse-based approach for predictive traffic management in Malaysian smart cities using fuzzy multi-criteria decision-making. Ma et al. [87] develop the concept of metaverses for parallel transportation, moving from general 3D traffic-environment construction toward virtual–real intelligent transportation management and control. Kuo and Choi [88] propose an AI-supported digital-technological framework for transportation and logistics operations, showing how metaverse technologies can support coordination among logistics, control, and planning processes. Wang [89] provides the theoretical foundation of parallel control and management for ITS, explaining how artificial systems, computational experiments, and parallel execution can support transportation control. Hu et al. [90] review simulation, digital twins, and parallel intelligence for autonomous driving, showing that virtual environments are essential for testing autonomous vehicle behavior before deployment. Together, these works support the predictive-analysis component shown in Figure 3, where smart roads are mirrored across multiple plausible futures rather than examined through one-off simulation runs.

A second application domain concerns adaptive traffic control and coordinated infrastructure management. Michailidis et al. [13] review reinforcement-learning methods for traffic-signal control and show how adaptive algorithms can improve signal decision-making under dynamic demand. Souravlias et al. [91] propose a parallel-computing approach for smart traffic lights, demonstrating the relevance of computational scalability for real-time signal optimization. Selvaraj et al. [92] introduce human-centered traffic management for smart cities and metaverse settings, emphasizing that control decisions must remain interpretable and usable for human operators. Zhao et al. [93] propose a collaborative metaverse–digital twin system for traffic perception, reasoning, and resource scheduling, which directly supports the adaptive-control and predictive-performance layer shown in Figure 3. Alam [94] introduces the Metaverse of Things as a smart-city concept that links sensing, computation, and actuation in urban environments.

A third application domain is proactive safety assessment and hazard detection. Castro et al. [25] provide a data-driven systematic review of transportation metaverse research and emphasize the need for computational modeling frameworks that can evaluate emerging risks. Irfan et al. [95] review transportation digital twin systems for traffic safety and mobility, highlighting their ability to represent safety indicators, near misses, and mobility risks. Ahilal et al. [96] propose a traffic metaverse with shared vehicle perception, showing how cooperative perception can support safer vehicle–road interaction. Mauro and Guerrieri [97] conducted a comparative life cycle assessment of conventional, turbo, and flower roundabouts by integrating pavement construction, maintenance operations, traffic emissions, and environmental costs into a unified evaluation framework. Their results showed that reclaimed asphalt pavement (RAP) and lime stabilization strategies can significantly reduce energy consumption, pollutant emissions, and long-term environmental impacts associated with transportation infrastructure systems. Bai et al. [98] develop an augmented-reality-based meta vehicle–road cooperation testing system, allowing vehicle–infrastructure interactions to be tested in controlled virtual environments. These studies support the proactive safety and hazard-detection component of Figure 3, where safety weaknesses can be identified before real-world crashes occur. The metaverse can also support infrastructure lifecycle management and resilience planning. Wang et al. [99] propose an efficient visual-perception framework for ITS in the metaverse, showing how virtual visual environments can support instructional perception, infrastructure monitoring, and decision support. Deveci et al. [52] further demonstrate how metaverse-based decision-support methods can prioritize sustainable urban-transportation alternatives under multi-criteria conditions. These approaches allow pavement condition, traffic loading, maintenance priorities, environmental exposure, and budget constraints to be evaluated within a persistent analytical environment. Finally, the smart road metaverse can support policy testing, governance, and multi-stakeholder collaboration. Ali and Nabeel [22] analyze how AI and metaverse-based transportation planning can contribute to sustainable development goals. Kuo and Choi [88] show that metaverse technologies can support operational and strategic decision-making in transportation and logistics systems. Sharifi et al. [100] review the metaverse as a future form of smart cities and discuss both co-benefits and trade-offs for sustainable development goals. Allam et al. [55] conceptualize the metaverse as a virtual form of smart cities and emphasize environmental, economic, and social sustainability dimensions. Uzun [59] discusses metaverse governance issues including privacy, identity, regulation, and institutional responsibility. Reddy et al. [82] frame governance around sustainability-oriented policy in the green metaverse. Owojori and Erasmus [101] argue that metaverse-based urban sustainability reporting can improve transparency and accountability in the built environment. These works support the socio-technical and policy-governance components shown in Figure 3, where pricing strategies, low-emission

zones, access regulations, safety rules, and equity implications can be tested virtually before implementation.

Overall, Figure 2 explains why smart roads emerge from the historical evolution of ITS, while Figure 3 explains how the metaverse reorganizes smart road technologies into a persistent, multi-future, and policy-aware decision environment. The smart road metaverse can be interpreted not as a sudden technological rupture, but rather as it represents a staged systems-integration process in which sensing, connectivity, prediction, control, safety assessment, infrastructure monitoring, and governance are integrated into a shared virtual environment. Its main value lies in enabling uncertainty-aware planning, coordinated operational control, proactive safety testing, and transparent policy evaluation before physical implementation.

4.2. Railway Metaverse

Railway transport is one of the most complex and safety-critical mobility domains, requiring tight integration of track infrastructure, rolling stock, signaling, power supply, and operational control. Capacity pressures, punctuality requirements and automated train operations have increased system complexity and operational uncertainty. Conventional analytical tools and microsimulation models can provide fine-grained information about individual components, but their episodic scope limits their ability to capture long-term interactions among asset aging, traffic flows, and human interventions. The metaverse has recently been proposed as a unifying paradigm that continuously mirrors physical railway systems and supports the exploration of parallel operational futures. Figure 4 illustrates this concept: digital twins, cyber-physical convergence and artificial-intelligence-driven intelligence form a persistent virtual ecosystem for railways. The elements depicted in the figure are examined below from the perspectives of operations, safety, lifecycle management, energy optimization, and human-system interaction.

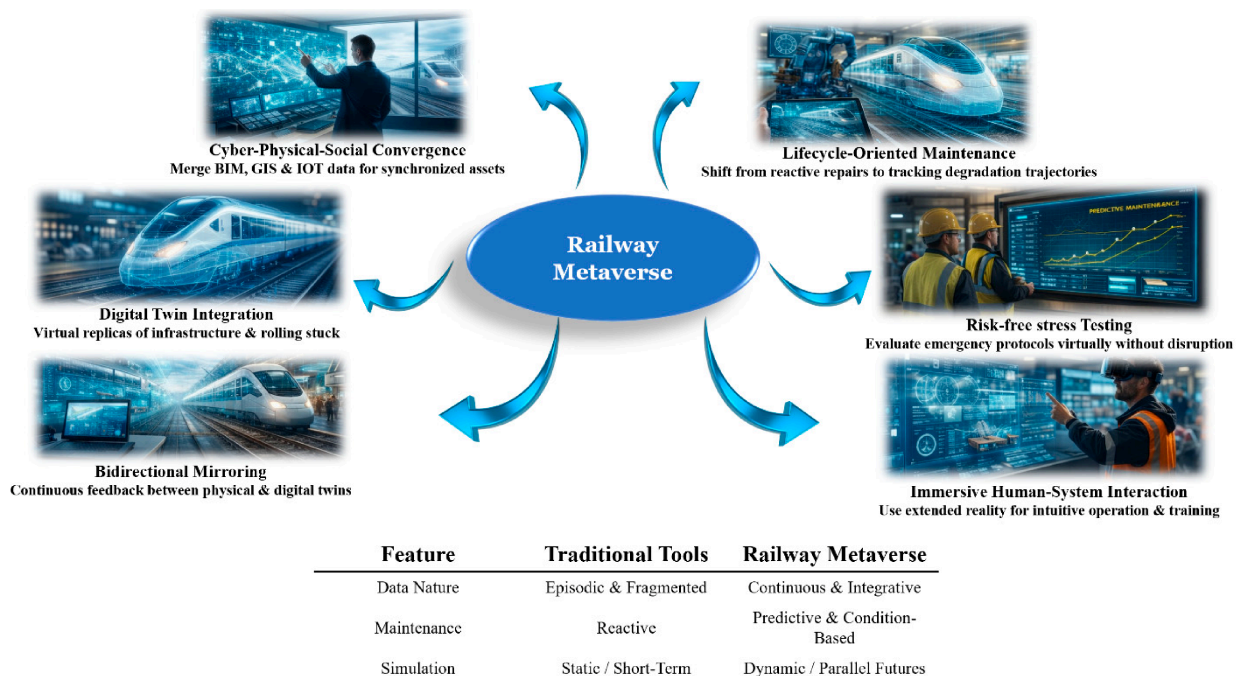


Figure 4. Conceptual overview of the railway metaverse as a unified digital ecosystem.

A central feature of the railway metaverse is the digital twin: a continuously updated virtual replica of infrastructure, rolling stock, signaling, and traffic flows. Researchers such as Tang et al. [102] and Bešinović [103] emphasize that railway digital twins integrate

high-fidelity geometric models with persistent sensor data and operational information, enabling synchronized representations of structural, operational, and contextual states. Corriere et al. [104] introduced a fuzzy-logic-based framework for evaluating railway station practical capacity under safety-oriented operating conditions. Their model integrates accident risk factors, operational reliability, train interference probabilities, and infrastructure constraints to support safer and more adaptive railway traffic management strategies. Guerrieri and Parla [105] argue that building information modeling (BIM) and geographical information systems (GIS) supply the structural and spatial context, while the Internet of Things (IoT) provides real-time condition monitoring. This convergence allows the shift from reactive maintenance to lifecycle-oriented frameworks that describe degradation trajectories, load-dependent usage patterns, and stochastic operational constraints. The digital twin may therefore be viewed as a foundational element within a broader metaverse ecosystem rather than a stand-alone analytical tool. Research by Tsvetkov et al. [106] and Li et al. [107] demonstrates that digital twins combined with real-time data and optimization algorithms can support timetable planning, conflict resolution, and adaptive capacity allocation. Integrating collaborative virtual-real environments into parallel traffic systems may facilitate controllers to optimize operational trade-offs—such as punctuality, safety, and energy efficiency—while managing disruptions more effectively via bidirectional interaction. Cooperative perception digital twins can leverage automotive edge clouds to sustain a live digital replica of active traffic environments [108]. Kurwi et al. [109] show that immersive interfaces, involving extended-reality representations of trains and networks, enhance situational awareness and facilitate human-in-the-loop decision-making during disturbances.

Lifecycle management benefits from persistent, integrated digital twins. Van Dinter et al. [110] demonstrate that digital twins provide real-time representations of physical assets and can generate/use data on asset degradation, condition, and performance to support predictive maintenance and lifecycle monitoring. Kazemi et al. [111] argue that DT-based systems enhance fault detection and support predictive and condition-based maintenance through continuous infrastructure monitoring, while Yeung et al. [112] highlight that digital twin-based scenario analysis enables comparison of alternative operational strategies and assessment of long-term system performance and resilience before implementation. Metaverse-oriented platforms may support energy management and sustainability analyses. Guerrieri and Ticali [113] discussed design standards for converting disused railway corridors into greenways dedicated to sustainable and soft mobility. Their work highlights how abandoned transportation infrastructures can be transformed into environmentally integrated mobility corridors supporting non-motorized transportation, landscape regeneration, and sustainable urban development. Scheepmaker et al. [114] emphasize that integrated railway simulation environments enable the joint optimization of train timetabling, traction power management, and regenerative braking strategies to improve overall energy efficiency and operational sustainability in rail systems. Guerrieri and Ticali [115] further explored the transformation of abandoned railway infrastructures into sustainable mobility corridors by emphasizing geometric design standards, accessibility requirements, and environmental integration strategies for greenway development. Their study highlights the role of infrastructure repurposing in promoting low-impact transportation and sustainable territorial regeneration. Tao et al. [116] emphasize that integrating sustainability assessment and resource-management functions into digital-twin environments can aid the evaluation of energy consumption, carbon emissions, and resource utilization under alternative operational scenarios, thereby supporting low-carbon and sustainable industrial decision-making. Human–system interaction is fundamentally reshaped by immersive, cognitively aligned interfaces. Extended-reality environments coupled with

real-time digital twins may allow operators and maintenance personnel to interact with complex system states intuitively [109]. Virtual reality (VR) shows potential for safety-relevant training by safely simulating dangerous scenarios, but its effectiveness needs further evaluation [117]. A VR training framework proposes adapting scenarios using performance measures plus real-time physiological and kinematic data, and adjusting feedback type, timing, and simulation variables accordingly [118]. Finally, researchers explore how artificial intelligence integrates with digital twins to create data-centric intelligence for railway systems. J. Sresakoolchai et al. [119] showed DT–RL integration reduced maintenance activities by 21% and defects by 68%, illustrating how an RL agent can be embedded in a DT and updated as new geometry, defect, and maintenance data arrive, and for a railway bridge DT, vibration data after train crossings are streamed, stored in a cloud data lake, and used periodically to retrain ML models, enabling continuous learning and adaptation to changing structural dynamics [120]. Another framework integrates spatial graph neural networks with temporal encoders on multi-source railway big data to support anomaly detection and predictive maintenance, explicitly modeling spatial relationships and temporal patterns for operational optimization [121]. Metaverse environments can make AI recommendations more interpretable by presenting them through immersive visualizations. A predictive maintenance framework for a metro operator provides natural language and visual explainability via dashboards so decision-makers can understand why failures are predicted and act accordingly [122]. Realistic virtual environments and digital twins are increasingly used in rail to test algorithms and strategies before field deployment. For instance, a framework for virtual performance testing of ATO algorithms uses a microscopic train simulator plus structured scenarios to test punctuality, accuracy, energy consumption, safety and comfort before real-world trials [123].

In summary, the railway metaverse offers a unified digital landscape where infrastructure, operations, energy systems, safety management, human factors and intelligent analytics are represented coherently and collaboratively explored. By overcoming the fragmentation of traditional tools, it provides a persistent, interactive and uncertainty-aware environment that supports integrative, adaptive and resilience-oriented architectures for next-generation railway systems.

4.3. Maritime Metaverse

The maritime industry is a critical pillar of global trade and multimodal transportation; it involves complex vessel movements, safety-critical processes and growing pressures related to energy efficiency and environmental sustainability. Traditional maritime information systems are often fragmented, reactive and limited in their capacity to capture dynamic interactions among vessels, ports, offshore infrastructure and logistics chains. In response, the “maritime metaverse” is emerging as an emerging digital architecture. By expanding beyond classical simulation and monitoring, it creates persistent, immersive and interconnected virtual environments wherein high-fidelity digital twins are synchronized with real-time data streams. Figure 5 provides a system-level conceptual overview of the maritime metaverse: it depicts how digital twins, AI-augmented intelligence and real-time data synchronization collectively support decision-making across traffic management, safety, energy, lifecycle management and human–system interaction. The figure serves as a unifying reference through which the multidimensional role of the metaverse in maritime transportation is analytically explored.

High-fidelity digital twins of ships, port terminals, offshore platforms and other marine assets ingest heterogeneous data streams (e.g., IoT sensors, AIS, satellite data, port-management systems) to create synchronized virtual representations. Ding et al. [124] developed DT-based decision support at Yangshan automated terminal uses real-time

monitoring with big-data engines for operational decisions, while Lovas et al. [125] demonstrated that terrestrial laser scanning can be utilized to capture high-density point clouds of complete ship hulls. The authors highlighted that converting this data into high-resolution geometric meshes enables the detection of structural deformations and provides precise inputs for hydrodynamic simulations, allowing cross-sections to be extracted at any desired location. Ship DTs require mutual data exchange between the physical and virtual environments; this bidirectional flow is the defining feature that distinguishes true DTs from static models [126]. Surveys highlight emerging data-driven ML methods and at-sea monitoring for corrosion-fatigue life prediction on marine structures [127]. Together, these works position digital twins as foundational elements of a maritime metaverse. Metaverse platforms create shared virtual environments where digital twins are synchronized with real-time AIS, radar, weather and port-traffic data. Ilias et al. [128] proposed the VesselAI architecture, which proposes high-fidelity maritime digital twins by fusing ship-board data (sensors, AIS, and autonomous logs) with external environmental datasets (weather, satellite, oceanographic, and port databases). This comprehensive data-fusion framework acts as a foundation for global traffic surveillance, collision prevention, and weather-resilient voyage optimization. AIS data from 4923 ships on the Yangtze show how segment-wise speed distributions relate to congestion; the method evaluates and justifies speed limits, offering a template to virtually tune limits in a DT before implementation [129]. Liu et al. [130] introduced an LSTM-based framework for projecting future vessel paths using Automatic Identification System (AIS) data. By embedding a specialized “traffic conflict situation” representation, their model significantly increases forecasting accuracy and system resilience, thereby enhancing collision prevention and surveillance operations within maritime Internet of Things (IoT) traffic services. Safety and risk assessment benefit from the metaverse’s immersive, scenario-based capabilities. Riordan et al. [131] developed a port-scale digital twin of Hamburg that interfaces a virtual Maritime Autonomous Surface Ship (MASS) with a high-resolution multibeam sonar simulator. This integrated framework enables the real-time detection of underwater hazards and immediate updates to nautical charts, significantly mitigating ship grounding risks in shallow navigable waters, while an immersive VR simulation for mooring risk assessment enhances learner motivation, enjoyment, and behavioral intent while lowering cognitive load compared to personal trainers, according to Makransky and Klingenberg [132]. Recent studies by Bai et al. [133] and Cao et al. [134] emphasize that current resilience models must integrate real-time recovery dynamics alongside richer datasets, such as AIS tracking information. The authors argue that incorporating these granular, dynamic variables is essential for providing robust, actionable support during operational decision-making in maritime shipping networks.

Persistent digital twins underpin lifecycle management for ports, terminals, shipyards and offshore structures. Integrated SHM frameworks for large hydro-steel structures and buildings build safety indices and evaluation databases from historical plus real-time data to support life-cycle safety assessment and anomaly detection [135]. Some studies note that ship digital twins are widely proposed to optimize fuel consumption, environmental emissions, and operational costs throughout the entire vessel lifecycle, including design, operation, maintenance, and planning [126,136]. However, both studies emphasize that current practical implementations remain fragmented, frequently failing to achieve the full, bidirectional data synchronization required for comprehensive asset management, whereas Kanchiralla et al. [137] propose a digital twin-based framework for hybrid ships that enables real-time life cycle assessment (LCA) to enhance environmental performance. The approach leverages live data and control mechanisms to optimize operational decisions for improved sustainability. Diaz et al. [138] emphasized that implementing augmented reality (AR) frameworks within ship engineering and quality management creates a unified envi-

ronment for instantaneous data exchange among design and production stakeholders. The authors established that this multi-party collaboration drastically improves engineering coordination and simplifies engineering change management across the shipyard. According to Kim [139], real-time life-cycle analysis via digital twins enables tracking and mitigation of greenhouse gas emissions in battery-hybrid shipping. By coupling fuel inventories and power plant models with live operational data, the framework can support real-time load-control optimization to dynamically minimize environmental impacts. Evaluating carbon footprints in the maritime sector requires systems that can withstand operational and environmental volatility. To address this, a hybrid-propulsion digital twin has been proposed that predicts vessel fuel demand and carbon intensity with an error margin of less than 5%. This approach allows operators to conduct precise, voyage-level emission audits under variable transit conditions [140]. To overcome the limitations of static database assumptions, a “Live-Life Cycle Assessment” methodology has been proposed that couples a MATLAB/Simulink ship performance simulator with dynamic ecological accounting. Tested on a PV-battery hybrid ferry, this framework directly incorporates simulated power profiles and climate variables into the assessment, enabling the identification of geographically specific carbon reduction potentials [141].

