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REVIEW ARTICLE

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A comprehensive review of artificial intelligence in transportation research

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Abstract Rapid urbanization and growing mobility demand are reshaping transportation systems, calling for more advanced intelligence and management capabilities. Artificial intelligence (AI) has emerged as a key enabler for enhancing perception, prediction, and decision-making in transportation. This paper presents a systematic review of AI applications across four major transportation domains: road, rail, air, and maritime systems. Rather than exhaustively surveying all published studies, this review adopts a thematic synthesis approach, organizing representative, recent research by major transportation modes and core AI application scenarios, with an emphasis on influential studies published in leading journals and conferences. The review examines representative applications and key functionalities within each domain, highlighting how AI techniques—such as deep learning, graph-based models, reinforcement learning, and emerging foundation models—are adapted to diverse transportation contexts. Furthermore, this paper analyzes key challenges, including data quality and sparsity, interpretability, uncertainty, and cross-domain generalization, and discusses emerging research directions such as foundation models, physics-informed learning, and continual adaptation. By integrating insights from both methodologies and real-world applications, this review provides insights for advancing intelligent, scalable, and resilient transportation systems.

Keywords artificial intelligence, road transportation, rail transportation, air transportation, maritime transportation, transportation systems

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1 Introduction

Transportation systems underpin modern economic activity and social life by enabling the movement of people, goods, and information across spatial scales. From daily commuting and logistics distribution to regional integration and global trade, transportation directly shapes productivity, accessibility, and quality of life. Modern transportation systems encompass multiple interconnected domains, including road, air, rail, and maritime transportation. Each domain operates under distinct physical constraints, operational mechanisms, and regulatory environments, yet they are tightly coupled through passenger flows, freight logistics, and shared infrastructure dependencies (Rose et al., 2006). These domains collectively form an integrated transportation ecosystem, in which intermodal transfers, and coordinated planning and operational decisions enable continuous interactions across modes. Understanding both the unique characteristics of each domain and its interdependencies is therefore essential for system-wide optimization.

As urbanization accelerates and mobility demand continues to grow, transportation systems are increasingly expected to deliver not only efficiency and reliability, but also safety, sustainability, and resilience under uncertainty. Recent advances in artificial intelligence (AI) have brought tremendous transformative potential to the transportation domains (Sadek, 2007; Bharadiya, 2023; Rong et al., 2025). Data-driven models now enable more accurate traffic prediction (Chen and Chen, 2022) and proactive safety management in road networks (Liu et al., 2022c; Shi et al., 2022), while AI-powered scheduling, demand prediction, and disruption recovery are reshaping air and rail operations (Wan et al., 2024). In maritime transportation, AI supports vessel trajectory prediction, port operations, and risk assessment under complex environmental conditions (Chen et al., 2024d; Durlik et al., 2024). Meanwhile, as shown in Fig. 1, AI techniques are being applied to a wide range of representative transportation tasks, including traffic and demand prediction, resource allocation, perception and monitoring, safety assessment, and system optimization. Across domains, methods such as deep learning, graph neural networks (GNNs) (Chen and Chen, 2022), reinforcement learning (Sonntag et al., 2025; RL), multimodal learning (Li and Liu, 2024), and, more recently, foundation models and large language models (LLMs) (Guo et al., 2024b; Chen et al., 2025) are being leveraged to address challenges arising from spatiotemporal complexity, data heterogeneity, and operational uncertainty. While the specific problem formulations vary by domain, these tasks share common methodological foundations and increasingly benefit from cross-domain methodological transfer.