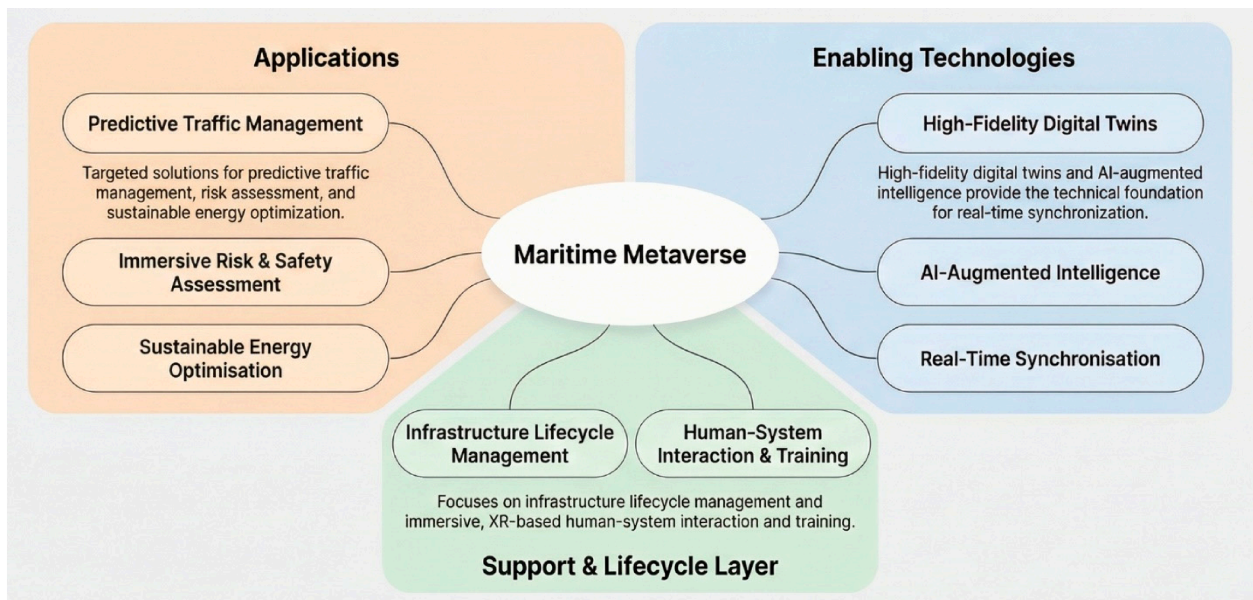


Figure 5. System-level overview of the maritime metaverse.

Extended-reality interfaces transform how maritime personnel interact with system data. Ujkani et al. [142] designed and evaluated a mixed-reality remote pilotage system that overlays 360-degree video feeds with live data streams, such as AIS telemetry, vessel waypoints, and bearings, directly into a virtual reality (VR) environment. The authors demonstrated that this immersive platform provides remote pilots with a highly integrated, real-time visualization of intricate traffic scenarios and vessel dynamics, thereby facilitating safer and more informed navigational decision-making. To enhance situational awareness during complex mooring operations, immersive VR safety simulations are structured around the core competencies of hazard anticipation, continuous monitoring, adaptive reaction, and continuous learning. This approach provides an interactive training environment where users can witness developing hazards firsthand and test procedural responses without real-world consequences [132]. Managing critical emergencies at sea requires seamless teamwork, which can be trained effectively using virtual reality (VR) systems dedicated to life-saving appliances (LSA). As demonstrated by Qiu et al. [143],

these immersive platforms enable multi-person collaborative training and synchronized role coordination, allowing crews to practice high-stakes evacuation and rescue workflows safely. According to a comprehensive review by Vukelic et al. [144], VR training systems effectively replicate rare, high-stakes maritime crises—such as shipboard fires, dynamic evacuations, and abandonment procedures. This digital rehearsal allows crews to repeatedly practice emergency protocols in a zero-risk environment. Maritime safety training within the metaverse can be enhanced by incorporating biometric sensors to capture human emotional states during simulated crises. As demonstrated by Hamed-Ahmed et al. [145], leveraging eye-tracking and facial-expression metrics allows for the iterative optimization of training system interfaces, task trackers, and visual prompts; these data-driven UI enhancements were shown to improve operational efficiency, reducing fire drill task times by 14–33%. However, AI models integrated with maritime digital twins create a smart decision-support layer. Spandonidis et al. [146] introduced a machine-learning-driven Key Performance Indicator (KPI) framework that couples high-frequency shipboard sensor data with Artificial Neural Network (ANN) models and hybrid data-fusion techniques. Their system accurately predicts dynamic vessel performance metrics, such as fuel consumption, while enabling early-stage fault detection to inform an interpretable decision-support platform designed specifically for non-expert operators. According to Raza et al. [147], a four-layer digital twin framework optimizes autonomous surface vessel development by embedding machine-learning-powered obstacle detection and path planning in a 3D virtual space. This setup provides a risk-free environment for training, testing, and validating navigation control strategies prior to deployment. However, next-generation marine traffic management relies on multi-layer AI frameworks that integrate edge and distributed computing to track and control autonomous vessels. By coordinating fleet-wide sensing and actuation data, this setup yields unified guidance, navigation, and control (GNC) capabilities inside dense traffic zones [148]. According to Wang et al. [149], AI-powered predictive maintenance agents process high-frequency shipboard sensor streams to identify anomalies, diagnose system faults, and avert mechanical failures. This autonomous approach optimizes maritime safety and significantly mitigates operational downtime. As validated by Pan et al. [150], utilizing a DRL-driven decision-making framework yields a 30.8% decrease in vessel collision rates and an immediate 20% expansion of safety margins over prior navigation methods, while maintaining strict regulatory compliance, and According to Wang et al. [151], utilizing a Deep Q-Network for discrete dynamic berth allocation effectively manages unpredictable vessel arrivals at container terminals. By outperforming conventional ant colony heuristics, this reinforcement learning framework shrinks cumulative vessel waiting times by roughly 58% to maximize terminal throughput. Live maritime risk mitigation can be optimized by deploying Automated Machine Learning (AutoML) pipelines to automatically isolate and rank high-impact safety variables. As established by Munim et al. [152], leveraging feature-importance metrics reveals that a vessel's gross tonnage, its current phase of operation, and the specific waterway category are vital parameters for generating accurate, real-time accident risk profiles. Wang et al. [153] propose a digital twin framework for port operations that utilizes extensive trajectory and environmental data for proactive failure prediction. Operating within a virtualized environment, this system acts as a decision-support layer for safety managers to prevent logistics risks. When assessing competency in marine engineering, simulator-based metrics have been shown to effectively predict real-world operational performance across varying tiers of technological fidelity. As demonstrated by Hjellvik and Mallam [154], there is no significant performance transfer discrepancy between fully immersive HMD environments and desktop simulations; instead, the success of the skill transfer is heavily moderated by the baseline motivation of the trainee.

By unifying these components—digital twins, operations management, safety assessment, lifecycle management, energy optimization, human–system interfaces and AI—the maritime metaverse offers a coherent digital ecosystem that shifts maritime governance from fragmented and reactive to integrative, predictive and collaborative. This holistic approach may enable stakeholders to test policies and technologies virtually, improving safety, efficiency, and sustainability before implementation.

4.4. Aviation Metaverse

Air transport systems constitute one of the most complex, safety-critical, and globally interconnected elements of modern mobility, featuring tightly coupled interactions among aircraft, airports, air traffic management (ATM), human operators, and regulatory institutions. The expansion of the low-altitude economy, alongside Advanced Air Mobility (AAM) and Urban Air Mobility (UAM) frameworks, relies on scaling thousands of Unmanned Aerial Vehicles (UAVs) and electric Vertical Takeoff and Landing (eVTOL) aircraft for logistics, passenger transport, and emergency operations [155,156]. However, the authors emphasized that this rapid influx of low-altitude aircraft exponentially intensifies airspace management complexities and introduces critical, real-time security vulnerabilities into the aviation ecosystem. In response, the aviation metaverse has emerged as a transformative digital paradigm that extends beyond traditional simulation and visualization approaches into persistent, immersive, and collaborative virtual environments. Figure 6 presents a conceptual overview of the aviation metaverse as an integrated digital ecosystem in which virtual airport operations, immersive air traffic management, aircraft maintenance, cybersecurity, regulatory frameworks, and real-time data synchronization coexist within a unified environment. Rather than representing a single application, Figure 6 illustrates the multidimensional structure of metaverse-enabled aviation systems and serves as a unifying framework for the operational, technical, and institutional dimensions discussed throughout this section. At the core of the aviation metaverse are high-fidelity digital twins of aircraft, airports, terminals, runways, and airspace sectors. Kapteyn et al. [157] introduced a mathematically rigorous probabilistic graphical model that serves as a foundational architecture for robust and scalable digital twin deployments. The authors demonstrated that this framework may facilitate flexible, dynamic decision-making across varied operational fields, validating its efficiency by successfully executing real-time calibration and state updates for Unmanned Aerial Vehicles (UAVs). Tavares et al. [158] applied digital twin technology to aircraft structural design and life cycle assessment, enabling simultaneous evaluation of structural integrity and sustainability performance. Jiang et al. [159] investigated methods for establishing continuous synchronization between physical and virtual systems, emphasizing the importance of real-time connectivity and bidirectional information exchange. Li et al. [160] proposed an interactive real-time monitoring framework for aircraft assembly fields based on digital twins and information traceability mechanisms. Sadeghi et al. [161] extended digital twins toward intelligent fleet monitoring and predictive diagnostics for electrified aviation systems. Together, these studies demonstrate how cyber–physical integration forms the technological backbone of metaverse-enabled aviation environments.

The aviation metaverse may also transform air traffic management from conventional radar-centric supervision toward immersive and collaborative operational environments. Liu et al. [162] introduced “parallel radar” systems that integrate digital twins with intelligent radar architectures for real-time airspace management. Wei et al. [163] highlighted the role of metaverse platforms in sustainable smart civil aviation, particularly for collaborative traffic management and operational visualization. Gerdes et al. [164] demonstrated that shared digital-human air traffic control environments improve situation awareness and

support the development of common mental models among controllers. Pepper et al. [165] proposed a probabilistic digital twin of the UK en-route airspace for training and evaluating AI-based air traffic control agents. Yiu et al. [166] developed a digital twin platform with virtual counterparts of flight and air traffic control operations to support intelligent automation and collaborative operational analysis. Chen et al. [167] further introduced a tangible digital twin framework with shared visualization capabilities for collaborative air traffic management operations. These studies collectively illustrate how immersive metaverse environments can improve conflict detection, predictive traffic analysis, and operational coordination under highly dynamic conditions. Airport operations and ground handling constitute another important application area of the aviation metaverse. Attar et al. [168] developed a simulation-based digital twin framework for optimizing multiple airside airport operations, including runway sequencing, gate assignment, and taxiway management. Liu et al. [169] proposed a digital twin-enabled framework for diagnosing and tracing the propagation of delays in airport ground services. According to De Bosscher et al. [170], marrying surrogate models with interpretable machine learning offers a computationally lightweight framework to analyze agent-based terminal dynamics. This method maintains emergent behavioral features while detailing how variable staffing and occupancy rates directly impact security checkpoint waiting times and passenger discretionary expenditures. Wong et al. [171] introduced a closed-loop digital twin system for air cargo load planning operations, enabling dynamic optimization of cargo distribution and aircraft loading procedures. Wu et al. [172] further emphasized that transportation digital twins can support integrated monitoring, predictive analytics, and adaptive optimization across airport infrastructures and operational systems.

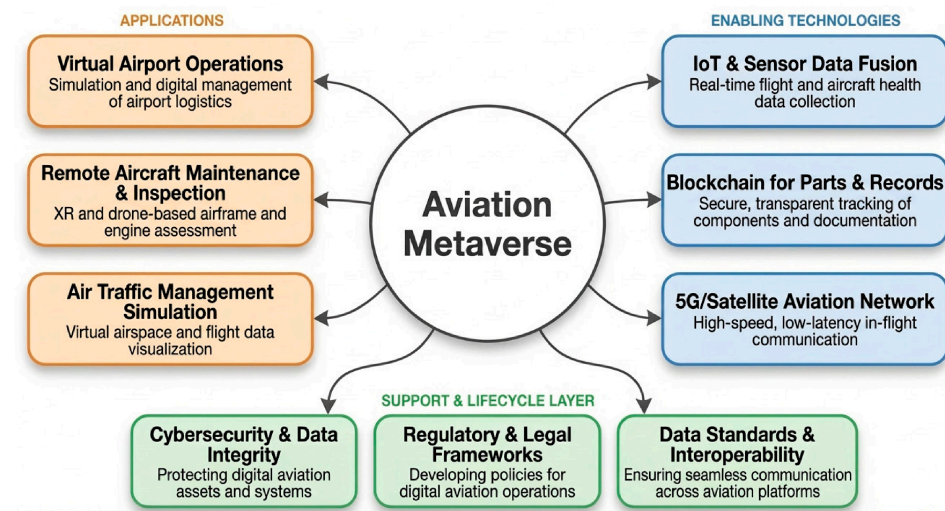


Figure 6. Conceptual overview of the aviation metaverse as a persistent and integrative digital environment for flight operations.

Training, human performance, and immersive human–machine interaction represent additional strengths of metaverse-enabled aviation systems. Immersive metaverse environments can significantly improve collaborative aviation training and operational preparedness [163]. Sun et al. [173] proposed a competency assessment model based on behavioral indicators for initial flight training. While Mark et al. [174] explored neuroadaptive pilot training using functional near-infrared spectroscopy (fNIRS) integrated into flight simulators. Nguyen et al. [175] discussed the ethical, technical, and practical implications of AI-generated aviation training materials, while Berlenga et al. [176] investigated aviation professionals’ concerns regarding AI-based operational systems. Zhu et al. [177] further analyzed trust formation in human–machine interaction environments, emphasizing

ing the importance of calibrated trust and transparent AI-supported interfaces. Collectively, these studies indicate that the aviation metaverse can support scalable, adaptive, and human-centric training ecosystems while simultaneously raising important ethical and cognitive considerations.

The aviation metaverse is also highly relevant for UAV operations and Advanced Air Mobility (AAM). Large language models (LLMs) serve as intelligent agents within digital ecosystems, enhancing the autonomous decision-making and 3D spatial reasoning capabilities of Unmanned Aerial Vehicles (UAVs) in dynamic, low-altitude airspace. These generative AI models enable advanced cognitive problem-solving, accelerating the transition toward autonomous agentic low-altitude mobility services [155]. Namuduri [156] proposed a digital twin-based framework for integrated airspace management in advanced air mobility systems. Causa and Fasano [178] developed a multiobjective planning framework for low-altitude missions in urban air mobility ecosystems. Xiong et al. [179] proposed a digital twin-based communication and flight-control architecture for AAM operations. Yiu et al. [166] demonstrated how virtual counterparts of flight and ATM operations can support intelligent automation in mixed-traffic environments. Kopyt and Dylicki [180] investigated the simulation and analysis of vertiport capacity for urban air mobility systems. These contributions collectively demonstrate that persistent virtual airspace environments provide a safe and scalable platform for testing emerging mobility concepts before deployment in real-world operations.

Environmental sustainability and lifecycle management constitute another major dimension of the aviation metaverse. Tavares et al. [158] combined digital twins with life cycle assessment methodologies for aircraft structural systems. Yang et al. [181] explored the integration of extended reality and lean methodologies into end-of-life aircraft disassembly planning. Papadaki and Maleviti [182] investigated sustainable aircraft decommissioning and recycling practices within circular aviation economies. Adu-Gyamfi [183] proposes a holistic aviation digital twin framework that incorporates end-of-life management to improve recycling efficiency and promote circularity across the asset lifecycle. This approach utilizes digital twins to help secure full component traceability, supporting a sustainable transition in the aerospace sector. Kabashkin [184] proposed a data-driven digital twin framework for aircraft lifecycle management. Accurately evaluating aviation acoustic footprints requires modeling tools that can adapt to volatile environmental conditions. To address this, a semi-empirical noise prediction framework has been introduced that utilizes a ray-tracing propagation kernel to calculate the effects of 3D atmospheric heterogeneity and wind-driven wave refraction. This approach allows airport operators and urban planners to achieve highly localized, realistic evaluations of noise propagation [185]. Babu Saheer et al. [186] reviewed air-quality modeling within digital twin frameworks for sustainable urban systems. Zaccaria et al. [187] proposed a framework for fleet monitoring and diagnostics of aero-engines using digital twins. Sadeghi et al. [161] review how digital twins, integrating computational fluid dynamics, finite element analysis, and AI, enhance aircraft condition and fleet monitoring through automated crack detection and accurate remaining useful life (RUL) prediction. This integrated approach improves operational safety and reduces maintenance costs for electrified aviation systems. These studies collectively demonstrate that metaverse-enabled aviation environments can support sustainability-oriented optimization, emissions reduction, lifecycle management, and environmentally informed policy analysis.

Finally, the aviation metaverse raises important cybersecurity, governance, regulatory, and ethical challenges. Wang et al. [188] proposed a blockchain-based secure sharing framework for aviation big data to improve integrity and interoperability among distributed aviation systems. Abdulla Alshamsi and Sipos [189] analyzed the legal implica-

tions associated with the aviation industry's transition toward metaverse environments. Vecchia et al. [190] proposed a SysML-based framework supporting EASA CS-23 digitalization and certification processes. Cartile et al. [191] discussed the digital transformation of aircraft certification and regulatory documentation. G et al. [192] emphasized that digital twins and cyber-physical systems represent a new frontier in computer modeling that requires standardized architectures and interoperability protocols. Nguyen et al. [175] emphasized concerns associated with AI-generated aviation training materials. Moreover, Berlenga et al. [176] highlighted ethical concerns related to AI-supported aviation systems, including operator deskilling, accountability, and trust. Together, these studies demonstrate that the successful deployment of aviation metaverse systems depends not only on technological innovation but also on robust governance mechanisms, cybersecurity protections, regulatory adaptation, and human-centered ethical frameworks. Overall, the aviation metaverse introduces a persistent, intelligent, and collaborative digital ecosystem that integrates high-fidelity digital twins, immersive interfaces, artificial intelligence, and real-time operational data into a unified environment. Across air traffic management, airport operations, training, sustainability assessment, advanced air mobility, and regulatory governance, metaverse-enabled frameworks extend conventional aviation capabilities from reactive monitoring toward predictive, system-wide optimization and resilience enhancement. Although important challenges remain regarding interoperability, cybersecurity, certification, ethical governance, and human trust, the aviation metaverse provides a scalable and risk-aware platform for testing, coordinating, and optimizing increasingly complex aviation ecosystems.

Although the transportation metaverse is increasingly presented in the literature as a transformative paradigm capable of reshaping future mobility systems (Table 1), the actual maturity and implementation readiness of existing applications remain highly heterogeneous across transportation domains. While certain technologies, such as digital twins, intelligent sensing infrastructures, and AI-assisted operational platforms, have already reached advanced stages of practical deployment in some sectors, many other metaverse-related concepts still remain largely conceptual or simulation-oriented. Furthermore, the degree of technological integration, real-time synchronization, human-machine interaction, governance embedding, and operational scalability differs significantly between road, railway, maritime, and aviation applications. As a result, the current state of transportation metaverse development cannot be interpreted as a uniform technological transition, but rather as a multi-stage and uneven evolutionary process characterized by varying levels of implementation maturity and system integration. To provide a clearer analytical interpretation of the current landscape and avoid overgeneralization about the practical readiness of metaverse-enabled transportation systems, Table 2 classifies the reviewed applications by implementation maturity and technological readiness levels. The proposed classification framework distinguishes between conceptual studies, simulation-based investigations, prototype developments, pilot implementations, and operational applications, thereby offering a comparative perspective on the current developmental status of metaverse technologies across different transportation environments.

Whereas metaverse-enabled transportation systems share several common technological foundations, their operational objectives, implementation constraints, and maturity levels differ considerably across transportation modes. Road systems emphasize real-time adaptive control and large-scale interaction management, whereas railway systems prioritize safety-critical synchronization and infrastructure coordination. Maritime applications mainly focus on logistics visibility, port digitalization, and remote operations, while aviation applications emphasize high-fidelity simulation, training, predictive maintenance, and operational safety. To synthesize these differences, Table 3 comparatively summarizes the

principal advantages, limitations, and current implementation maturity associated with metaverse applications across major transportation domains.

Table 1. Main features of metaverse applications in different transport systems.

Transportation Mode	Core Metaverse Application Areas	Key Enabling Technologies	Decision Support and Operational Benefits	Safety and Risk Management Capabilities	Infrastructure and Lifecycle Management	Sustainability and Energy Optimization Features	Human–System Interaction and Training
Road	Predictive traffic analysis, adaptive control, coordinated infrastructure management, safety assessment, and policy testing.	Digital twins, IoT sensing, AI-driven analytics, Extended reality (XR), Edge computing, V2X communication, and software-defined control.	Enables comparative reasoning across parallel futures and robust decision evaluation under uncertainty through synchronized digital environments.	Proactive risk management using conflict indicators and near-miss simulations; tracks infrastructure vulnerabilities without recorded accidents.	Long-term exploration of degradation trajectories and intervention strategies; integrates pavement condition and environmental data.	Evaluation of low-emission zones and policy impacts on environmental limits and sustainability indicators across simulated futures.	Collaborative exploration via immersive interfaces; shared situational awareness across institutional boundaries for planners and operators.
Rail	Operations and traffic management, safety analysis, maintenance, energy management, and workforce training.	Digital twins, Building Information Modeling (BIM), GIS, IoT sensor networks, AI (ML/DL/GNNs), and XR.	Adaptive train scheduling and rescheduling; conflict detection and resolution; multi-objective optimization of punctuality and energy.	Simulation of signaling failures, infrastructure degradation, and malfunctions; proactive stress-testing of emergency responses.	Tracking degradation and usage intensity; virtual inspection and scenario-based evaluation of maintenance and investment prioritization.	Optimization of traction power and regenerative braking, life-cycle assessment (LCA) and carbon accounting embedded in Digital twins.	Immersive XR environments for driver and dispatcher situational awareness; simulation of rare critical scenarios and emergency events.
Maritime	Navigation, port efficiency, energy and environmental performance, and logistics/supply chain coordination.	Digital twins, IoT sensors, Automatic Identification System (AIS), Radar, Satellite observations, AI forecasting, and XR interfaces.	Predictive simulation of traffic evolution and risk propagation; coordinated decision-making between operators, pilots, and port authorities.	Advanced analysis of collision avoidance and grounding risk; modeling cascading failures from weather or cyber-physical vulnerabilities.	Persistent digital twin of ports and offshore structures; structural health monitoring; evaluation of rehabilitation and decommissioning.	Optimization of speed, route planning, and berth-side energy; modeling greenhouse gas emissions and auxiliary power using LCA tools.	High-fidelity simulation of berthing maneuvers and navigation; adaptive training modules for port personnel and pilots.
Aviation	Air traffic management (ATM), airport operations, pilot/crew training, safety assurance, and AAM integration.	High-fidelity digital twins, AI/ML, Avionics data, ADS-B trajectories, Radar, IoT airport sensors, and XR cockpits.	3D visualization of airspace and conflict geometries; dynamic exploration of ‘what-if’ scenarios for trajectory and gate assignment.	Risk-free evaluation of conflict detection for mixed traffic (drones/eVTOL); assessment of airspace capacity and separation standards.	Full lifecycle management of aircraft and airport systems from design and certification to predictive maintenance and recycling.	Spatiotemporally explicit modeling of CO ₂ , NO _x , and noise; evaluation of sustainable aviation fuels (SAF) and electrification.	Immersive multi-user platforms for pilots and controllers; behavioral and physiological tracking for performance assessment.

Table 2. Technological maturity levels of metaverse applications across transportation modes.

Maturity Level	Description	Typical Characteristics	Transportation Examples
Conceptual	Visionary/theoretical frameworks	Governance visions, architecture proposals	Smart road metaverse governance frameworks
Simulation-Based	Virtual experiments and digital simulations	Traffic simulations, scenario evaluation	AI traffic twins, rail operation simulations
Prototype	Early stage technological demonstrators	Limited functional integration	XR-assisted port operations
Pilot	Real-world limited deployment	Controlled field testing	Airport digital twin pilots
Operational	Fully integrated deployment	Real-time synchronization and decision support	Advanced ATM digital twin systems

As shown in Table 3, transportation metaverse applications remain highly heterogeneous in both technological maturity and operational readiness. While certain enabling technologies such as digital twins, AI-driven analytics, and immersive visualization have already reached pilot or partially operational stages in railway and aviation systems, fully

integrated metaverse environments capable of persistent multi-actor coordination and governance-aware decision-making remain largely conceptual. This observation further supports the argument that the transportation metaverse should currently be interpreted as an evolving systems-integration paradigm rather than a fully deployable technology.

Table 3. Comparative advantages, limitations, and implementation maturity of metaverse applications across transportation modes.

Transportation Mode	Main Advantages of Metaverse Integration	Main Limitations/Challenges	Current Implementation Maturity
Smart Roads/ITS	Real-time traffic management; adaptive infrastructure control; integration of CAVs and V2X systems; predictive traffic analysis; multi-scenario policy evaluation	High data heterogeneity; cybersecurity risks; interoperability challenges; scalability under large urban networks; uncertainty in human behavior	Prototype/Early Pilot
Railway Systems	High-fidelity infrastructure monitoring; predictive maintenance; timetable coordination; operational safety enhancement; digital twin integration	Strict safety certification requirements; legacy infrastructure compatibility; synchronization complexity; high implementation costs	Pilot/Partial Operational
Maritime Transport	Port digitalization; fleet coordination; cargo visibility; remote vessel monitoring; logistics optimization	Limited global standardization; satellite communication latency; fragmented international governance; cybersecurity vulnerabilities	Conceptual/Pilot
Aviation Systems	Advanced simulation and training; predictive maintenance; airspace management support; safety-oriented operational modeling	Extremely strict regulatory constraints; certification complexity; high infrastructure costs; data privacy and operational-security concerns	Pilot/Partial Operational
Multimodal Transportation Systems	Integrated mobility coordination; system-wide optimization; shared digital environments; collaborative policy testing	Institutional fragmentation; interoperability between heterogeneous systems; governance ambiguity; high computational requirements	Conceptual/Early Prototype

5. Opportunities, Limitations, and Open Research Challenges of Metaverse Adoption in Transportation Systems

The greatest promise of the transportation metaverse lies not in its ability to enhance individual modes of transport but in its potential to reshape system-level reasoning, coordination and learning across heterogeneous domains. A persistent, shared digital environment anchored in real infrastructure conditions and institutional constraints can become a common analytical substrate for modeling, exploring, and governing multimodal transport subsystems coherently [193]. By providing continuously synchronized digital twins for roads, railways, ports, airports, vehicles, and control centers, the metaverse may enable decision-makers to move beyond isolated performance improvements towards comparative analyses of strategies across time horizons, organizational scales, and uncertainty regimes [194]. Critical to this vision is the ability to explore multiple internally consistent futures concurrently, where differing demand patterns, control policies, incident scenarios and regulatory interventions are simulated side by side without reducing uncertainty to a single forecast [195]. Infrastructure, therefore, becomes the stabilizing frame through which all virtual futures are constrained, guaranteeing that system-level knowledge remains rooted in practice rather than speculative abstraction [196]. By fostering multi-scale coordination between real-time operations, tactical management and long-range planning, the metaverse has the potential to become an integrative operating architecture

for resilient, uncertainty-aware governance of increasingly complex and interdependent transportation systems.

Despite these opportunities, metaverse deployments face substantial technical and infrastructural constraints. Persistent virtual environments require continuous, high-fidelity data streams to capture the evolving states of physical systems. In practice, sensing infrastructures remain fragmented and fallible: sensor noise, calibration drift, intermittent failures and uneven spatial coverage introduce uncertainty that propagates through digital twins and affects predictive results [197]. These problems become acute when large networks, distributed assets and multi-resolution models must be synchronized across physical and virtual systems in real time. Data-driven twins must integrate physics-based simulation with operational data and feed performance insights back into the virtual representation. High-resolution twins also demand substantial computing power, storage and communications bandwidth, raising latency, energy-consumption and robustness challenges. Interoperability remains a persistent bottleneck because legacy control systems, proprietary platforms and mode-specific data standards hinder seamless knowledge exchange [198]. These factors illustrate that the transportation metaverse is constrained not by a single missing technology but by the difficulty of orchestrating sensing, computation, communication and integration infrastructures at scales and reliabilities that exceed current deployment-ready systems.

Technological feasibility does not guarantee successful implementation; organizational and operational factors shape whether metaverse platforms influence real decision-making. Contemporary transport services rely on established institutional frameworks, control mechanisms and workflows built around conventional monitoring and decision-support tools. Introducing immersive, data-rich environments often requires redefining roles, responsibilities and lines of communication, and may face resistance from practitioners concerned about operational risk or the loss of familiar practices [199]. Skills deficits in data interpretation, human–AI communication and immersive-interface design can erode the business value of metaverse platforms, regardless of technical capability [200]. Metaverse applications typically involve multiple organizations, increasing coordination complexity and raising questions about decision authority and accountability. Fragmented governance, characteristic of ports, airports, and urban road networks, amplifies these issues; organizational readiness and institutional alignment thus become key determinants of whether metaverse technologies catalyze systemic change or remain confined to isolated pilots.

Immersive digital environments alter operators' perception, cognitive workload and trust dynamics. High-dimensional visualizations can improve situational awareness but may impose additional cognitive load due to greater information density, visual complexity, and interactive demands, particularly under time pressure or abnormal conditions [201]. Operators must continually evaluate the reliability, timeliness and completeness of digitally mediated system states, especially when virtual cues diverge from physical observations [202]. Misplaced trust in simulated or predictive inputs can lead to automation bias, reduced vigilance and delayed intervention, which is particularly hazardous in safety-critical domains such as air traffic control and railway operations [203]. Usability challenges—navigation, interaction precision and ergonomics—may hinder routine integration into workflows [204]. These observations highlight the need to calibrate human–machine interfaces so that metaverse environments augment human reasoning rather than displace it. Advanced interface design, targeted training and governance frameworks that uphold accountability and situational awareness are essential prerequisites for safe and effective human-in-the-loop decision support [205].

The deployment of metaverse-based transport systems is also conditioned by governance and regulatory frameworks that historically have been oriented toward physical

infrastructure, certified hardware and deterministic procedures. Existing legal regimes often lack clear provisions for decisions made within persistent virtual environments, complicating questions of liability and accountability when digital analyses influence safety-critical operations [206]. Security certification (e.g., NIST SP800-53) is usually done at design time; for self-adaptive systems whose functional and security conditions change at runtime, “static security solutions are insufficient” and adaptation may require dynamic certification, which is difficult due to complex dependencies [207]. Disagreements over data ownership, access rights and intellectual property further complicate the cross-organizational data sharing required for sustainable, shared platforms [208]. Without common standards for data models, interoperability and validation, integration efforts risk platform fragmentation and vendor lock-in [209]. The intensity of these challenges varies across transport domains; highly regulated sectors such as aviation and rail face particularly stringent certification and liability constraints, whereas less regulated road or urban mobility applications may have greater flexibility. Ultimately, in data-driven intelligent transportation systems, metaverse concepts (e.g., parallel virtual/real ITS, Metaverse on Wheels) introduce new data flows and AI-based services whose influence, limitations, and open issues remain unresolved, including security and privacy [77]. Metaverse-enabled transport platforms raise far-reaching ethical, privacy and social issues that stem from their persistent, data-intensive and predictive nature. Continuously operating virtual environments capture high-resolution sensor and behavioral data, raising concerns over surveillance, data exploitation and erosion of individual privacy [210].

Algorithmic bias represents another threat: models trained on partial or skewed data could disproportionately disadvantage certain user groups, exacerbating existing disparities in safety, accessibility or service provision [211]. Unequal access to metaverse infrastructure and digital skills risks widening the digital divide, allowing well-resourced institutions and regions to capitalize on advanced tools while socially disadvantaged populations are excluded [212]. These risks manifest differently across transport modes; aviation raises questions about passenger profiling and data sovereignty, while urban road systems confront issues of equity and accessibility. Addressing these concerns requires embedding ethical values, privacy-preserving data governance and equity considerations into the design and deployment of metaverse infrastructures so that technological advancement aligns with societal objectives [213]. Realizing the vision of a transportation metaverse requires addressing several open research challenges. A key technical frontier is the design of scalable, real-time digital twins capable of co-simulating massive, heterogeneous networks while maintaining fidelity, stability and responsiveness amid deep uncertainty and rapidly evolving conditions [214]. Developing collective-intelligence frameworks that orchestrate multiple learning and optimization agents within shared virtual environments remains an open problem; most current approaches rely on isolated or centralized decision models [215]. Explainable and interpretable AI-based decision-support systems are critical for operator trust and regulatory acceptance, yet current metaverse platforms often lack transparent reasoning mechanisms [216]. Systematic exploration of human-in-the-loop governance models and appropriate divisions of authority between automated analytics and human decision-makers is necessary to enhance accountability and situational awareness [217]. Finally, cross-modal research is needed to understand how challenges and opportunities differ between self-organizing road networks, virtual airspace management for dense manned–unmanned traffic and smart port systems integrating logistics, energy and environmental coordination [218]. Interdisciplinary collaboration among transportation engineering, computer science, human factors and institutional analysis will be essential to establish the metaverse as a foundational platform for future transportation governance.

Overall, the opportunities, limitations, and open research challenges discussed in this section demonstrate that the transformative potential of the transportation metaverse extends far beyond isolated technological experimentation and should instead be interpreted as a system-level operational paradigm capable of restructuring how transportation systems are planned, governed, monitored, and optimized under uncertainty. Although individual metaverse applications already show promising capabilities in predictive analytics, immersive simulation, collaborative decision-making, and infrastructure synchronization, their broader implementation remains constrained by interconnected technical, organizational, regulatory, human-centered, and ethical barriers. As summarized in Table 3, these challenges are not independent phenomena but highly interrelated dimensions of a broader socio-technical transition. Technical and infrastructural limitations—including synchronization fidelity, interoperability, and computational scalability—directly influence operational reliability and decision-support accuracy. Simultaneously, governance and certification constraints affect institutional adoption, while human-factor challenges influence trust, usability, and operational safety within immersive environments. Organizational fragmentation, insufficient digital readiness, and unresolved accountability structures further complicate cross-domain implementation, especially in multimodal transportation ecosystems involving heterogeneous stakeholders and distributed infrastructures. In parallel, ethical concerns associated with privacy, algorithmic bias, surveillance, and unequal access demonstrate that metaverse deployment cannot be treated solely as a technological problem, but must instead incorporate broader societal and governance considerations from the earliest design stages.

Consequently, the transportation metaverse should not be interpreted merely as a collection of immersive visualization tools or isolated digital twins, but rather as an emerging integrative architecture capable of linking persistent virtual environments, real-time operational data, advanced analytics, and human-centered governance into a unified and continuously adaptive ecosystem. In this context, Table 4 provides a structured synthesis of the principal dimensions shaping future metaverse adoption in transportation systems, including technical infrastructure, human factors, governance, organizational structures, and ethical implications. The table additionally highlights the associated risks, stakeholder impacts, and inferred policy or research needs required for large-scale implementation. Collectively, these findings indicate that future progress in transportation metaverse systems will depend not only on advances in AI, sensing, simulation, and digital twins, but also on the development of interoperable standards, privacy-preserving governance frameworks, scalable real-time synchronization architectures, and transparent human-in-the-loop decision models. Ultimately, the transportation metaverse represents a transition from fragmented and reactive mobility-management practices toward persistent, uncertainty-aware, and collaboratively governed transportation ecosystems capable of supporting more resilient, transparent, and adaptive mobility futures.

Table 4. Challenges, risks, impact, and policy needs in several fields of transportation systems related to metaverse applications.

Category	Key Dimensions	Detailed Description	Key Challenges and Risks	Impact on Stakeholders	Research or Policy Needs (Inferred)
Technical and Infrastructural	Data Fidelity, Synchronization, Interoperability, and Computation	Dependencies on continuous high-fidelity data streams from heterogeneous sensors and the need for real-time synchronization between physical and virtual systems at scale.	Sensor noise, calibration drift, legacy system incompatibility, high energy consumption, and latency issues in safety-critical domains like aviation and rail.	Degraded predictive performance for operators and potential system instability during peak loads.	Development of scalable real-time digital twins and standardized data protocols to ensure deterministic performance and cross-domain exchange.

Table 4. Cont.