A growing body of literature has reviewed AI applications within individual transportation domains, including road (Olugbade et al., 2022; Chen et al., 2023a; Mostafa et al., 2025; Tsigdinos et al., 2025; Zhang et al., 2025b), air (Li, 2025; Fondevila-Gascón et al., 2025; Yan et al., 2024c; Zhao et al., 2026), rail (Ficzere, 2023; Zhang and Zhang, 2023), and maritime (Zhang et al., 2022b; Talpur et al., 2025). These surveys have provided valuable insights into domain-specific problems, data sources, and algorithmic advances. Nevertheless, existing reviews remain fragmented in several important respects. First, most surveys focus on a single transportation mode (Chen et al., 2023a; Tsigdinos et al., 2025), such as road, rail, maritime, or air transportation, making it difficult to identify common methodological trends and transferable AI paradigms across domains. Second, many reviews focus on specific algorithms or individual applications (e.g., traffic prediction, autonomous driving, and port operations) rather than examining how AI supports broader transportation systems across perception, prediction, optimization, and decision-making. Third, the rapid emergence of foundation models, multimodal learning, and generative AI has substantially reshaped transportation research in recent years, yet these developments are only partially covered in earlier surveys. More importantly, transportation systems are becoming increasingly interconnected rather than independent. Passenger mobility, freight logistics, and infrastructure operations frequently span multiple transportation modes. The rapid evolution of AI—particularly the emergence of large-scale foundation models—along with heightened attention to autonomous driving (Zhao et al., 2024; Huang et al.,

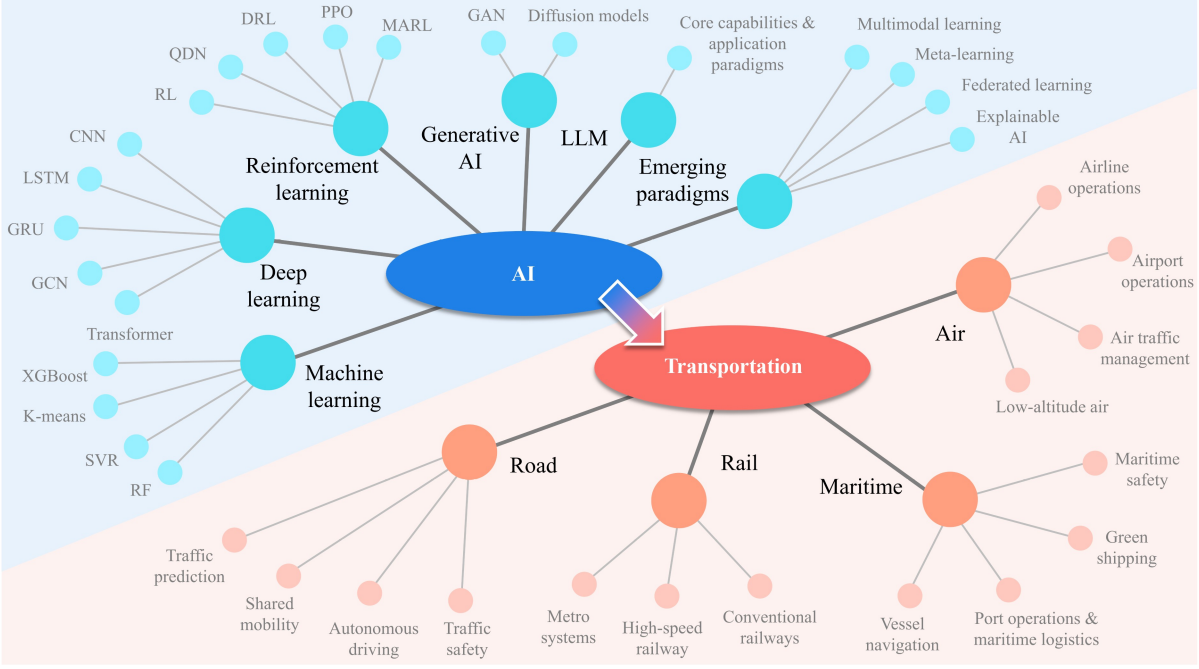


Fig. 1 Overview of AI theory.

2025), low-altitude aviation (Zhang and Han, 2026; Yao et al., 2026), and integrated mobility systems (Coppola et al., 2025), is blurring traditional domain boundaries and creating new opportunities for cross-modal innovation. Consequently, reviewing each transportation mode in isolation provides only a partial understanding of current AI developments in transportation and limits the identification of common research challenges and future opportunities.

Motivated by these gaps, this review provides a comprehensive thematic synthesis of AI research across road, rail, maritime, and air transportation. Rather than reviewing each transportation mode independently, it identifies common AI paradigms, compares representative application scenarios, summarizes shared technical challenges, and discusses emerging research directions, including foundation models, physics-informed learning, continual learning, and cross-domain knowledge transfer. By establishing a unified perspective across transportation modes, this review not only bridges methodological fragmentation but also reveals common AI paradigms, transferable methodological insights, and shared research challenges that are difficult to identify within single-domain surveys.

In terms of literature retrieval, the objective of this work is not to provide a complete bibliographic inventory, but rather to offer a coherent framework for understanding current progress and to identify future research directions. Therefore, instead of exhaustively collecting every publication in the rapidly expanding field of AI-enabled transportation, we organize the review around four major transportation domains (road, rail, maritime, and air transportation) and further classify the literature by representative application scenarios within each domain. Literature selection prioritized studies that 1) introduced representative or influential AI methodologies, 2) demonstrated substantial practical relevance to transportation systems, 3) were published in high-quality peer-reviewed journals or leading conferences, and 4) reflected recent advances, particularly those reported within the last five years. Meanwhile, because AI-enabled transportation encompasses diverse transportation modes and application scenarios, the literature search was conducted using a task-oriented strategy rather than a fixed set of predefined keywords. Specifically, representative application areas within each transportation domain were first identified (e.g., traffic prediction, autonomous driving, railway maintenance, maritime safety, vessel trajectory prediction, and flight delay prediction), and the corresponding AI-related terms (e.g., AI, machine learning, deep learning, GNNs, reinforcement learning, and generative AI) were then combined with these application-specific topics to retrieve representative studies. Additional influential publications were identified through citation tracing of highly cited papers and recent review articles.

2 Artificial intelligence in road transportation

Road transportation systems are inherently complex, shaped by heterogeneous traveler behaviors, diverse vehicle types, infrastructure constraints, and the continual influence of environmental and operational disruptions. Managing such systems involves a wide spectrum of tasks—from monitoring network conditions and regulating traffic flow to supporting emerging mobility services and ensuring roadway safety. As road networks grow more interconnected and data-rich, traditional analytical approaches face increasing difficulty in capturing the nonlinear dynamics and rapid temporal variations that characterize modern mobility.

AI introduces new capabilities to address these challenges by extracting patterns from high-volume traffic data, learning behavioral regularities from mobility traces, and interpreting sensor information from increasingly connected and automated vehicles (CAVs). As shown in Fig. 2, these data-driven methods have shown particular promise in improving our ability to predict traffic states, support more adaptive mobility management,

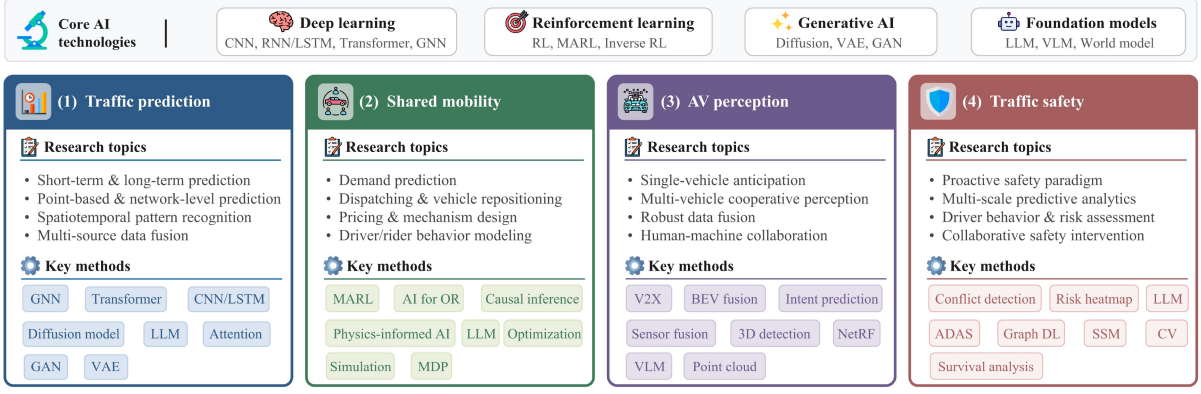


Fig. 2 Diagram of the main areas of road transportation.

enhance perception capabilities for automated systems, and better identify safety-relevant anomalies. Building on these developments, this section focuses on four representative areas where AI is contributing significantly to road transportation research and practice: 1) precise and reliable traffic prediction, 2) efficient and seamless shared mobility, 3) enhanced perception for autonomous driving, and 4) predictive and proactive traffic safety.