Category	Key Dimensions	Detailed Description	Key Challenges and Risks	Impact on Stakeholders	Research or Policy Needs (Inferred)
Human Factors	Cognitive Workload, Trust, and Usability	The shift in how operators perceive and act upon system states via high-dimensional visualizations and interactive representations.	Information overload, automation bias, reduced vigilance, and ergonomic design flaws leading to delayed human intervention in safety-critical contexts.	Operators may suffer from cognitive fatigue or misplaced trust in simulated outputs.	Investigation of human-in-the-loop governance models to define boundaries between automated reasoning and human authority.
Governance and Regulatory	Legal Frameworks, Certification, and Standards	The alignment of adaptive, data-driven virtual environments with physical-centric regulatory approval regimes.	Uncertainty regarding liability/accountability for virtual-based decisions and conflict between static certification processes and evolving digital twins.	Regulators struggle with auditability; platform providers face risks of technological lock-in due to lack of standards.	Regulatory innovation to grant legal recognition to hybrid digital decisions and coordinated standardization of data models.
Organizational and Operational	Institutional Structures and Decision Pathways	Integration of immersive environments into established hierarchical control frameworks and standardized workflows.	Resistance to change, disruption of established practices, skill gaps in human-AI collaboration, and ambiguity in decision authority across fragmented governance.	Operational personnel may face role redefinition; management faces increased coordination complexity in ports and urban networks.	Institutional alignment strategies and specialized training programs for data interpretation and immersive interface use.
Ethical and Societal	Privacy, Equity, and Algorithmic Bias	The socio-technical implications of continuous surveillance, predictive analytics, and access to advanced mobility tools.	Data misuse, erosion of individual privacy, algorithmic discrimination against user groups, and the widening of the digital divide.	Vulnerable populations may face exclusion; passengers in aviation may face acute profiling risks.	Embedding privacy-preserving data governance and equity considerations directly into the design and deployment phases.

6. A Metaverse-Based Framework for Smart Roads

This section introduces a metaverse-centric framework that translates the theoretical concepts discussed in the previous sections into a structured reference architecture for smart road systems. The framework is not designed as a single-corridor pilot or a narrowly defined technological prototype. Instead, it is formulated as a system-level architecture that can support integrated decision-making across long-term infrastructure planning, medium-term policy and control design, and short-term operational management. Smart roads are selected as the representative application domain because they involve dense interactions among infrastructure, connected and automated vehicles, road users, sensing systems, traffic operators, public authorities, and regulatory actors. This makes them a suitable environment for examining how metaverse-enabled coordination can improve transport governance under uncertainty. The proposed framework conceptualizes the metaverse not merely as a visualization interface or an advanced digital twin, but as a persistent, policy-aware, and multi-actor operational layer. It connects physical sensing, digital representation, predictive intelligence, human decision-making, and governance feedback within a unified cyber-physical environment. This position is consistent with Zhao et al. [93], who proposed a collaborative metaverse-digital twin system for traffic perception, reasoning, and resource scheduling, showing how physical infrastructure, virtual twin resources, and traffic situation awareness can be integrated into a closed perception-reasoning-scheduling loop. In the present framework, this logic is extended from operational traffic management toward a broader smart road governance architecture.

Figure 7 presents the layered architecture of the metaverse-enabled smart road ecosystem. The figure illustrates four interacting layers, moving from physical infrastructure and data acquisition to the metaverse core, functional intelligence domains, and strategic governance outcomes. It also shows two continuous feedback channels: policy and strategy updates on the left side, and continuous operational feedback on the right side. These feedback loops are essential because the smart road metaverse is not treated as a static modeling environment, but as a continuously evolving decision-support ecosystem. Figure 7, therefore, provides the structural basis for the seven procedural stages described below. The

relationship between the layered architecture in Figure 7 and the seven procedural stages is one of structural dependency rather than a direct one-to-one mapping. Stages 1 and 2, namely physical grounding and persistent virtualization, are mainly rooted in Layer 1 and Layer 2, where infrastructure sensing, V2X communication, traffic perception, edge computing, and long-term digital state management are established. Stages 3 and 4, namely policy-aware logic and parallel mobility universes, are mainly operationalized in Layer 2 and Layer 3, where embedded rules, governance objectives, multi-future simulation, and uncertainty exploration are implemented. Stage 5, cross-universe learning, operates mainly within Layer 3 by using predictive performance analysis, adaptive traffic control, proactive risk management, and infrastructure lifecycle intelligence. Stages 6 and 7, human-in-the-loop decision support and continuous governance feedback, are strongly connected to Layer 4, where uncertainty-aware decisions, validated infrastructure actions, collaborative decision environments, and anticipatory governance are produced.

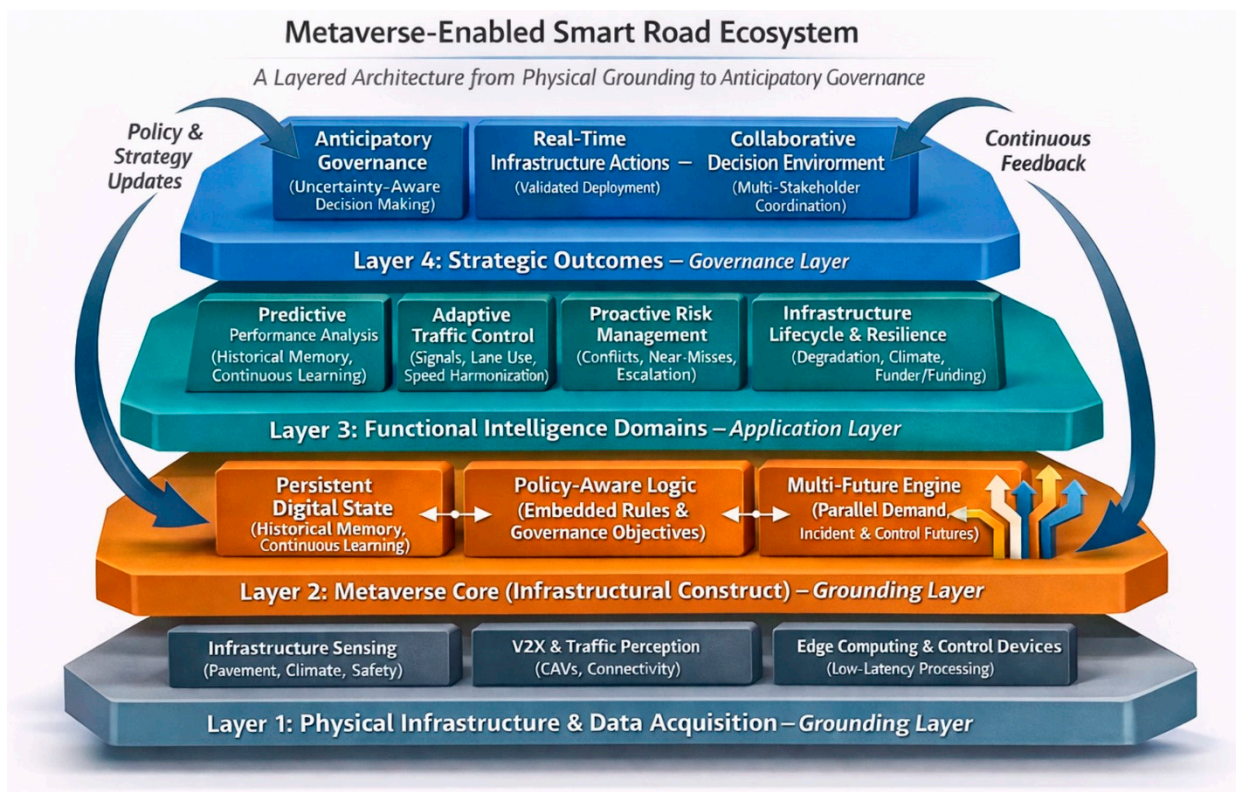


Figure 7. Layered architecture of the metaverse-enabled smart road ecosystem, from physical grounding to anticipatory governance.

The proposed framework describes the smart road metaverse as a multi-actor, multi-layer decision environment in which heterogeneous system entities interact through persistent virtual representations. These entities include road segments, intersections, sensors, pavement assets, roadside units, connected infrastructure, vehicle fleets, CAVs, and road users. User behavior may be represented through agent-based models, behavioral rules, or learned policies, depending on the application scope. In parallel, operational actors such as traffic managers, infrastructure operators, road authorities, public agencies, and policymakers are included as decision-makers who supervise, validate, modify, or constrain virtual recommendations. These actors operate across strategic, tactical, and operational decision layers. Strategic decisions concern infrastructure investment, regulatory scenarios, and lifecycle planning. Tactical decisions concern policy implementation, resilience planning, lane-use strategies, and traffic control design. Operational decisions concern

real-time signal control, lane allocation, speed harmonization, incident response, and emergency coordination.

The first stage proposes the empirical foundation of the smart road metaverse through physical grounding. In this stage, heterogeneous sensing, communication, and monitoring systems are integrated into a coherent data layer. These systems may include pavement and climate sensors, traffic detectors, video analytics, LiDAR, radar, connected infrastructure, V2X communication, and edge devices. Chen et al. [76] showed that roadside perception, RSUs, and edge computing are central components of smart roads because they enable real-time vehicle–road cooperation and improve safety and traffic efficiency. Their study also emphasized that the large-scale deployment of smart road infrastructure requires not only technical feasibility but also sustainable business and institutional models. Therefore, in the present framework, physical grounding is not only a sensing requirement but also a governance requirement. It may ensure that virtual operations remain traceable, observable, and anchored to real infrastructure conditions.

The second stage contributes to episodic digital models in a persistent metaverse environment that evolves continuously with the physical road system. Unlike conventional simulations, which are usually built for specific scenarios or limited time horizons, the smart road metaverse maintains historical memory, real-time state updates, and accumulated operational knowledge. Pan et al. [219] demonstrated that digital twins can support real-time monitoring, decision-making, and control when combined with multi-level computing architectures involving edge, fog, and cloud layers. This is directly relevant to smart roads because different traffic disturbances may require different computational responses. Minor disturbances may be handled at the edge, while more complex events may require cloud-based coordination. However, persistence also creates new methodological challenges, especially data drift, model degradation, and uncertainty accumulation. Gupta et al. [220] addressed this issue through TWIN-ADAPT, a continuous-learning digital twin framework that updates anomaly classification models under changing data distributions. Their contribution supports the need for recalibration mechanisms within the smart road metaverse so that the virtual representation does not become disconnected from evolving physical conditions.

The third stage embeds policies, regulations, and operational constraints into the internal logic of the smart road metaverse. Rather than applying policy as an external filter after simulation, this framework treats rules and governance objectives as native components of the virtual environment. These may include speed limits, lane-use restrictions, access control, emission thresholds, safety requirements, maintenance constraints, equity objectives, and emergency-response protocols. Uzun [59] argued that metaverse governance faces a regulatory pacing problem because institutional frameworks often evolve more slowly than immersive digital technologies. This is especially important for transport systems, where decisions may affect public safety, liability, privacy, and infrastructure access. Yang [83] further argued that metaverse governance should be supported by technical standards that ensure compatibility, security, and coordinated stakeholder participation. Accordingly, the present framework embeds policy-aware logic into the metaverse core, as shown in Figure 7, to ensure that all virtual experiments remain institutionally interpretable and operationally legitimate.

The fourth stage formalizes the concept of parallel mobility universes. In this stage, the smart road metaverse can represent multiple internally consistent futures of the same physical road system. These parallel universes may share the same infrastructure, initial traffic state, and regulatory context, but diverge according to demand evolution, incident occurrence, weather conditions, behavioral assumptions, control strategies, CAV-penetration rates, and infrastructure degradation patterns. Zhou et al. [221] reviewed resilience in

transportation systems and emphasized the importance of metrics, mathematical models, and strategies for enhancing system performance under disruptions. Their work supports the use of multiple future trajectories rather than single deterministic scenarios. Engholm and Kristoffersson [222] further showed that Many-Objective Robust Decision Making can help transport policy analysis under deep uncertainty by exploring trade-offs, sensitivities, and vulnerabilities across many possible futures. In this framework, parallel mobility universes serve the same purpose: they allow decision-makers to compare alternative futures and identify strategies that remain acceptable under uncertainty.

The fifth stage uses the coexistence of parallel mobility universes to enable cross-universe learning and predictive analytics. By comparing multiple constrained futures, the smart road metaverse can identify recurring patterns, fragile decisions, resilient strategies, and trade-offs among performance, safety, equity, emissions, and infrastructure lifecycle objectives. Tang et al. [223] showed that uncertainty-aware decision-making can improve autonomous vehicle safety by incorporating prediction uncertainty into the decision process. Their work is particularly relevant because smart roads will increasingly interact with CAVs whose behavior depends on perception, prediction, and control uncertainty. In the proposed framework, predictive models do not aim to identify one “most likely” future. Instead, they estimate robustness, confidence, and variability across alternative futures. This supports safer and more transparent decision-making, especially when the system faces non-stationary demand, rare incidents, or behavioral regime shifts.

The sixth stage translates metaverse-generated insights into practical decision support and controlled intervention while preserving human accountability. The framework does not assume full automation. Instead, it adopts a human-in-the-loop decision model in which operators, traffic managers, public authorities, and technical experts interact with recommendations generated by the metaverse. Soltanshahi and Maier [224] proposed a human–AI blockchain metaverse architecture in which human intelligence and AI agents interact through adaptive decision layers. Their work supports the idea that metaverse intelligence should not exclude human judgment, especially when decisions involve uncertainty, institutional legitimacy, or public accountability. Kumar et al. [218] also showed that human-in-the-loop learning improves trust, safety, and interpretability compared with fully automated systems. Similarly, Nunes et al. [225] emphasized that human involvement in cyber–physical systems improves adaptability but also requires attention to privacy, reliability, and user acceptance. In the smart road metaverse, human-in-the-loop decision support allows operators to evaluate trade-offs, validate recommendations, override unsafe suggestions, and authorize real-world interventions.

The seventh stage closes the cyber–physical loop through continuous feedback, governance oversight, and adaptive learning. Once operational decisions are implemented, their outcomes are recorded and returned to the metaverse environment. This allows model recalibration, policy revision, performance monitoring, and accountability assessment. The continuous feedback channel in Figure 7 represents this process. It may ensure that real-time infrastructure actions, traffic responses, safety outcomes, and user behavior are not only observed but also used to improve future decisions. At the governance level, this stage ensures that the system does not evolve only according to algorithmic efficiency, but remains constrained by institutional responsibility, ethical limits, transparency requirements, and public-interest objectives.

Overall, the proposed framework is scientifically grounded because each stage builds on established research in smart roads, digital twins, transportation resilience, robust decision-making, uncertainty-aware control, human-in-the-loop systems, and metaverse governance. Its novelty lies not in claiming that all individual technologies are new, but in integrating persistence, parallelism, policy embedding, cross-universe learning, and

human-supervised governance into a single smart road metaverse architecture. The framework is also feasible because it can be implemented incrementally. Physical sensing and V2X systems can support the first layer; digital twins and edge-cloud computing can support the metaverse core; predictive models and robust decision tools can support functional intelligence; and human-in-the-loop governance can support validated deployment. Although the framework is instantiated for smart roads, its principles are transferable to other transport domains such as railways, airports, ports, and multimodal urban mobility systems. Therefore, it should be interpreted not as a mode-specific solution, but as a generalizable reference architecture for integrating metaverse-enabled environments into transport planning, management, and governance.

7. Future Research Directions and Implications for Transport Planning, Management, and Operations

Using the metaverse-oriented framework established in Section 5, this section moves beyond architectural design and develops a future-oriented research agenda for metaverse-enabled smart road systems. The proposed framework demonstrates how physical infrastructure sensing, persistent digital representation, predictive intelligence, adaptive control, and governance-oriented decision-making can be systematically connected within a metaverse environment. However, it should not be interpreted as a mature or fully deployable solution. Rather, it represents a baseline configuration that exposes unresolved scientific, computational, institutional, and ethical challenges. The objective of this section is therefore not to restate the general challenges of metaverse technologies, but to identify the research directions required to move metaverse-enabled transportation systems from conceptual prototypes toward scalable, reliable, explainable, legally compliant, and socially legitimate operational paradigms.

A primary research direction concerns the development of scalable and uncertainty-aware digital twin architectures for transportation networks. Rasheed et al. [193] conceptualize digital twins as adaptive digital models of physical systems and emphasize their potential value for monitoring, prediction, optimization, and decision support in complex engineering systems. However, Arin et al. show that digital twin implementation still faces major barriers related to data integration, standardization, privacy, cybersecurity, and technical expertise [226]. These limitations are particularly important in smart road systems, where the physical environment is dynamic, heterogeneous, and influenced by human behavior, vehicle automation, weather, incidents, and infrastructure degradation. Future research should therefore examine how digital twin architectures can be extended from localized assets and short-term simulations toward network-level, persistent, and multi-resolution models. Such models must maintain stable synchronization between real and virtual systems while supporting long simulation horizons and multiple levels of spatial and temporal detail.

This scalability challenge is closely connected to the use of artificial intelligence and metaverse-based simulation in transportation planning. Ali and Nabeel [194] showed that the integration of AI and metaverse technologies can improve transport planning by supporting more adaptive, resilient, and data-driven decision-making. Zhang et al. [79] further propose the concept of parallel vision for intelligent transportation systems in the metaverse, where virtual traffic spaces, computational experiments, and real-world feedback are combined to improve perception, reasoning, and control. These studies suggest that future smart road metaverses should not merely visualize current traffic conditions, but should generate multiple possible futures, evaluate competing policies, and feed robust decisions back into the physical system. In this direction, future research should focus on the design of multi-future simulation engines capable of representing

demand variability, incident propagation, control failures, user response, and infrastructure constraints across different scenarios.

Another important research direction is the explicit modeling of uncertainty. Irfan et al. [95] emphasize that transportation digital twins require hierarchical architectures that can support traffic safety, mobility, and environmental applications at different operational scales. However, most existing digital twin applications still tend to produce deterministic outputs rather than confidence-aware recommendations. Battula et al. [195] highlight the importance of uncertainty quantification in digital twins, particularly for addressing sensor noise, data variability, model mismatch, and unpredictable disturbances. Future research should therefore develop uncertainty-aware transportation metaverses that report not only predicted states, but also confidence intervals, sensitivity measures, robustness indicators, and failure probabilities. This is essential for using metaverse outputs in safety-critical planning and operational contexts.

The proposed framework also raises significant questions about collective intelligence and multi-agent coordination. In a metaverse-enabled smart road system, vehicles, infrastructure components, traffic controllers, digital twins, public authorities, service providers, and users may all act as autonomous or semi-autonomous agents. To enhance situational awareness across intelligent transportation networks, cooperative perception digital twins can be deployed in edge-cloud environments to preserve a live digital replica of the transit ecosystem. As illustrated by Tihanyi et al. [227], this architecture integrates heterogeneous sensor streams from vehicles and local infrastructure nodes into a unified, high-fidelity spatial model that optimizes object tracking and traffic monitoring accuracy. From a broader control perspective, Chen and Ren [228] show that multi-agent systems require formal mechanisms for consensus, cooperation, formation control, and distributed coordination. Future research should therefore explore how multi-agent reinforcement learning, game-theoretic negotiation, distributed optimization, and rule-based governance can be combined to support coordinated decision-making in smart road metaverses. A key challenge is to prevent locally optimal agent behavior from producing globally inefficient, unsafe, or institutionally unacceptable outcomes.

Explainability and human-machine governance represent another major research frontier. Human-centered XAI explicitly prioritizes user and situational context, reflection, and actionability over purely algorithmic concerns [229]. This is highly relevant for metaverse-enabled transportation systems, where decision-makers may need to interpret complex outputs generated by AI models, digital twins, and multi-agent simulations. Gorgoni further stresses that algorithmic decision-making raises fundamental concerns about human responsibility, agency, opacity, discrimination, and accountability in an increasingly algorithmic society [230]. Future research must therefore clarify how complex metaverse outputs can be made intelligible to engineers, planners, operators, regulators, and the public. This requires more than improved visualization interfaces. It requires transparent assumptions, traceable data flows, explainable causal relationships, auditable decision histories, and clearly defined boundaries between algorithmic recommendation and human authority.

Legal and institutional governance must evolve in parallel with technical development. Frosio and Obafemi [209] examine regulated data access in the metaverse and show that immersive environments generate complex forms of data, including spatial, biometric, behavioral, and eye-tracking information, which require new accountability mechanisms. Jørgensen and Ma analyze digital twins under European law and show that digital twin systems are affected by overlapping regulatory domains, including privacy, cybersecurity, transparency, interoperability, data governance, and AI accountability [231]. Wang et al. also identify security, privacy, scalability, interoperability, and identity protection as fun-

damental challenges for metaverse systems [232]. These findings indicate that future smart road metaverses must be designed with compliance-by-design, privacy-by-design, and security-by-design principles from the beginning. Future research should therefore investigate how certification, validation, liability allocation, data access rules, and audit procedures can be operationalized for adaptive transportation metaverses.

Ethical considerations should also be embedded as internal design constraints rather than treated as external compliance requirements. Mureddu et al. show that local digital twins raise ethical and legal concerns related to personal information protection, algorithmic transparency, data governance, and responsible adoption [233]. Tabassum et al. further demonstrate that the integration of generative AI and metaverse environments creates new risks related to misinformation, bias, privacy, and the responsible generation of digital content [234]. These issues are particularly important in transportation because decisions may affect accessibility, safety, surveillance, environmental exposure, and the distribution of mobility benefits. Future research should therefore examine how equity, fairness, privacy protection, inclusiveness, and public trust can be encoded into the design of metaverse-enabled smart road systems. This includes evaluating whether such systems disproportionately benefit highly connected users, automated vehicles, or technologically advanced regions while excluding vulnerable users or less digitized communities.

Institutional adaptation is another unresolved issue. Metaverse governance requires institutional arrangements capable of addressing privacy, ethics, regulatory coordination, and platform accountability [83]. Also, blockchain-based decentralized governance may suffer from concentrated voting power, dependency risks, and governance capture [60]. However, interoperability can serve as a critical structural pillar that requires comprehensive policy initiatives and unified technical standards [194]. This foundational framework is vital to allow diverse platforms and sub-environments to interface seamlessly across data, technological, human, and institutional dimensions. These studies indicate that future transportation metaverses cannot rely only on technical innovation or decentralized mechanisms. They require institutional models that define the roles of public agencies, private operators, technology providers, regulators, and citizens. Future research should therefore explore governance structures for public–private collaboration, standardization, platform interoperability, and democratic oversight in transportation metaverse ecosystems.

Finally, future research should extend metaverse-enabled smart road frameworks toward cross-modal and system-level mobility integration. Although the framework proposed in Section 5 focuses on smart road infrastructure, real-world mobility is interconnected across road, rail, air, maritime, micromobility, walking, and public transport systems. Smart mobility in smart cities involves multiple interdependent challenges, including parking, routing, emissions, road safety, traffic management, and multimodal service coordination [74]. Future research should therefore examine how persistent virtual environments can synchronize heterogeneous digital twins across transport modes. This includes aligning demand models, pricing policies, emissions management, infrastructure constraints, disruption response, and accessibility objectives within a unified analytical environment. Such integration would allow planners to evaluate long-term investment strategies across multiple possible futures, while operators could anticipate cascading disruptions across modes before they materialize in the physical system.

Collectively, these research directions show that the successful implementation of metaverse-enabled transportation systems requires more than technology deployment. Scalable and uncertainty-aware digital twins are needed to represent complex road networks over time. Multi-agent intelligence is required to coordinate heterogeneous actors and decision layers. Explainable human–machine governance is essential to maintain accountability and trust. Legal, ethical, and institutional frameworks must evolve to regulate

data-intensive, adaptive, and immersive decision environments. Cross-modal integration is also necessary to avoid isolated digital deployments and realize the system-level benefits of transportation metaverses. Therefore, the transportation metaverse should be understood not as a digital end-product, but as a socio-technical paradigm for rethinking planning, management, operation, and governance in future mobility systems.

8. Conclusions

Transportation systems increasingly experience deep uncertainty, tightly coupled interactions among heterogeneous actors, and reliance on data-driven, automated decision-making across planning, management, and operational horizons. Although advances in sensing, simulation, and artificial intelligence significantly extend analytic capacity, these tools are typically implemented in fragmented, piecemeal, and mode-specific setups, which may not be able to identify, in the near future, the wider global interactions among players in their ecosystem, as well as long-term dynamics. Despite recent progress, transportation governance is stymied by a lack of flexibility in analyzing alternative futures, coordinating across institutional divisions, and adjusting actions to changing circumstances. This paper aims to fill this structural gap by reframing the metaverse not as an emerging visualization technology, but rather as a persistent, policy-aware digital environment that supports coherent, uncertainty-aware reasoning for complex transportation systems. The article contributes several interdependent approaches to describe the emerging metaverse-mediated transportation (metaverse-enabled) systems. First, it introduces a systems-level understanding of the transportation metaverse, moving beyond mode-specific implementation and tool-focused concepts, situating it as a consistent, policy-attuned operating environment for transportation governance. Second, it offers a critical cross-modal overview of the opportunities, constraints, and open research questions related to metaverse deployment, covering key technical, organizational, human, regulatory, and ethical issues. Third, the research proposes an explicit metaverse-driven model, instantiated in smart road systems, to demonstrate how persistent virtualisation, parallel futures, embedded constraints, and human-in-the-loop decision support can be integrated within a single architectural logic. Finally, the paper offers a forward-looking research agenda that defines the methodological and institutional pathways for evolving metaverse-enhanced transportation systems from conceptual prototypes to sustainable, socially legitimate modes of operation. At the same time, smart road systems are used less as a case in point and more as a case for investigating the practical and institutional dimensions of metaverse adoption in transport. Roads are among the most complex, frequently used transportation infrastructures and are characterized by high asset interaction density, heterogeneous vehicle fleets, human users, and multiple levels of public governance. Meanwhile, smart roads are becoming more sophisticated and have already been deployed with sensing, communication, and control technologies to enable continuous virtualisation and real-time data inclusion. Such conditions place road networks at the crossroads of technological innovation, behavior and regulation so that the framework can be tested under rigorous operational and governance challenges. As a result, the smart road framework is relevant as an illustrative reference architecture, serving as the concept that underpins other modes of transportation, rather than a mode-specific or narrowly scoped approach. While this framework will serve the scope of smart road structures, its principles and theoretical logic are not specific to one mode of transportation but are applied to integrated modes of mobility. At the system level, persistent virtualisation, uncertainty-sensitive reasoning, and policy-embedded decision support together create a shared platform for tackling challenges across road, rail, air, and maritime transport, despite variations in operating conditions and legal frameworks. In rail services, these principles apply to safety-critical coordination and capacity management

during disasters and disruptions, and, in aviation, provide possible approaches toward explainable, certified virtual decision environments for more automated airspace operations. Lifecycle-based digital twins that integrate logistics, energy consumption and environmental performance in a shared virtual environment may prove useful for a range of maritime and port systems. The metaverse-based approach outlined in this paper suggests a way forward for more integrated, resilient, and adaptive mode-to-mode transportation planning and operations, emphasizing common governance frameworks and cross-modal coherence over stand-alone technology deployment. The study's findings should be analyzed critically, taking into account its scope and purpose. However, such a theory-driven approach, based on pre-existing frameworks and practical technological resources, is merely a conceptual and architectural contribution that should be treated as theoretical, not as a well-utilized or empirically validated system. The paper does not attempt to offer a series of concrete performance appraisals and evidence for broad, integrated deployments, even though such assessments are context-bound and influenced by institutional, regulatory, and data availability limitations. Furthermore, the feasibility and impact of metaverse-enabled transportation systems will be determined by structural designs, organizational preparedness, governance competence, and societal acceptance, which vary greatly across regions, modes, and ways of transportation. Such restrictions are not a challenge to the overall validity of the framework; they delimit certain areas and indicate where empirical research/pilot experiments are crucial to supplement the conceptual progress in this study. The analyses and models presented in this paper encourage a wider re-analysis of the role of the metaverse in transportation systems, replacing it with more complex digital tools for a single, whole-world operating paradigm toward uncertainty-aware mobility governance. Instead of serving as a secondary layer for visualization or simulation, the metaverse is conceived as a persistent, policy-embedded environment within which infrastructure states, analytical models, and human decision-making co-evolve over time. Under this paradigm, experimentation, learning, and coordination are ongoing rather than random, allowing transportation systems to anticipate and adapt to conditions rather than respond. This view posits that the potential for transformation in the transportation metaverse does not stem from technological advancements. Still, the revolution can change how planning, management, and operational decisions are made, managed, and validated. By framing the metaverse as an operational model rather than a single technology, this paper lays a foundation for future research and practice, and guides the sustainable and ethical design of resilient, transparent, and socially accountable transportation systems.

Author Contributions: Conceptualization, M.K. and M.G.; methodology, M.K.; formal analysis, M.K.; investigation, M.K.; writing—original draft preparation, M.K.; writing—review and editing, M.K. and M.G.; supervision, M.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: This study is based on the analysis and synthesis of previously published literature. No new datasets were generated or analyzed during the current study.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AAM	Advanced Air Mobility
ADS-B	Automatic Dependent Surveillance–Broadcast
AIS	Automatic Identification System

ATM	Air Traffic Management
BIM	Building Information Modeling
CAVs	Connected and Autonomous Vehicles
GIS	Geographic Information Systems
IoT	Internet of Things
ITS	Intelligent Transportation Systems
LCA	Life Cycle Assessment
ML	Machine Learning
DL	Deep Learning
GNNs	Graph Neural Networks
V2X	Vehicle-to-Everything Communication
V2V	Vehicle-to-Vehicle Communication
V2I	Vehicle-to-Infrastructure Communication
XR	Extended Reality
UAVs	Unmanned Aerial Vehicles
eVTOL	Electric Vertical Take-Off and Landing
SAF	Sustainable Aviation Fuel

References

1. International Transport Forum. *ITF Transport Outlook 2023: Executive Summary*; OECD Publishing: Paris, France, 2023. Available online: <https://www.itf-oecd.org/sites/default/files/repositories/itf-transport-outlook-2023-summary-en.pdf> (accessed on 19 February 2026).
2. INRIX. *INRIX 2024 Global Traffic Scorecard: Employees & Consumers Returned to Downtowns, Traffic Delays & Costs Grew*; INRIX: Kirkland, WA, USA, 2025. Available online: <https://inrix.com/press-releases/2024-global-traffic-scorecard-us/> (accessed on 19 February 2026).
3. Rowan, D.; He, H.; Hui, F.; Yasir, A.; Mohammed, Q. A systematic review of machine learning-based microscopic traffic flow models and simulations. *Commun. Transp. Res.* **2025**, *5*, 100164. [[CrossRef](#)]
4. Algherbal, E.A.; Ratrou, N.T. A Comparative Analysis of Currently Used Microscopic, Macroscopic, and Mesoscopic Traffic Simulation Software. *Transp. Res. Procedia* **2025**, *84*, 495–503. [[CrossRef](#)]
5. Kaddoura, I.; Unterfinger, M.; Hettlinger, T.; Rakow, C.; Rieser, M. A large-scale hybrid micro- and mesoscopic simulation approach for railway operation. *Procedia Comput. Sci.* **2024**, *238*, 714–721. [[CrossRef](#)]
6. Bueno-Ferrer, Á.; De Pablo Valenciano, J.; De Burgos Jiménez, J. Unveiling the Potential of Metaheuristics in Transportation: A Path Towards Efficiency, Optimization, and Intelligent Management. *Infrastructures* **2024**, *10*, 4. [[CrossRef](#)]
7. Owais, M. Transit network design problem: A half century of methodological research. *Innov. Infrastruct. Solut.* **2026**, *11*, 3. [[CrossRef](#)]
8. Mahmoudi, R.; Saidi, S.; Wirasinghe, S.C. A critical review of analytical approaches in public bus transit network design and operations planning with focus on emerging technologies and sustainability. *J. Public Transp.* **2024**, *26*, 100100. [[CrossRef](#)]
9. Li, H.; Zhou, J.; Xu, K. Evolution of Green Vehicle Routing Problem: A Bibliometric and Visualized Review. *Sustainability* **2023**, *15*, 16149. [[CrossRef](#)]
10. Soto-Concha, R.; Morillo-Torres, D.; Escobar, J.W.; Mena-Reyes, J.F.; Linfati, R. Mixed-Integer Linear Programming Models for the Vehicle Routing Problem with Release Times and Reloading at Mobile Satellites. *Mathematics* **2025**, *13*, 3638. [[CrossRef](#)]
11. Chau, M.L.Y.; Gkiotsalitis, K. A systematic literature review on the use of metaheuristics for the optimisation of multimodal transportation. *Evol. Intel.* **2025**, *18*, 36. [[CrossRef](#)]
12. Zhang, Y.; Zhang, S.; Dinavahi, V. A survey of machine learning applications in advanced transportation systems: Trends, techniques, and future directions. *eTransportation* **2025**, *24*, 100417. [[CrossRef](#)]
13. Michailidis, P.; Michailidis, I.; Lazaridis, C.R.; Kosmatopoulos, E. Traffic Signal Control via Reinforcement Learning: A Review on Applications and Innovations. *Infrastructures* **2025**, *10*, 114. [[CrossRef](#)]
14. Lai, X.; Yang, Z.; Xie, J.; Liu, Y. Reinforcement learning in transportation research: Frontiers and future directions. *Multimodal Transp.* **2024**, *3*, 100164. [[CrossRef](#)]
15. Ali, R.; Ali, A.; Naem, H.M.Y.; Asad, M.; Alsarhan, T.; Heyat, M.B.B. A Comprehensive Survey of Deep Learning-Based Traffic Flow Prediction Models for Intelligent Transportation Systems. *ICCK Trans. Adv. Comput. Syst.* **2025**, *1*, 117–137. [[CrossRef](#)]
16. Li, C.; Bai, L.; Yao, L.; Waller, S.T.; Liu, W. A Bibliometric Analysis and Review on Reinforcement Learning for Transportation Applications. *arXiv* **2022**. Available online: <http://arxiv.org/abs/2210.14524> (accessed on 19 February 2026). [[CrossRef](#)]

17. Ostroukh, A.V.; Kuffinova, N.G.; Podberezkin, A.A.; Subbotin, B.S.; Podgorny, A.V. Use Digital Twins and the Metaverse to Analysis Data in the Agglomeration Transport Network. In *2023 Intelligent Technologies and Electronic Devices in Vehicle and Road Transport Complex (TIRVED)*, Moscow, Russia; IEEE: Piscataway, NJ, USA, 2023; pp. 1–5. Available online: <https://ieeexplore.ieee.org/document/10332750/> (accessed on 19 February 2026). [CrossRef]
18. Politi, T.; Denazis, S.; Koufopavlou, O.; Antonopoulos, C.; Faliagka, E.; Prevedourou, D.; Kostis, N.; Tranoris, C.; Voros, N.; Christophorou, C.; et al. Exploiting Digital Twins and Metaverse Technologies for the Digital Transformation of City Transportation. In *Climate Crisis and Resilient Transportation Systems*; Nathanail, E.G., Gavanas, N., Adamos, E., Eds.; Lecture Notes in Intelligent Transportation and Infrastructure; Springer Nature: Cham, Switzerland, 2025; pp. 841–854. Available online: https://link.springer.com/chapter/10.1007/978-3-031-82818-8_63 (accessed on 19 February 2026).
19. Hosseini, M.A.; Roozbahani, M.H.; Sayyah, A. AI-driven digital twin architecture for urban bus fleet life-cycle cost analysis in a metaverse environment. *Sustain. Cities Soc.* **2025**, *130*, 106611. [CrossRef]
20. Jamshidi, M.; Yahya, S.I.; Nouri, L.; Hashemi-Dezaki, H.; Rezaei, A.; Chaudhary, M.A. A High-Efficiency Diplexer for Sustainable 5G-Enabled IoT in Metaverse Transportation System and Smart Grids. *Symmetry* **2023**, *15*, 821. [CrossRef]
21. Wang, J.; Hao, Y.; Hu, L.; Fortino, G.; Alqahtani, S.A.; Chen, M. Urban Sensing of Virtual Internet of Things for Metaverse. *IEEE Sens. J.* **2024**, *24*, 5675–5686. [CrossRef]
22. Ali, W.; Nabeel, M. Augmenting transportation planning with AI and the metaverse: A meta-analytic approach to advancing sustainable development goals. *Life Cycle Reliab. Saf. Eng.* **2025**, 1–21. [CrossRef]
23. Xu, M.; Niyato, D.; Chen, J.; Zhang, H.; Kang, J.; Xiong, Z.; Mao, S.; Han, Z. Generative AI-Empowered Simulation for Autonomous Driving in Vehicular Mixed Reality Metaverses. *IEEE J. Sel. Top. Signal Process.* **2023**, *17*, 1064–1079. [CrossRef]
24. Sarwatt, D.S.; Yujia, L.; Jianguo, D.; Yunchuan, S.; Huansheng, N. Metaverse for intelligent transportation systems (ITS): A comprehensive review of technologies, applications, implications, challenges and future directions. *IEEE Trans. Intell. Transp. Syst.* **2024**, *25*, 6290–6308. [CrossRef]
25. Castro, C.; Leiva, V.; Basso, F. A Data-Driven Systematic Review of the Metaverse in Transportation: Current Research, Computational Modeling, and Future Trends. *Comput. Model. Eng. Sci.* **2025**, *144*, 1481–1543. [CrossRef]
26. Mystakidis, S. Metaverse. *Encyclopedia* **2022**, *2*, 486–497. [CrossRef]
27. Dionisio, J.D.N.; Burns, W.G., III; Gilbert, R. 3D Virtual worlds and the metaverse: Current status and future possibilities. *ACM Comput. Surv.* **2013**, *45*, 34. [CrossRef]
28. Andrade, A. Game engines: A survey. *EAI Endorsed Trans. Game-Based Learn.* **2015**, *2*, 150615. [CrossRef]
29. Trenholme, D.; Smith, S.P. Computer game engines for developing first-person virtual environments. *Virtual Real.* **2008**, *12*, 181–187. [CrossRef]
30. Chia, A. The metaverse, but not the way you think: Game engines and automation beyond game development. *Crit. Stud. Media Commun.* **2022**, *39*, 191–200. [CrossRef]
31. Greenhalgh, C.; Benford, S. Supporting Rich and Dynamic Communication in Large-Scale Collaborative Virtual Environments. *Presence Teleoper. Virtual Environ.* **1999**, *8*, 14–35. [CrossRef]
32. Moghaddam, S.S.; Shirvani Moghaddam, K. Sustainable Broadband Internet: Current Status and Future Directions. *IEEE Access* **2025**, *13*, 204416–204455. [CrossRef]
33. Wang, Y.; Siau, K.L.; Wang, L. Metaverse and Human-Computer Interaction: A Technology Framework for 3D Virtual Worlds. In *HCI International 2022—Late Breaking Papers: Interacting with eXtended Reality and Artificial Intelligence*; Chen, J.Y.C., Fragomeni, G., Degen, H., Ntoa, S., Eds.; Lecture Notes in Computer Science; Springer Nature: Cham, Switzerland, 2022; pp. 213–221. Available online: https://link.springer.com/10.1007/978-3-031-21707-4_16 (accessed on 19 February 2026). [CrossRef]
34. Wiederhold, B.K. Virtual Reality in the 1990s: What Did We Learn? *CyberPsychol. Behav.* **2000**, *3*, 311–314. [CrossRef]
35. Korkut, E.H.; Surer, E. Visualization in virtual reality: A systematic review. *Virtual Real.* **2023**, *27*, 1447–1480. [CrossRef]
36. Lee, H.; Woo, D.; Yu, S. Virtual Reality Metaverse System Supplementing Remote Education Methods: Based on Aircraft Maintenance Simulation. *Appl. Sci.* **2022**, *12*, 2667. [CrossRef]
37. Mandala, V.; Jeyarani, M.A.R.; Kousalya, A.; Pavithra, M.; Arumugam, M. An Innovative Development with Multidisciplinary Perspective in Metaverse Integrating with Blockchain Technology with Cloud Computing Techniques. In *2023 International Conference on Inventive Computation Technologies (ICICT)*, Lalitpur, Nepal; IEEE: Piscataway, NJ, USA, 2023; pp. 1182–1187. Available online: <https://ieeexplore.ieee.org/document/10134108/> (accessed on 19 February 2026). [CrossRef]
38. Zhang, H.; Lee, S.; Lu, Y.; Yu, X.; Lu, H. A Survey on Big Data Technologies and Their Applications to the Metaverse: Past, Current and Future. *Mathematics* **2022**, *11*, 96. [CrossRef]
39. Schlichting, M.S.; Fuchter, S.K.; Schlichting, M.S.; Alexander, K. Metaverse: Virtual and Augmented Reality Presence. In *2022 International Symposium on Measurement and Control in Robotics (ISMCR)*, Houston, TX, USA; IEEE: Piscataway, NJ, USA, 2022; pp. 1–6. Available online: <https://ieeexplore.ieee.org/document/9950565/> (accessed on 19 February 2026). [CrossRef]
40. Hatami, M.; Qu, Q.; Chen, Y.; Kholidy, H.; Blasch, E.; Ardiles-Cruz, E. A Survey of the Real-Time Metaverse: Challenges and Opportunities. *Future Internet* **2024**, *16*, 379. [CrossRef]