2.1 AI for precise and reliable traffic prediction

Accurate traffic prediction is a pivotal engine for intelligent transportation infrastructure; its implementation facilitates dynamic route guidance, adaptive signal control (Sun et al., 2025), and network-wide operational management (Shaygan et al., 2022). Traffic prediction encompasses a wide range of indicators, including average speed, flow, density, travel time, and categorical traffic states, each offering different insights into network performance.

Traffic prediction tasks can be categorized by their temporal horizon. Short-term prediction, typically ranging from the next few minutes to several hours (e.g., 5-min, 15-min, or 1-h intervals), focuses on capturing rapid fluctuations and stochastic variations in traffic flow. These tasks require models with strong responsiveness and real-time inference capabilities and are widely applied in traffic guidance, ramp metering, and dynamic routing (Barros et al., 2015). Medium- and long-term prediction, spanning several hours to multiple days, emphasizes the extraction of periodic and recurrent patterns, such as morning–evening peak cycles or weekday–weekend differences. Such predictions support the formulation of traffic management strategies, maintenance planning, and travel demand management (Wang et al., 2021d). From a spatial perspective, traffic prediction problems include point-based prediction, which aims to predict traffic states at a single sensor or road segment, and network-level prediction, which models the evolution of traffic states across multiple interconnected links.

AI has significantly advanced traffic prediction capabilities by leveraging large-scale mobility data and learning representations of complex spatiotemporal dependencies (Sayed et al., 2023). A broad spectrum of AI techniques has been developed, each exploiting different structural properties of traffic data. Convolutional neural networks (CNNs) model spatial correlations by treating road networks or grid-based traffic measurements as images (Zong et al., 2026; Zhang et al., 2020), enabling the effective extraction of local spatial patterns, such as congestion propagation and neighboring flow dependencies. Recurrent neural networks (RNNs) and their variants, particularly long short-term memory networks (LSTMs) (Zhang, 2024; Fang et al., 2024b), demonstrate exceptional capabilities in characterizing time-varying patterns and decoding the complex temporal dynamics intrinsic to traffic flow evolution, thereby mitigating vanishing gradients in long sequences. Transformer architectures, powered by attention mechanisms (Pan et al., 2022), further extend this capability by capturing long-range temporal interactions and dynamically prioritizing informative time steps, which is particularly useful under non-recurrent or irregular traffic conditions. The integration of GNNs has marked a major methodological shift by explicitly modeling road network topology (Fan et al., 2025a; Liu et al., 2022a). GNNs can capture directional propagation patterns, upstream–downstream interactions, and global network structures that traditional grid-based or sequence models cannot fully represent. As traffic data sources continue to diversify, density ratio models (Zhu et al., 2019), Gaussian process (Zhu et al., 2023b), high-dimensional fuzzy models (Wang et al., 2025e), attention-based spatiotemporal models, generative models (e.g., diffusion models) (Li et al., 2025b), and multimodal learning frameworks (Zhu, 2020; Zong et al., 2026) have emerged to jointly utilize heterogeneous inputs such as weather, incidents, special events, POI distributions, and probe vehicle trajectories. Recently, the transportation research community has begun exploring the potential of LLMs and foundation models (Guo et al., 2024b) to incorporate semantic knowledge, encode human mobility patterns, perform reasoning over sparse data, and provide explainable insights—offering promising avenues for prediction systems constrained by data scarcity or needing higher interpretability. However, current foundation models are primarily pretrained on general-purpose corpora rather than transportation data. Their ability to reason about traffic dynamics heavily depends on domain adaptation and the integration of external knowledge. Moreover, although these models demonstrate promising zero-shot and few-shot capabilities, standardized benchmarks for evaluating reasoning quality, robustness, and operational usefulness in traffic prediction remain largely unavailable.