41. Huynh-The, T.; Pham, Q.V.; Pham, X.Q.; Nguyen, T.T.; Han, Z.; Kim, D.S. Artificial intelligence for the metaverse: A survey. *Eng. Appl. Artif. Intell.* **2023**, *117*, 105581. [CrossRef]
42. Baidya, T.; Moh, S. Comprehensive survey on resource allocation for edge-computing-enabled metaverse. *Comput. Sci. Rev.* **2024**, *54*, 100680. [CrossRef]
43. Murala, D.K.; Panda, S.K. Metaverse: A Study on Immersive Technologies. In *Metaverse and Immersive Technologies*, 1st ed.; Chandrashekhar, A., Saheb, S.H., Panda, S.K., Balamurugan, S., Peng, S., Eds.; Wiley: Hoboken, NJ, USA, 2023; pp. 1–41. Available online: <https://onlinelibrary.wiley.com/doi/10.1002/9781394177165.ch1> (accessed on 19 February 2026). [CrossRef]
44. Lee, J.; Kundu, P. Integrated cyber-physical systems and industrial metaverse for remote manufacturing. *Manuf. Lett.* **2022**, *34*, 12–15. [CrossRef]
45. Park, S.M.; Kim, Y.G. A Metaverse: Taxonomy, Components, Applications, and Open Challenges. *IEEE Access* **2022**, *10*, 4209–4251. [CrossRef]
46. Wang, H.; Ning, H.; Lin, Y.; Wang, W.; Dhelim, S.; Farha, F.; Ding, J.; Daneshmand, M. A Survey on the Metaverse: The State-of-the-Art, Technologies, Applications, and Challenges. *IEEE Internet Things J.* **2023**, *10*, 14671–14688. [CrossRef]
47. Lv, Z.; Shang, W.L.; Guizani, M. Impact of Digital Twins and Metaverse on Cities: History, Current Situation, and Application Perspectives. *Appl. Sci.* **2022**, *12*, 12820. [CrossRef]
48. Wang, X.; Wang, J.; Wu, C.; Xu, S.; Ma, W. Engineering Brain: Metaverse for future engineering. *AI Civ. Eng.* **2022**, *1*, 2. [CrossRef]
49. Akbar, U.; Ali, W. Digital Twin and Metaverse Integration for Predictive Traffic Management in Malaysian Smart Cities: A Fuzzy Multi-Criteria Decision-Making Approach. *Soft Comput. Fusion Appl.* **2025**, *2*, 134–145. [CrossRef]
50. Zheng, G.; Yuan, L. A review of QoE research progress in metaverse. *Displays* **2023**, *77*, 102389. [CrossRef]
51. Porcu, S.; Floris, A.; Atzori, L. Quality of Experience in the Metaverse: An Initial Analysis on Quality Dimensions and Assessment. In *2022 14th International Conference on Quality of Multimedia Experience (QoMEX), Lippstadt, Germany*; IEEE: Piscataway, NJ, USA, 2022; pp. 1–4. Available online: <https://ieeexplore.ieee.org/document/9900897/> (accessed on 19 February 2026). [CrossRef]
52. Deveci, M.; Mishra, A.R.; Gokasar, I.; Rani, P.; Pamucar, D.; Ozcan, E. A Decision Support System for Assessing and Prioritizing Sustainable Urban Transportation in Metaverse. *IEEE Trans. Fuzzy Syst.* **2023**, *31*, 475–484. [CrossRef]
53. Zhu, H.Y.; Hieu, N.Q.; Hoang, D.T.; Nguyen, D.N.; Lin, C.T. A Human-Centric Metaverse Enabled by Brain-Computer Interface: A Survey. *IEEE Commun. Surv. Tutor.* **2024**, *26*, 2120–2145. [CrossRef]
54. Khanna, P.; Karim, R.; Kumari, J. Issues and Challenges in Implementing the Metaverse in the Industrial Contexts from a Human-System Interaction Perspective. In *International Congress and Workshop on Industrial AI and eMaintenance 2023*; Kumar, U., Karim, R., Galar, D., Kour, R., Eds.; Lecture Notes in Mechanical Engineering; Springer Nature: Cham, Switzerland, 2024; pp. 303–318. Available online: https://link.springer.com/10.1007/978-3-031-39619-9_22 (accessed on 19 February 2026). [CrossRef]
55. Allam, Z.; Sharifi, A.; Bibri, S.E.; Jones, D.S.; Krogstie, J. The Metaverse as a Virtual Form of Smart Cities: Opportunities and Challenges for Environmental, Economic, and Social Sustainability in Urban Futures. *Smart Cities* **2022**, *5*, 771–801. [CrossRef]
56. Yang, L.; Ni, S.T.; Wang, Y.; Yu, A.; Lee, J.A.; Hui, P. Interoperability of the Metaverse: A Digital Ecosystem Perspective Review. *IEEE Eng. Manag. Rev.* **2025**, *53*, 29–54. [CrossRef]
57. Jung, H. Design of an Architecture for Interoperability between heterogeneous Metaverse platforms. In *2023 14th International Conference on Information and Communication Technology Convergence (ICTC), Jeju Island, Republic of Korea*; IEEE: Piscataway, NJ, USA, 2023; pp. 1500–1503. Available online: <https://ieeexplore.ieee.org/document/10393581/> (accessed on 19 February 2026). [CrossRef]
58. Perey, C. Interoperability is a Fundamental Requirement for the Open Metaverse. In *2024 IEEE International Symposium on Emerging Metaverse (ISEMV), Bellevue, WA, USA*; IEEE: Piscataway, NJ, USA, 2024; pp. 21–24. Available online: <https://ieeexplore.ieee.org/document/10764601/> (accessed on 19 February 2026). [CrossRef]
59. Uzun, M.M. Metaverse Governance. In *Metaverse*; Esen, F.S., Tinmaz, H., Singh, M., Eds.; Studies in Big Data; Springer Nature: Singapore, 2023; pp. 231–244. Available online: https://link.springer.com/10.1007/978-981-99-4641-9_16 (accessed on 19 February 2026). [CrossRef]
60. Goldberg, M.; Schär, F. Metaverse governance: An empirical analysis of voting within Decentralized Autonomous Organizations. *J. Bus. Res.* **2023**, *160*, 113764. [CrossRef]
61. Yan, X.; Zhang, H.; Wu, C. Research and Development of Intelligent Transportation Systems. In *2012 11th International Symposium on Distributed Computing and Applications to Business, Engineering & Science, Guilin, China*; IEEE: Piscataway, NJ, USA, 2012; pp. 321–327. Available online: <http://ieeexplore.ieee.org/document/6385299/> (accessed on 20 February 2026). [CrossRef]
62. Gamboa-Rosales, N.K.; Celaya-Padilla, J.M.; Hernandez-Gutierrez, A.L.; Moreno-Baez, A.; Galván-Tejada, C.E.; Galván-Tejada, J.I.; González-Fernández, E.; Gamboa-Rosales, H.; López-Robles, J.R. Visualizing the Intellectual Structure and Evolution of Intelligent Transportation Systems: A Systematic Analysis of Research Themes and Trends. *Sustainability* **2020**, *12*, 8759. [CrossRef]
63. Avci, İ.; Koca, M. Intelligent Transportation System Technologies, Challenges and Security. *Appl. Sci.* **2024**, *14*, 4646. [CrossRef]
64. Walch, M.; Schirrer, A.; Neubauer, M. Impact assessment of cooperative intelligent transport systems (C-ITS): A structured literature review. *Eur. Transp. Res. Rev.* **2025**, *17*, 11. [CrossRef]

65. Abdelkader, G.; Elgazzar, K.; Khamis, A. Connected Vehicles: Technology Review, State of the Art, Challenges and Opportunities. *Sensors* **2021**, *21*, 7712. [CrossRef]
66. Zhang, J.; Wang, F.Y.; Wang, K.; Lin, W.H.; Xu, X.; Chen, C. Data-Driven Intelligent Transportation Systems: A Survey. *IEEE Trans. Intell. Transp. Syst.* **2011**, *12*, 1624–1639. [CrossRef]
67. Machin, M.; Sanguesa, J.A.; Garrido, P.; Martinez, F.J. On the use of artificial intelligence techniques in intelligent transportation systems. In *2018 IEEE Wireless Communications and Networking Conference Workshops (WCNCW), Barcelona, Spain*; IEEE: Piscataway, NJ, USA, 2018; pp. 332–337. Available online: <https://ieeexplore.ieee.org/document/8369029/> (accessed on 20 February 2026). [CrossRef]
68. Guerrieri, M. Smart Roads Geometric Design Criteria and Capacity Estimation Based on AV and CAV Emerging Technologies. A Case Study in the Trans-European Transport Network. *Int. J. ITS Res.* **2021**, *19*, 429–440. [CrossRef]
69. Khanmohamadi, M.; Guerrieri, M. Advanced Sensor Technologies in CAVs for Traditional and Smart Road Condition Monitoring: A Review. *Sustainability* **2024**, *16*, 8336. [CrossRef]
70. Guerrieri, M.; Khanmohamadi, M. COM-Roundabout: The first smart commutable and self-regulating roundabout for HDVs and CAVs. *Int. J. Transp. Sci. Technol.* **2025**, in press. [CrossRef]
71. Dey, K.; Fries, R.; Ahmed, S. Future of Transportation Cyber-Physical Systems—Smart Cities/Regions. In *Transportation Cyber-Physical Systems*; Elsevier: Amsterdam, The Netherlands, 2018; pp. 267–307. Available online: <https://linkinghub.elsevier.com/retrieve/pii/B9780128142950000113> (accessed on 20 February 2026). [CrossRef]
72. Neirrotti, P.; De Marco, A.; Cagliano, A.C.; Mangano, G.; Scorrano, F. Current trends in Smart City initiatives: Some stylised facts. *Cities* **2014**, *38*, 25–36. [CrossRef]
73. Docherty, I.; Marsden, G.; Anable, J. The governance of smart mobility. *Transp. Res. Part A Policy Pract.* **2018**, *115*, 114–125. [CrossRef]
74. Goumiri, S.; Yahiaoui, S.; Djahel, S. Smart Mobility in Smart Cities: Emerging challenges, recent advances and future directions. *J. Intell. Transp. Syst.* **2025**, *29*, 81–117. [CrossRef]
75. Almatar, K.M. Smart transportation planning and its challenges in the Kingdom of Saudi Arabia. *Sustain. Futures* **2024**, *8*, 100238. [CrossRef]
76. Chen, R.; Gao, L.; Liu, Y.; Guan, Y.L.; Zhang, Y. Smart Roads: Roadside Perception, Vehicle-Road Cooperation, and Business Model. *IEEE Netw.* **2025**, *39*, 311–318. [CrossRef]
77. Njoku, J.N.; Nwakanma, C.I.; Amaizu, G.C.; Kim, D. Prospects and challenges of Metaverse application in data-driven intelligent transportation systems. *IET Intell. Trans. Sys.* **2023**, *17*, 1–21. [CrossRef]
78. Zhang, R.; Yang, Z.; Dai, T.; Sun, D.J.; Ma, S.; Zhao, X. MAGAE: Multi-Level Alignment Over Aggregation Semantic Graph With Attribute Enhancement for Text-Based Vehicle Retrieval. *IEEE Trans. Intell. Transp. Syst.* **2025**, *26*, 13704–13720. [CrossRef]
79. Zhang, H.; Luo, G.; Li, Y.; Wang, F.Y. Parallel Vision for Intelligent Transportation Systems in Metaverse: Challenges, Solutions, and Potential Applications. *IEEE Trans. Syst. Man Cybern. Syst.* **2023**, *53*, 3400–3413. [CrossRef]
80. Guerrieri, M.; Corriere, F.; Parla, G.; Ticali, D. Estimation of pollutant emissions from road traffic by image processing techniques: A case study in a suburban area. *ARPN J. Eng. Appl. Sci.* **2013**, *8*, 668–676.
81. Papadopoulos, T.; Evangelidis, K.; Kaskalis, T.H.; Evangelidis, G. The Metaverse Is Geospatial: A System Model Architecture Integrating Spatial Computing, Digital Twins, and Virtual Worlds. *ISPRS Int. J. Geo-Inf.* **2025**, *14*, 126. [CrossRef]
82. Reddy, C.A.; Teja, D.S.; Khan, P. Governance and Policy for a Green Metaverse. In *Green Metaverse: Fuzzy Logic Approaches to Sustainable Virtual Worlds*; Kautish, S., Kar, R., Abreu, A., Eds.; Information Systems Engineering and Management; Springer Nature: Cham, Switzerland, 2026; pp. 153–169. Available online: https://link.springer.com/10.1007/978-3-032-08183-4_9 (accessed on 20 February 2026). [CrossRef]
83. Yang, L. Recommendations for metaverse governance based on technical standards. *Humanit. Soc. Sci. Commun.* **2023**, *10*, 253. [CrossRef]
84. Weinberger, M. What Is Metaverse?—A Definition Based on Qualitative Meta-Synthesis. *Future Internet* **2022**, *14*, 310. [CrossRef]
85. Schöbel, S.; Tingelhoff, F. Overcoming challenges to enable the potential of metaverse platforms: A qualitative approach to understand value creation. *AIS Trans. Hum.-Comput. Interact.* **2023**, *15*, 1–21. [CrossRef]
86. Lv, Z.; Xie, S.; Li, Y.; Hossain, M.S.; El Saddik, A. Building the metaverse using digital twins at all scales, states, and relations. *Virtual Real. Intell. Hardw.* **2022**, *4*, 459–470. [CrossRef]
87. Ma, H.; Yao, X.; Wang, X. Metaverses for Parallel Transportation: From General 3D Traffic Environment Construction to Virtual-Real I2 TS Management and Control. In *2024 IEEE 4th International Conference on Digital Twins and Parallel Intelligence (DTPPI), Wuhan, China*; IEEE: Piscataway, NJ, USA, 2024; pp. 598–603. Available online: <https://ieeexplore.ieee.org/document/10778876/> (accessed on 20 February 2026). [CrossRef]
88. Kuo, H.T.; Choi, T.M. Metaverse in transportation and logistics operations: An AI-supported digital technological framework. *Transp. Res. Part E Logist. Transp. Rev.* **2024**, *185*, 103496. [CrossRef]

89. Wang, F.Y. Parallel Control and Management for Intelligent Transportation Systems: Concepts, Architectures, and Applications. *IEEE Trans. Intell. Transp. Syst.* **2010**, *11*, 630–638. [[CrossRef](#)]
90. Hu, X.; Li, S.; Huang, T.; Tang, B.; Huai, R.; Chen, L. How Simulation Helps Autonomous Driving: A Survey of Sim2real, Digital Twins, and Parallel Intelligence. *IEEE Trans. Intell. Veh.* **2024**, *9*, 593–612. [[CrossRef](#)]
91. Souravlias, D.; Luque, G.; Alba, E.; Parsopoulos, K.E. Smart Traffic Lights: A First Parallel Computing Approach. In *2016 International Conference on Intelligent Networking and Collaborative Systems (INCoS), Ostrava, Czech Republic*; IEEE: Piscataway, NJ, USA, 2016; pp. 229–236. Available online: <http://ieeexplore.ieee.org/document/7695177/> (accessed on 20 February 2026). [[CrossRef](#)]
92. Selvaraj, D.C.; Dressler, F.; Chiasserini, C.F. Human-Centered Traffic Management Supporting Smart Cities and the Metaverse. In *2023 IEEE International Conference on Metaverse Computing, Networking and Applications (MetaCom), Kyoto, Japan*; IEEE: Piscataway, NJ, USA, 2023; pp. 171–176. Available online: <https://ieeexplore.ieee.org/document/10271899/> (accessed on 20 February 2026). [[CrossRef](#)]
93. Zhao, Z.; Bi, Z.; Wang, Y.; Xie, X. A collaborative metaverse-digital twin system for traffic perception, reasoning, and resource scheduling. *Artif. Intell. Rev.* **2025**, *59*, 52. [[CrossRef](#)]
94. Alam, T. Metaverse of Things (MoT) Applications for Revolutionizing Urban Living in Smart Cities. *Smart Cities* **2024**, *7*, 2466–2494. [[CrossRef](#)]
95. Irfan, M.S.; Dasgupta, S.; Rahman, M. Toward Transportation Digital Twin Systems for Traffic Safety and Mobility: A Review. *IEEE Internet Things J.* **2024**, *11*, 24581–24603. [[CrossRef](#)]
96. Ahilal, A.; Braud, T.; Lee, L.H.; Chen, H.; Hui, P. Toward A Traffic Metaverse with Shared Vehicle Perception. *IEEE Comm. Stand. Mag.* **2023**, *7*, 40–47. [[CrossRef](#)]
97. Mauro, R.; Guerrieri, M. Comparative life-cycle assessment of conventional (double lane) and non-conventional (turbo and flower) roundabout intersections. *Transp. Res. Part D Transp. Environ.* **2016**, *48*, 96–111. [[CrossRef](#)]
98. Bai, X.; Dong, P.; Huang, Y.; Kumari, S.; Yu, H.; Ren, Y. An AR-Based Meta Vehicle Road Cooperation Testing Systems: Framework, Components Modeling, and an Implementation Example. *IEEE Internet Things J.* **2024**, *11*, 23460–23474. [[CrossRef](#)]
99. Wang, J.; Chen, Y.; Ji, X.; Dong, Z.; Gao, M.; Sing Lai, C. Metaverse Meets Intelligent Transportation System: An Efficient and Instructional Visual Perception Framework. *IEEE Trans. Intell. Transp. Syst.* **2024**, *25*, 14986–15001. [[CrossRef](#)]
100. Sharifi, A.; Amirzadeh, M.; Khavarian-Garmsir, A.R. The metaverse as a future form of smart cities: A systematic literature review of co-benefits and trade-offs for sustainable development goals. *Cities* **2025**, *161*, 105879. [[CrossRef](#)]
101. Owojori, O.M.; Erasmus, L.J. Urban sustainability reporting through the metaverse: Advancing transparency and accountability in the built environment. *EDPACS* **2025**, *70*, 34–62. [[CrossRef](#)]
102. Tang, R.; De Donato, L.; Bešinović, N.; Flammini, F.; Goverde, R.M.P.; Lin, Z.; Liu, R.; Tang, T.; Vittorini, V.; Wang, Z. A literature review of Artificial Intelligence applications in railway systems. *Transp. Res. Part C Emerg. Technol.* **2022**, *140*, 103679. [[CrossRef](#)]
103. Bešinović, N. Resilience in railway transport systems: A literature review and research agenda. *Transp. Rev.* **2020**, *40*, 457–478. [[CrossRef](#)]
104. Corriere, F.; Di Vincenzo, D.; Guerrieri, M. A logic fuzzy model for evaluation of the railway station's practice capacity in safety operating conditions. *Arch. Civ. Eng.* **2013**, *59*, 3–19. [[CrossRef](#)]
105. Guerrieri, M.; Parla, G. Smart Tramway Systems for Smart Cities: A Deep Learning Application in ADAS Systems. *Int. J. Intell. Transp. Syst. Res.* **2022**, *20*, 745–758. [[CrossRef](#)]
106. Tsvetkov, V.; Shaytura, S.V.; Ordov, K.V. Digital management railway. In *Proceedings of the International Scientific and Practical Conference on Digital Economy (ISCDE 2019), Chelyabinsk, Russia*; Atlantis Press: Paris, France, 2019. Available online: <https://www.atlantis-press.com/article/125924588> (accessed on 21 February 2026). [[CrossRef](#)]
107. Li, H.; Zhu, Q.; Zhang, L.; Ding, Y.; Guo, Y.; Wu, H.; Wang, Q.; Zhou, R.; Liu, M.; Zhou, Y. Integrated representation of geospatial data, model, and knowledge for digital twin railway. *Int. J. Digit. Earth* **2022**, *15*, 1657–1675. [[CrossRef](#)]
108. Bernal, E.; Wu, Q.; Spiriyagin, M.; Cole, C. Augmented digital twin for railway systems. *Veh. Syst. Dyn.* **2024**, *62*, 67–83. [[CrossRef](#)]
109. Kurwi, S.; Demian, P.; Blay, K.B.; Hassan, T.M. Collaboration through Integrated BIM and GIS for the Design Process in Rail Projects: Formalising the Requirements. *Infrastructures* **2021**, *6*, 52. [[CrossRef](#)]
110. Van Dinter, R.; Tekinerdogan, B.; Catal, C. Predictive maintenance using digital twins: A systematic literature review. *Inf. Softw. Technol.* **2022**, *151*, 107008. [[CrossRef](#)]
111. Kazemi, M.J.; Rashidi, M.; Kang, W.H.; Siahkouhi, M. Toward Smart Railway Infrastructure Predictive and Optimised Maintenance Through Digital Twin (DT) System. *Sensors* **2026**, *26*, 2333. [[CrossRef](#)] [[PubMed](#)]
112. Yeung, T.; Martinez, J.G.; Schlenger, J.; Borrmann, A.; Sacks, R. Integrating digital twin and agent-based simulation to support adaptive production system design in building projects. *Autom. Constr.* **2025**, *180*, 106550. [[CrossRef](#)]
113. Guerrieri, M.; Ticali, D. Design standards for converting unused railway lines into greenways. In *ICSDC 2011: Integrating Sustainability Practices in the Construction Industry—Proceedings of the International Conference on Sustainable Design and Construction, 2011*; American Society of Civil Engineers (ASCE): Reston, VA, USA, 2012; pp. 654–660. [[CrossRef](#)]

114. Scheepmaker, G.M.; Goverde, R.M.; Kroon, L.G. Review of energy-efficient train control and timetabling. *Eur. J. Oper. Res.* **2017**, *257*, 355–376. [[CrossRef](#)]
115. Guerrieri, M.; Parla, G.; Ticali, D. A theoretical and experimental approach to reconstructing the transverse profile of worn-out rails. *Ing. Ferrovi.* **2012**, *67*, 23–37.
116. Tao, F.; Xiao, B.; Qi, Q.; Cheng, J.; Ji, P. Digital twin modeling. *J. Manuf. Syst.* **2022**, *64*, 372–389. [[CrossRef](#)]
117. Lerner, D.; Mohr, S.; Schild, J.; Göring, M.; Luiz, T. An immersive multi-user virtual reality for emergency simulation training: Usability study. *JMIR Serious Games* **2020**, *8*, e18822. [[CrossRef](#)]
118. Zahabi, M.; Abdul Razak, A.M. Adaptive virtual reality-based training: A systematic literature review and framework. *Virtual Real.* **2020**, *24*, 725–752. [[CrossRef](#)]
119. Sresakoolchai, J.; Kaewunruen, S. Railway infrastructure maintenance efficiency improvement using deep reinforcement learning integrated with digital twin based on track geometry and component defects. *Sci. Rep.* **2023**, *13*, 2439. [[CrossRef](#)]
120. Armijo, A.; Zamora-Sánchez, D. Integration of railway bridge structural health monitoring into the internet of things with a digital twin: A case study. *Sensors* **2024**, *24*, 2115. [[CrossRef](#)]
121. Quan, L.; Wang, M.; Baihang, L.; Ziwen, Z. Integration of deep learning and railway big data for environmental risk prediction models and analysis of their limitations. *Front. Environ. Sci.* **2025**, *13*, 1550745. [[CrossRef](#)]
122. García-Méndez, S.; de Arriba-Pérez, F.; Leal, F.; Veloso, B.; Malheiro, B.; Burguillo-Rial, J.C. An explainable machine learning framework for railway predictive maintenance using data streams from the metro operator of Portugal. *Sci. Rep.* **2025**, *15*, 27495. [[CrossRef](#)] [[PubMed](#)]
123. Bochmann, P.; Jaekel, B. Measures and Methods for the Evaluation of ATO Algorithms. *Appl. Sci.* **2022**, *12*, 4570. [[CrossRef](#)]
124. Ding, Y.; Zhang, Z.; Chen, K.; Ding, H.; Voss, S.; Heilig, L.; Chen, Y.; Chen, X. Real-Time Monitoring and Optimal Resource Allocation for Automated Container Terminals: A Digital Twin Application at the Yangshan Port. *J. Adv. Transp.* **2023**, *2023*, 6909801. [[CrossRef](#)]
125. Lovas, T.; Somogyi, Á.J.; Simongáti, G. Laser scanning ship hulls to support hydrodynamic simulations. *Period. Polytech. Civ. Eng.* **2022**, *66*, 291–297. [[CrossRef](#)]
126. Mauro, F.; Kana, A.A. Digital twin for ship life-cycle: A critical systematic review. *Ocean Eng.* **2023**, *269*, 113479. [[CrossRef](#)]
127. Yang, Y.; Chen, C.; Zhuang, Y.; Suo, Z. Reviewing the progress of corrosion fatigue research on marine structures. *Front. Mater.* **2024**, *11*, 1399292. [[CrossRef](#)]
128. Ilias, L.; Tsapelas, G.; Kapsalis, P.; Michalakopoulos, V.; Korpakakis, G.; Mouzakitis, S.; Askounis, D. Leveraging extreme scale analytics, AI and digital twins for maritime digitalization: The VesselAI architecture. *Front. Big Data* **2023**, *6*, 1220348. [[CrossRef](#)]
129. Wang, L.; Li, Y.; Wan, Z.; Yang, Z.; Wang, T.; Guan, K.; Fu, L. Use of AIS data for performance evaluation of ship traffic with speed control. *Ocean Eng.* **2020**, *204*, 107259. [[CrossRef](#)]
130. Liu, R.W.; Liang, M.; Nie, J.; Lim, W.Y.; Zhang, Y.; Guizani, M. Deep learning-powered vessel trajectory prediction for improving smart traffic services in maritime Internet of Things. *IEEE Trans. Netw. Sci. Eng.* **2022**, *9*, 3080–3094. [[CrossRef](#)]
131. Riordan, J.; Constapel, M.; Trslac, P.; Dooly, G.; Oeffner, J.; Schneider, V. Ship anti-grounding with a maritime autonomous surface ship and digital twin of Port of Hamburg. In *OCEANS 2023-Limerick, Ireland, 5–8 June 2023*; IEEE: Piscataway, NJ, USA, 2023; pp. 1–8.
132. Makransky, G.; Klingenberg, S. Virtual reality enhances safety training in the maritime industry: An organizational training experiment with a non-WEIRD sample. *J. Comput. Assist. Learn.* **2022**, *38*, 1127–1140. [[CrossRef](#)]
133. Bai, X.; Ma, Z.; Zhou, Y. Data-driven static and dynamic resilience assessment of the global liner shipping network. *Transp. Res. Part E Logist. Transp. Rev.* **2023**, *170*, 103016. [[CrossRef](#)]
134. Cao, Y.; Xin, X.; Jarumaneeroj, P.; Li, H.; Feng, Y.; Wang, J.; Wang, X.; Pyne, R.; Yang, Z. Data-driven resilience analysis of the global container shipping network against two cascading failures. *Transp. Res. Part E Logist. Transp. Rev.* **2025**, *193*, 103857. [[CrossRef](#)]
135. Sivasuriyan, A.; Vijayan, D.S.; Górski, W.; Wodzyński, L.; Vaverková, M.D.; Koda, E. Practical implementation of structural health monitoring in multi-story buildings. *Buildings* **2021**, *11*, 263. [[CrossRef](#)]
136. Zhang, H.; Li, G.; Hatledal, L.I.; Chu, Y.; Ellefsen, A.; Han, P.; Major, P.; Skulstad, R.; Wang, T.; Hildre, H.P. A digital twin of the research vessel gunnerus for lifecycle services: Outlining key technologies. *IEEE Robot. Autom. Mag.* **2022**, *30*, 6–19. [[CrossRef](#)]
137. Kanchiralla, F.M.; Brynolf, S.; Malmgren, E.; Hansson, J.; Grahn, M. Life-cycle assessment and costing of fuels and propulsion systems in future fossil-free shipping. *Environ. Sci. Technol.* **2022**, *56*, 12517–12531. [[CrossRef](#)]
138. Diaz, R.; Smith, K.; Bertagna, S.; Bucci, V. Digital transformation, applications, and vulnerabilities in maritime and shipbuilding ecosystems. *Procedia Comput. Sci.* **2023**, *217*, 1396–1405. [[CrossRef](#)]
139. Kim, H. A real-time lifecycle analysis model with digital twin and novel control method for enhancing the environmental performance of electric/hybrid propulsion ships. *Ocean Eng.* **2025**, *329*, 121195. [[CrossRef](#)]
140. Vasilikis, N.; Geertsma, R.; Coraddu, A. A digital twin approach for maritime carbon intensity evaluation accounting for operational and environmental uncertainty. *Ocean Eng.* **2023**, *288*, 115927. [[CrossRef](#)]

141. Park, C.; Jeong, B.; Zhou, P.; Jang, H.; Kim, S.; Jeon, H.; Nam, D.; Rashedi, A. Live-Life cycle assessment of the electric propulsion ship using solar PV. *Appl. Energy* **2022**, *309*, 118477. [[CrossRef](#)]
142. Ujkani, A.; Hohnrath, P.; Grundmann, R.; Burmeister, H.C. Enhancing maritime navigation with mixed reality: Assessing remote pilotage concepts and technologies by in situ testing. *J. Mar. Sci. Eng.* **2024**, *12*, 1084. [[CrossRef](#)]
143. Qiu, S.; Ren, H.; Wang, D.; Qu, Y.; Sun, J. Research on an educational virtual training system for ship life-saving appliances. *Comput. Appl. Eng. Educ.* **2024**, *32*, e22708. [[CrossRef](#)]
144. Vukelic, G.; Ogrizovic, D.; Bernecic, D.; Glujic, D.; Vizentin, G. Application of VR technology for maritime firefighting and evacuation training—A review. *J. Mar. Sci. Eng.* **2023**, *11*, 1732. [[CrossRef](#)]
145. Hamed-Ahmed, M.H.; Ramil-López, D.; Fraga-Lamas, P.; Fernández-Caramés, T.M. Towards an Emotion-Aware Metaverse: A Human-Centric Shipboard Fire Drill Simulator. *Technologies* **2025**, *13*, 253. [[CrossRef](#)]
146. Spandonidis, C.; Iliopoulos, V.; Athanasopoulos, I. Machine learning-powered KPI framework for real-time, sustainable ship performance management. *J. Mar. Sci. Eng.* **2025**, *13*, 1440. [[CrossRef](#)]
147. Raza, M.; Prokopova, H.; Huseynzade, S.; Azimi, S.; Lafond, S. Towards integrated digital-twins: An application framework for autonomous maritime surface vessel development. *J. Mar. Sci. Eng.* **2022**, *10*, 1469. [[CrossRef](#)]
148. Martelli, M.; Viridis, A.; Gotta, A.; Cassarà, P.; Di Summa, M. An outlook on the future marine traffic management system for autonomous ships. *IEEE Access* **2021**, *9*, 157316–157328. [[CrossRef](#)]
149. Wang, L.; Ma, C.; Feng, X.; Zhang, Z.; Yang, H.; Zhang, J.; Chen, Z.; Tang, J.; Chen, X.; Lin, Y.; et al. A survey on large language model based autonomous agents. *Front. Comput. Sci.* **2024**, *18*, 186345. [[CrossRef](#)]
150. Pan, R.; Zhang, W.; Wang, S.; Kang, S. Deep reinforcement learning model for Multi-Ship collision avoidance decision making design implementation and performance analysis. *Sci. Rep.* **2025**, *15*, 21250. [[CrossRef](#)] [[PubMed](#)]
151. Wang, P.; Li, J.; Cao, X. Discrete dynamic berth allocation optimization in container terminal based on Deep Q-Network. *Mathematics* **2024**, *12*, 3742. [[CrossRef](#)]
152. Munim, Z.H.; Sørli, M.A.; Kim, H.; Alon, I. Predicting maritime accident risk using Automated Machine Learning. *Reliab. Eng. Syst. Saf.* **2024**, *248*, 110148. [[CrossRef](#)]
153. Wang, K.; Xu, H.; Wang, H.; Qiu, R.; Hu, Q.; Liu, X. Digital twin-driven safety management and decision support approach for port operations and logistics. *Front. Mar. Sci.* **2024**, *11*, 1455522. [[CrossRef](#)]
154. Hjellvik, S.; Mallam, S. Training transfer validity of virtual reality simulator assessment. *Virtual Real.* **2024**, *28*, 165. [[CrossRef](#)]
155. Tian, Y.; Lin, F.; Li, Y.; Zhang, T.; Zhang, Q.; Fu, X.; Huang, J.; Dai, X.; Wang, Y.; Tian, C.; et al. UAVs meet LLMs: Overviews and perspectives towards agentic low-altitude mobility. *Inf. Fusion* **2025**, *122*, 103158. [[CrossRef](#)]
156. Namuduri, K. Digital twin approach for integrated airspace management with applications to advanced air mobility. *IEEE Open J. Veh. Technol.* **2023**, *4*, 693–700. [[CrossRef](#)]
157. Kapteyn, M.G.; Pretorius, J.V.; Willcox, K.E. A probabilistic graphical model foundation for enabling predictive digital twins at scale. *Nat. Comput. Sci.* **2021**, *1*, 337–347. [[CrossRef](#)] [[PubMed](#)]
158. Tavares Sérgio, M.O.; Ribeiro, J.A.; Ribeiro, B.A.; de Castro, P.M. Aircraft structural design and life-cycle assessment through digital twins. *Designs* **2024**, *8*, 29. [[CrossRef](#)]
159. Jiang, H.; Qin, S.; Fu, J.; Zhang, J.; Ding, G. How to model and implement connections between physical and virtual models for digital twin application. *J. Manuf. Syst.* **2021**, *58*, 36–51. [[CrossRef](#)]
160. Li, Y.; Liu, W.; Zhang, Y.; Zhang, W.; Gao, C.; Chen, Q.; Ji, Y. Interactive real-time monitoring and information traceability for complex aircraft assembly field based on digital twin. *IEEE Trans. Ind. Inform.* **2023**, *19*, 9745–9756. [[CrossRef](#)]
161. Sadeghi, A.; Bellavista, P.; Song, W.; Yazdani-Asrami, M. Digital twins for condition and fleet monitoring of aircraft: Toward more-intelligent electrified aviation systems. *IEEE Access* **2024**, *12*, 99806–99832. [[CrossRef](#)]
162. Liu, Y.; Shen, Y.; Fan, L.; Tian, Y.; Ai, Y.; Tian, B.; Liu, Z.; Wang, F.Y. Parallel radars: From digital twins to digital intelligence for smart radar systems. *Sensors* **2022**, *22*, 9930. [[CrossRef](#)] [[PubMed](#)]
163. Wei, Z.; Wang, S.; Wang, F.; Shui, L. Metaverse for sustainable smart civil aviation: Technologies, applications, and challenges. *Computer* **2025**, *58*, 71–81. [[CrossRef](#)]
164. Gerdes, I.; Jameel, M.; Materne, L.J.; Bruder, C. Synergies in the skies: Situation awareness and shared mental model in digital-human air traffic control teams. *Aerospace* **2025**, *12*, 472. [[CrossRef](#)]
165. Pepper, N.; Keane, A.; Hodgkin, A.; Gould, D.; Henderson, E.; Lauritsen, L.; Vlahos, C.; De Ath, G.; Everson, R.; Cannon, R.; et al. A Probabilistic Digital Twin of UK en Route Airspace. In Proceedings of the AIAA SCITECH 2026 Forum 2026, Orlando, FL, USA, 12–16 January 2026; p. 1794.
166. Yiu, C.Y.; Ng, K.K.; Lee, C.H.; Chow, C.T.; Chan, T.C.; Li, K.C.; Wong, K.Y. A digital twin-based platform towards intelligent automation with virtual counterparts of flight and air traffic control operations. *Appl. Sci.* **2021**, *11*, 10923. [[CrossRef](#)]
167. Chen, K.; Nadirsha, T.N.; Lilith, N.; Alam, S.; Svensson, Å. Tangible digital twin with shared visualization for collaborative air traffic management operations. *Transp. Res. Part C Emerg. Technol.* **2024**, *161*, 104546. [[CrossRef](#)]