Despite these remarkable advances, no single modeling paradigm consistently performs best across all traffic prediction scenarios. Model performance is strongly influenced by traffic dynamics, data availability, prediction horizon, and deployment requirements. In addition to common AI challenges such as data quality, interpretability, and computational efficiency, traffic prediction presents several domain-specific challenges arising from the spatiotemporal evolution of traffic, network-wide dependency propagation, and the need for reliable prediction under continuously changing traffic conditions. The major challenges are summarized as follows.

1) Generalization under non-recurrent traffic dynamics. Most traffic prediction models learn regular patterns from historical observations, yet real traffic is frequently disrupted by incidents, adverse weather, roadworks, public events, or policy interventions. Such events alter traffic propagation mechanisms and often invalidate historical correlations, making reliable prediction under

unseen conditions a persistent challenge. To address traffic prediction degradation during extreme weather, Lin et al. (2026) proposed a physics-informed GNN that integrates physical constraints with data-driven learning to ensure reliable and interpretable traffic prediction under rainfall-induced urban flooding events. Zheng et al. (2026) developed a spatio-temporal incident-aware dynamic graph convolutional network that utilizes a dynamic time warping-based algorithm to screen critical traffic events and employs a multi-feature fusion module to jointly learn spatio-temporal, weather, and incident characteristics.

2) Long-range spatiotemporal dependency modeling. Unlike many prediction tasks that treat observations as independent samples, traffic prediction requires modeling traffic evolution over both space and time. Congestion propagates through upstream-downstream road segments, interacts with network topology, and exhibits multiscale temporal dependencies ranging from minutes to daily or weekly periodicity. Capturing these coupled dependencies while maintaining scalability remains a fundamental challenge. Recent studies consistently suggest that combining attention mechanisms with graph representations provides a more effective solution than modeling spatial or temporal dependencies independently. For example, Wang et al. (2025d) proposed a Transformer-based framework that employs an adaptive spatio-temporal relation learning mechanism to fuse feature, spatial, and temporal embeddings via a learnable parameterization network, effectively capturing long-range dependencies for advanced traffic flow prediction. To address spatial and temporal imbalance issues in traffic flow prediction, Tang et al. (2025a) proposed a deep learning framework that integrates space-dependent and time-dependent attention mechanisms to dynamically capture multi-scale spatial correlations and varying historical temporal importance, achieving superior performance on real-world data sets. Moreover, to capture the complex pattern diversity driven by spatial heterogeneity and multi-scale temporal variations, Chen and Wu (2026) proposed a framework that decoupled spatiotemporal sequences to extract discriminative contextual representations and employed a data-driven interactive learning module to dynamically reconstruct graph structures for uncovering both global and local dependencies, outperforming state-of-the-art baselines across various prediction horizons.

3) Uncertainty quantification. Traffic prediction inherently involves stochasticity due to human behavior, incidents, and environmental variability. At the same time, traffic managers often need to determine whether predicted congestion is sufficient to trigger diversion strategies or whether risk levels warrant proactive safety measures. Therefore, providing confidence intervals or probabilistic distributions—rather than deterministic values—is crucial for risk-aware decision-making. To address this need, practical systems are increasingly adopting uncertainty-aware models based on Bayesian networks (BNs), quantile regression, ensemble predictors, and generative modeling techniques. For example, Mallick et al. (2024) proposed a scalable deep ensemble uncertainty quantification method for spatiotemporal GNNs by combining Gaussian-assumption-free quantile regression, Bayesian hyperparameter optimization, and Gaussian copula-based ensemble generation to effectively decompose and estimate both data and model uncertainty in traffic prediction. Karim and Nower (2024) proposed a probabilistic spatiotemporal GCN model that employs a dynamic adjacency matrix to capture time-varying traffic dependencies. These approaches provide confidence intervals or full predictive distributions, enabling risk-informed decision-making. Nevertheless, uncertainty estimation remains underexplored compared with deterministic prediction, and its integration into operational traffic management systems remains limited.

4) Network-wide real-time prediction. Practical traffic management requires simultaneous prediction over thousands of interconnected road segments with minute-level update frequencies. Balancing prediction accuracy, computational efficiency, and deployment latency remains a major challenge for large-scale operational systems. While advanced spatiotemporal graph networks are accurate, their high computational cost limits their real-time deployment in large urban networks, where prediction horizons must be refreshed every minute. Engineering efforts increasingly focus on optimizing inference pipelines through model pruning, knowledge distillation, operator fusion, and hardware-friendly GNN architectures designed for edge computing. For example, Zhang et al. (2024a) proposed a lightweight multilayer perceptron for real-time traffic flow prediction that uses knowledge distillation from a complex spatiotemporal GNN to encode spatiotemporal information within a simple multilayer perceptron architecture, achieving competitive accuracy at significantly lower computational cost. In addition, parallel computing frameworks and incremental-update strategies are also being adopted to support near-instantaneous prediction updates, ensuring timely information delivery for operational decision-making. For instance, Zhang et al. (2025f) proposed a spatio-temporal graph Transformer network to handle large-scale traffic data for accurate flow prediction efficiently.

5) Cross-city and cross-network generalization. In real applications, traffic models are often deployed across multiple cities or regions with different road geometries, traffic demand structures, and driving cultures. Models trained on a single network typically degrade significantly when applied elsewhere, requiring costly retraining and additional data collection. Recent engineering-oriented research explores topology-invariant representations, domain adaptation frameworks, and city-agnostic pretraining using large-scale mobility data sets. These

approaches aim to reduce data collection burdens and accelerate model rollout across diverse networks. For example, Xu et al. (2025) proposed a cross-city knowledge transfer framework that leverages a shared multi-graph feature extractor, a linear Transformer-based feature-matching module, and a joint meta-learning method to achieve accurate cross-city traffic prediction while reducing data dependency in the target city.

6) Robust prediction under incomplete and noisy observations. Although data sparsity and missing observations are common challenges across AI applications, they are particularly critical for traffic prediction because forecasting relies on continuous spatiotemporal observations over entire road networks. Missing or low-coverage observations not only reduce local prediction accuracy but also distort the propagation of traffic states across connected links. To mitigate these issues, researchers are increasingly relying on cross-source data fusion (e.g., combining floating-car data, camera data, and crowd-sourced mobility traces) and spatial transfer methods that infer missing information from neighboring links or structurally similar roads. For example, to estimate instant traffic conditions across blind-spot intersections, a heterogeneous data fusion paradigm was introduced by Zhu (2020). This approach synthesizes network topologies, GPS traces from floating taxis, and historical intersection logs through an advanced conditional generative adversarial architecture that embeds both graph convolutional networks (GCNs) and U-Net modules. In addition, cross-city model transfer and meta-learning approaches are also being explored to support regions with minimal historical data, providing more robust predictions in sparse-data scenarios. For example, Zhang et al. (2025e) proposed a cross-city domain adaptation model that addresses data scarcity by fusing dynamic time warping and auxiliary urban data to quantify domain differences. Li et al. (2022a) developed a two-stage physics-informed transfer learning framework guided by macroscopic fundamental diagram constraints to enable link-level traffic flow knowledge transfer across similar network regions, addressing data insufficiency, data set shift, and cold-start problems in fine-grained traffic prediction. Furthermore, real-world sensor networks frequently suffer from noise, intermittent failures, calibration drift, or extreme-weather-induced disruptions. Such anomalies or omissions can propagate through prediction pipelines, leading to unreliable short-term predictions. Practical systems increasingly adopt automated data-cleaning procedures, anomaly detection algorithms, and graph-based spatiotemporal data reconstruction models to maintain data integrity. For instance, a consolidated short-term traffic prediction architecture was introduced by Chen et al. (2019) to maintain estimation stability amidst fluctuating and erratic traffic environments. By synthesizing gradient boosting regression decision trees with a LASSO-based feature filtering mechanism, the approach achieves resilient performance across heterogeneous flow regimes. Xu et al. (2023b) proposed an attentive graph neural process that integrates Gaussian process modeling with deep probabilistic learning to jointly perform network-level traffic speed prediction and data imputation while explicitly quantifying prediction uncertainty for reliability-aware transportation system management.