168. Attar, A.; Babaee, M.; Raissi, S.; Nojavan, M. Airside Optimization Framework Covering Multiple Operations in Civil Airport Systems with a Variety of Aircraft: A Simulation-Based Digital Twin. *Systems* **2024**, *12*, 394. [[CrossRef](#)]
169. Liu, C.; Zhang, Y.; Chen, Y.; Liu, S.; Hu, S.; Luo, Q.; Chen, L. Digital Twin-Enabled Delay Diagnosis Traceability and Propagation Process for Airport Flight Ground Service. *Int. J. Intell. Syst.* **2024**, *2024*, 7458758. [[CrossRef](#)]
170. De Bosscher, B.C.; Ziabari, S.S.; Sharpanskykh, A. A comprehensive study of agent-based airport terminal operations using surrogate modeling and simulation. *Simul. Model. Pract. Theory* **2023**, *128*, 102811. [[CrossRef](#)]
171. Wong, E.Y.; Mo, D.Y.; So, S. Closed-loop digital twin system for air cargo load planning operations. *Int. J. Comput. Integr. Manuf.* **2021**, *34*, 801–813. [[CrossRef](#)]
172. Wu, D.; Zheng, A.; Yu, W.; Cao, H.; Ling, Q.; Liu, J.; Zhou, D. Digital twin technology in transportation infrastructure: A comprehensive survey of current applications, challenges, and future directions. *Appl. Sci.* **2025**, *15*, 1911. [[CrossRef](#)]
173. Sun, H.; Yang, F.; Zhang, P.; Hu, Q. Behavioral indicator-based initial flight training competency assessment model. *Appl. Sci.* **2023**, *13*, 6346. [[CrossRef](#)]
174. Mark, J.A.; Kraft, A.E.; Ziegler, M.D.; Ayaz, H. Neuroadaptive training via fNIRS in flight simulators. *Front. Neuroergon.* **2022**, *3*, 820523. [[CrossRef](#)]
175. Nguyen, B.; Sonnenfeld, N.; Finkelstein, L.; Alonso, A.; Gomez, C.; Duruaku, F.; Jentsch, F. Using AI tools to develop training materials for aviation: Ethical, technical, and practical concerns. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 27–29 September 2023*; SAGE Publications: Los Angeles, CA, USA, 2023; Volume 67, pp. 1343–1349.
176. Berlenga, I.; Chambel, M.J.; Curral, L. Ethical Concerns of Aviation Professionals Towards AI-Based Systems: An Exploratory Study Understanding Motives Behind Non-acceptance of AI. In *Economic Sustainability Potentiated by Artificial Intelligence*; Springer Nature: Singapore, 2025; pp. 21–47.
177. Zhu, Y.; Hua, G.; Liu, X.; Wang, C.; Tang, M. Trust in machines: How personality trait shapes static and dynamic trust across different human–machine interaction modalities. *Front. Psychol.* **2025**, *16*, 1539054. [[CrossRef](#)] [[PubMed](#)]
178. Causa, F.; Fasano, G. Multiobjective modular strategic planning framework for low-altitude missions within the urban air mobility ecosystem. *IEEE Trans. Aerosp. Electron. Syst.* **2023**, *60*, 474–489. [[CrossRef](#)]
179. Xiong, K.; Chen, Z.; Xie, J.; Qin, Y.; Leng, S.; Yuen, C. Digital twin-based SIM communication and flight control for advanced air mobility. *IEEE Trans. Netw. Sci. Eng.* **2025**, *13*, 728–744. [[CrossRef](#)]
180. Kopyt, A.; Dylicki, S. Urban Air Mobility Vertiport’s Capacity Simulation and Analysis. *Aerospace* **2025**, *12*, 560. [[CrossRef](#)]
181. Yang, Y.; Keivanpour, S.; Imbeau, D. Integrating X-reality and lean into end-of-life aircraft parts disassembly sequence planning: A critical review and research agenda. *Int. J. Adv. Manuf. Technol.* **2023**, *127*, 2181–2210. [[CrossRef](#)] [[PubMed](#)]
182. Papadaki, D.; Maleviti, E. Sustainable Practices for Aircraft Decommissioning and Recycling in a Circular Aviation Economy. *Processes* **2025**, *13*, 3649. [[CrossRef](#)]
183. Adu-Gyamfi, B.A. The role of digital twin technology in enhancing sustainable aviation transition: A state-of-the-art review and future direction. *J. Open Innov. Technol. Mark. Complex.* **2025**, *12*, 100693. [[CrossRef](#)]
184. Kabashkin, I. Digital twin framework for aircraft lifecycle management based on data-driven models. *Mathematics* **2024**, *12*, 2979. [[CrossRef](#)]
185. Wu, C.; Redonnet, S. Aircraft noise impact prediction with incorporation of meteorological effects. *Transp. Res. Part D Transp. Environ.* **2023**, *125*, 103945. [[CrossRef](#)]
186. Babu Saheer, L.; Garbagna, L.; Sasidharan, M. Systematic review of air quality modeling in digital twins for sustainable green cities. *Discov. Environ.* **2025**, *3*, 199. [[CrossRef](#)]
187. Zaccaria, V.; Stenfelt, M.; Aslanidou, I.; Kyprianidis, K.G. Fleet monitoring and diagnostics framework based on digital twin of aero-engines. In *Turbo Expo: Power for Land, Sea, and Air, 11 June 2018*; American Society of Mechanical Engineers: New York, NY, USA, 2018; Volume 51128, p. V006T05A021.
188. Wang, Q.; Wu, Z.; Lu, Y. A Multi-Layer Secure Sharing Framework for Aviation Big Data Based on Blockchain. *Future Internet* **2025**, *17*, 361. [[CrossRef](#)]
189. Alshamsi, M.A.; Sipos, A. The Legal Implications of The Aviation Industry’s Entrance to The Metaverse. *Access Just. E. Eur.* **2024**, *7*, 285. [[CrossRef](#)]
190. Della Vecchia, P.; Mirabella, C.; Tuccillo, M.; Riboldi, C.E.; Fioriti, M.; Shahini, F.; Roncolini, F. A SysML-based framework towards EASA CS-23 digitalization: An MBSE approach. *Transp. Res. Interdiscip. Perspect.* **2026**, *36*, 101810.
191. Cartile, A.; Marsden, C.; Liscouët-Hanke, S. Digital Transformation in Aircraft Design and Certification: Developing Requirements for Modeling Regulatory Documentation. *Aerospace* **2025**, *12*, 724. [[CrossRef](#)]
192. Vidyalakshmi, G.; Gopikrishnan, S.; Boulila, W.; Koubaa, A.; Srivastava, G. Digital twins and cyber-physical systems: A new frontier in computer modeling. *Comput. Model. Eng. Sci.* **2025**, *143*, 51. [[CrossRef](#)]
193. Rasheed, A.; San, O.; Kvamsdal, T. Digital twin: Values, challenges and enablers from a modeling perspective. *IEEE Access* **2020**, *8*, 21980–22012. [[CrossRef](#)]

194. Ali, M.; Naeem, F.; Kaddoum, G.; Hossain, E. Metaverse communications, networking, security, and applications: Research issues, state-of-the-art, and future directions. *IEEE Commun. Surv. Tutor.* **2023**, *26*, 1238–1278. [[CrossRef](#)]
195. Battula, S.; Alla, S.N.; Ramana, E.V.; Kiran Kumar, N.; Bhanu Murthy, S. Uncertainty Quantification for Digital Twins in Smart Manufacturing and Robotics: A Review. *J. Phys. Conf. Ser.* **2024**, *2837*, 012059. [[CrossRef](#)]
196. Hasan, A.; Salvo Rossi, P. A unified sensor and actuator fault diagnosis in digital twins for remote operations. *Mech. Syst. Signal Process.* **2025**, *222*, 111778. [[CrossRef](#)]
197. Acharya, S.; Khan, A.A.; Päivärinta, T. Interoperability levels and challenges of digital twins in cyber–physical systems. *J. Ind. Inf. Integr.* **2024**, *42*, 100714. [[CrossRef](#)]
198. Xiong, M.; Wang, H. Digital twin applications in aviation industry: A review. *Int. J. Adv. Manuf. Technol.* **2022**, *121*, 5677–5692. [[CrossRef](#)]
199. Loia, F.; Maltempo, C.; Marrapodi, R.; Mele, S.; Iacono, M.P.; Martinez, M. The Dark Side of the Metaverse: Managing Conflict and Human Resource Management Challenges in Virtual Environments. In *The International Research & Innovation Forum, 7–11 April 2025*; Springer Nature: Cham, Switzerland, 2025; pp. 39–56.
200. Capolupo, N.; Loia, F.; Adinolfi, P. Bright and dark sides of the metaverse. A look into the future from an organizational perspective. *puntOorg Int. J.* **2025**, *10*, 256–277. [[CrossRef](#)]
201. Hou, Y.; Xie, Q.; Zhang, N.; Lv, J. Cognitive load classification of mixed reality human computer interaction tasks based on multimodal sensor signals. *Sci. Rep.* **2025**, *15*, 13732. [[CrossRef](#)]
202. Dasgupta, A.; Arendt, D.L.; Franklin, L.R.; Wong, P.C.; Cook, K.A. Human Factors in Streaming Data Analysis: Challenges and Opportunities for Information Visualization. *Comput. Graph. Forum* **2018**, *37*, 254–272. [[CrossRef](#)]
203. Wang, B.T.; Burdon, M. Automating trustworthiness in digital twins. In *Automating Cities: Design, Construction, Operation and Future Impact*; Springer: Singapore, 2021; pp. 345–365.
204. Iqbal, D.; Buhnova, B. Model-based Approach for Building Trust in Autonomous Drones through Digital Twins. In Proceedings of the 2022 IEEE International Conference on Systems, Man, and Cybernetics (SMC), Prague, Czech Republic, 9–12 October 2022; pp. 656–662.
205. Srinivas Acharyulu, P.V.; Seetharamaiah, P. A framework for safety automation of safety-critical systems operations. *Saf. Sci.* **2015**, *77*, 133–142. [[CrossRef](#)]
206. Lemonnier, A.; Adélé, S.; Dionisio, C. Acceptability of autonomous trains with different grades of automation by potential users: A qualitative approach. *Travel Behav. Soc.* **2023**, *33*, 100641. [[CrossRef](#)]
207. Jahan, S.; Riley, I.; Walter, C.; Gamble, R.F.; Pasco, M.; McKinley, P.K.; Cheng, B.H. MAPE-K/MAPE-SAC: An interaction framework for adaptive systems with security assurance cases. *Future Gener. Comput. Syst.* **2020**, *109*, 197–209. [[CrossRef](#)]
208. Christensen, J.M.; Stefani, T.; Anilkumar Girija, A.; Hoemann, E.; Vogt, A.; Werbilo, V.; Durak, U.; Köster, F.; Krüger, T.; Hallerbach, S. Formulating an Engineering Framework for Future AI Certification in Aviation. *Aerospace* **2025**, *12*, 482. [[CrossRef](#)]
209. Frosio, G.; Obafemi, F. Augmented accountability: Data access in the metaverse. *Comput. Law Secur. Rev.* **2025**, *59*, 106196. [[CrossRef](#)]
210. Sakka, S.; Liagkou, V.; Ferreira, A.; Stylios, C. Digital Boundaries and Consent in the Metaverse: A Comparative Review of Privacy Risks. *J. Cybersecur. Priv.* **2026**, *6*, 24. [[CrossRef](#)]
211. Laiz-Ibanez, H.; Mendaña-Cuervo, C.; Carus Candas, J.L. The metaverse: Privacy and information security risks. *Int. J. Inf. Manag. Data Insights* **2025**, *5*, 100373. [[CrossRef](#)]
212. Johri, A.; Joshi, P.; Kumar, S.; Joshi, G. Metaverse for Sustainable Development in a bibliometric analysis and systematic literature review. *J. Clean. Prod.* **2024**, *435*, 140610. [[CrossRef](#)]
213. Zallio, M.; Clarkson, P.J. Designing the metaverse: A study on inclusion, diversity, equity, accessibility and safety for digital immersive environments. *Telemat. Inform.* **2022**, *75*, 101909. [[CrossRef](#)]
214. Zhang, Y.; Yu, Z.; Zhang, J.; Wang, L.; Luan, T.H.; Guo, B.; Yuen, C. Learning Decentralized Traffic Signal Controllers with Multi-Agent Graph Reinforcement Learning. *IEEE Trans. Mob. Comput.* **2024**, *23*, 7180–7195. [[CrossRef](#)]
215. Wang, X.; Huang, J.; Tian, Y.L.; Wang, F.Y. Agi in metaverse for smart cities and societies: A cyber physical social approach. In *2024 Australian & New Zealand Control Conference (ANZCC), 1–2 February 2024*; IEEE: Piscataway, NJ, USA, 2024; pp. 61–66.
216. Cohen, J.; Huan, X. Uncertainty-aware explainable AI as a foundational paradigm for digital twins. *Front. Mech. Eng.* **2024**, *9*, 1329146. [[CrossRef](#)]
217. Lalithadevi, B.; Krishnaveni, S. A Comprehensive Survey on Enhancing Digital Twin Security Systems with Explainable AI Techniques. In *2025 3rd International Conference on Intelligent Data Communication Technologies and Internet of Things (IDCIoT), 5–7 February 2025*; IEEE: Piscataway, NJ, USA, 2025; pp. 535–542.
218. Kumar, S.; Datta, S.; Singh, V.; Datta, D.; Kumar Singh, S.; Sharma, R. Applications, Challenges, and Future Directions of Human-in-the-Loop Learning. *IEEE Access* **2024**, *12*, 75735–75760. [[CrossRef](#)]
219. Pan, Y.H.; Qu, T.; Wu, N.Q.; Khalgui, M.; Huang, G.Q. Digital Twin Based Real-time Production Logistics Synchronization System in a Multi-level Computing Architecture. *J. Manuf. Syst.* **2021**, *58*, 246–260. [[CrossRef](#)]

220. Gupta, R.; Tian, B.; Wang, Y.; Nahrstedt, K. TWIN-ADAPT: Continuous learning for digital twin-enabled online anomaly classification in iot-driven smart labs. *Future Internet* **2024**, *16*, 239. [[CrossRef](#)]
221. Zhou, Y.; Wang, J.; Yang, H. Resilience of Transportation Systems: Concepts and Comprehensive Review. *IEEE Trans. Intell. Transp. Syst.* **2019**, *20*, 4262–4276. [[CrossRef](#)]
222. Engholm, A.; Kristoffersson, I. Exploring Many-Objective Robust Decision Making for managing uncertainty in climate policy analysis for the transport sector. *Transp. Res. Interdiscip. Perspect.* **2025**, *32*, 101524. [[CrossRef](#)]
223. Tang, X.; Yang, K.; Wang, H.; Wu, J.; Qin, Y.; Yu, W.; Cao, D. Prediction-Uncertainty-Aware Decision-Making for Autonomous Vehicles. *IEEE Trans. Intell. Veh.* **2022**, *7*, 849–862. [[CrossRef](#)]
224. Soltanshahi, M.; Maier, M. Metaversal intelligence: Unifying human-AI interactions in human-in-the-loop AIB-Metaverse. *Comput. Netw.* **2025**, *269*, 111425. [[CrossRef](#)]
225. Nunes, D.S.; Zhang, P.; Silva, J.S. A Survey on Human-in-the-Loop Applications Towards an Internet of All. *IEEE Commun. Surv. Tutor.* **2015**, *17*, 944–965. [[CrossRef](#)]
226. Arin, I.A.; Meyliana; Warnars, H.L.H.S.; Murad, D.F. A Systematic Literature Review of Recent Trends and Challenges in Digital Twin Implementation. In *2023 10th International Conference on ICT for Smart Society (ICISS)*; IEEE: Piscataway, NJ, USA, 2023.
227. Tihanyi, V.; Rövid, A.; Remeli, V.; Vincze, Z.; Csonthó, M.; Pethő, Z.; Szalai, M.; Varga, B.; Khalil, A.; Szalay, Z. Towards cooperative perception services for its: Digital twin in the automotive edge cloud. *Energies* **2021**, *14*, 5930. [[CrossRef](#)]
228. Chen, F.; Ren, W. On the control of multi-agent systems: A survey. *Found. Trends Syst. Control* **2019**, *6*, 339–499. [[CrossRef](#)]
229. Ridley, M. Human-centered explainable artificial intelligence: An Annual Review of Information Science and Technology (ARIST) paper. *J. Assoc. Inf. Sci. Technol.* **2025**, *76*, 98–120. [[CrossRef](#)]
230. Gorgoni, G. Stay Human. The quest for responsibility in the algorithmic society. *J. Ethics Leg. Technol.* **2020**, *2*, 31–47.
231. Jørgensen, B.N.; Ma, Z.G. Digital Twins Under EU Law: A Unified Compliance Framework Across Smart Cities, Industry, Transportation, and Energy Systems. *Electronics* **2025**, *14*, 4881. [[CrossRef](#)]
232. Wang, Y.; Su, Z.; Zhang, N.; Xing, R.; Liu, D.; Luan, T.H.; Shen, X. A survey on metaverse: Fundamentals, security, and privacy. *IEEE Commun. Surv. Tutor.* **2022**, *25*, 319–352. [[CrossRef](#)]
233. Mureddu, F.; Paciaroni, A.; Pavelka, T.; Pemberton, A.; Remotti, L.A. Rights and Responsibilities: Legal and Ethical Considerations in Adopting Local Digital Twin Technology. In *Decide Better: Open and Interoperable Local Digital Twins*; Springer Nature: Cham, Switzerland, 2025; pp. 291–317.
234. Tabassum, A.; Elmahjub, E.; Padela, A.I.; Zwitter, A.; Qadir, J. Generative AI and the metaverse: A scoping review of ethical and legal challenges. *IEEE Open J. Comput. Soc.* **2025**, *6*, 348–359. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.