Overall, recent advances in traffic prediction reveal a clear trend toward integrating spatiotemporal learning, physical knowledge, and heterogeneous contextual information. Rather than relying on a single AI paradigm, future traffic prediction systems are likely to combine complementary methodologies to improve robustness, generalization, and operational applicability under diverse traffic conditions.

2.2 AI for efficient and seamless shared mobility

Modern urban transit networks have deeply incorporated shared mobility ecosystems, which flexibly deliver on-demand transportation services—ranging from ride-hailing and micro-mobility options like bicycle-sharing to emerging shared autonomous vehicles (SAVs). The core operational challenge for these platforms is the real-time matching of a fluctuating, geographically dispersed supply of vehicles with a similarly dynamic user demand (Zhu et al., 2023a). To orchestrate this complex system, research has converged upon four fundamental pillars. First, platforms must accurately predict demand to anticipate user needs (Yin et al., 2023; Chen et al., 2024e). Second, informed by these predictions, they must intelligently dispatch vehicles and manage supply through order matching and repositioning. Third, the market is governed by economic and behavioral mechanisms, such as pricing, that require careful design. Finally, system performance depends on the micro-level actions of its users, requiring a granular understanding of individual driver and rider behavior. Meanwhile, AI has emerged as a critical tool for addressing challenges across these interconnected domains.

The ability to accurately predict demand is the bedrock of proactive shared mobility operations. While early deep learning models using CNNs and LSTMs established important groundwork, their rigid structural assumptions struggled to capture the complex, network-based relationships inherent to urban transportation. To overcome this, research shifted toward graph-based models and Transformer-based models, which explicitly model network topology, allowing influence to propagate across non-adjacent yet connected regions (Zhang et al., 2021a; Xu et al., 2023a; Xu et al., 2024a; Shen et al., 2024). Although GNNs and Transformer-based models consistently outperform earlier CNN- and LSTM-based approaches on large-scale urban data sets, their advantages become less pronounced in smaller cities or data-limited environments, where model complexity may exceed the

available information. This limitation has motivated a promising direction in physics-informed AI that enhances deep learning by integrating established transportation theories. By embedding classical principles, such as gravity models, as soft constraints or priors in frameworks like Gaussian processes, these hybrid approaches achieve greater robustness and generalizability (Li et al., 2024a). Even with sophisticated network representations, predicting demand disturbances caused by exogenous factors like large-scale events or adverse weather remains challenging, as the relevant information is often unstructured. To address this, LLMs are being adopted to interpret and synthesize deep contextual factors from heterogeneous data. With their powerful semantic comprehension, LLMs can generate rich, contextualized embeddings that empower more specialized downstream prediction models (Yuan et al., 2024). Furthermore, recognizing that a single-mode focus overlooks crucial interactions with other transit options, another research frontier focuses on jointly predicting demand across multiple services (e.g., ride-hailing and public transit) to capture their synergistic and competitive dynamics (Xu et al., 2022).

Informed by these increasingly accurate demand predictions, the central operational challenge becomes the real-time matching of supply and demand through intelligent dispatching and vehicle repositioning. This is a large-scale dynamic combinatorial optimization problem with multi-faceted objectives, such as maximizing order fulfillment and minimizing empty mileage. Initial approaches relied on traditional operations research (OR), which formulates the problem using mathematical programming. However, OR-based paradigms often take too long to converge when dealing with the immense scale of real-world problems. This computational challenge led researchers to adopt RL, which offers a more flexible, data-driven framework (Mao et al., 2020). Compared with conventional optimization methods, RL offers greater adaptability to stochastic and dynamically changing environments. While single-agent RL represented a significant advance, it struggled to capture the decentralized nature of a market with thousands of independent drivers. Consequently, multi-agent RL (MARL) has emerged as a more powerful paradigm in which each driver is modeled as an agent learning a cooperative policy, leading to more robust and scalable system-wide coordination (Xie et al., 2023). Meanwhile, pure RL approaches often require extensive interactions for training and may struggle to satisfy operational constraints, motivating the development of hybrid AI–optimization frameworks that combine learning capability with optimization guarantees. The burgeoning field of "AI for Operational Research" (AI for OR) is proving more impactful by combining the strengths of both domains. Rather than replacing classic OR solvers, AI enhances them. For instance, an RL agent can be trained to learn a highly effective heuristic for vehicle-trip assignments, which then dramatically prunes the search space for a traditional mixed-integer programming solver, enabling near-optimal solutions at a fraction of the computational cost (Wang and Guo, 2022). This synergy is especially critical for computationally intensive tasks such as ride-pooling, which require solving a dynamic vehicle routing problem (VRP) in real time.

While dispatching and repositioning represent the direct, physical control of vehicle supply, platforms also wield a powerful indirect lever: the design of economic mechanisms. For decades, game theory has provided a formal framework for modeling the strategic interactions between the platform, drivers, and riders. However, its assumptions of perfect rationality can be limiting in practice. RL offers a more adaptive, data-driven alternative, where the platform learns an optimal pricing policy through direct interaction with the environment (Chen et al., 2024a). A critical limitation of these adaptive approaches, however, is their propensity to confuse correlation with causation. For example, a platform might observe that a price surge is followed by increased driver supply and incorrectly infer a strong causal link, when in fact both were caused by a confounding factor, such as the end of a major sporting event. Such spurious correlations lead to fragile policies that fail under new conditions. This fundamental challenge has propelled the integration of causal inference, a more sophisticated methodology that allows platforms to estimate the true causal impact of their interventions and develop more robust policies (Xie et al., 2026). Recently, the introduction of SAVs has altered this landscape. An SAV fleet is a fully compliant workforce with no personal preferences and deterministic operational costs. This simplifies control but places the entire intelligence burden on the central algorithm. Pricing for SAVs thus shifts from incentivizing a human supply-side to exclusively managing demand, preventing congestion, and maximizing revenue in a perfectly obedient system.

Ultimately, the efficacy of both system-level optimization and economic policies depends on a granular, AI-driven understanding of individual user behavior. A central research challenge is to move beyond aggregate assumptions and capture the profound heterogeneity in user preferences and decision-making. The core problems involve accurately modeling key actions such as a driver's trip acceptance, log-off timing, or a passenger's cancellation decision (Urata et al., 2021). Methodologically, this domain evolved from traditional econometric approaches, such as discrete choice models, which offer interpretable parameters but often lack the predictive power to handle complex, nonlinear relationships. To address this gap, the field turned to high-performance machine learning, with gradient-boosting frameworks becoming widely employed for their predictive performance on structured, tabular data. Nevertheless, such elevated predictive fidelity frequently compromises the

model's capacity to elucidate the underlying behavioral mechanisms of traffic participants. To resolve this trade-off, an important line of research involves developing hybrid models that fuse learned deep representations—such as user embeddings from activity sequences—into classical choice structures, seeking to synthesize the predictive power of AI with the explanatory capacity of econometrics (Li et al., 2023c).

Overall, recent studies indicate that the primary role of AI in shared mobility has shifted from improving isolated prediction or dispatching algorithms toward enabling system-level coordination across demand prediction, fleet management, pricing, and multimodal integration. Future research is therefore expected to emphasize collaborative optimization among multiple mobility services while balancing operational efficiency, user equity, and system sustainability.

2.3 AI-enabled advanced perception for autonomous driving

Comprehensive scene understanding and spatio-temporal interpretation of the ego-surroundings constitute the primary cornerstone underpinning autonomous driving systems, particularly when deployed in volatile urban traffic environments. Within automated vehicular systems, the integration of artificial intelligence into environmental perception signifies a paradigm leap, transcending the mere expansion of physical detection ranges for obstacles. From a transportation systems perspective, its core value lies in transcending local, instantaneous, and purely visual awareness. This paradigm shift enables vehicles to: (i) identify potential risks occluded from direct view, (ii) anticipate traffic disturbances before they propagate into instability, and (iii) infer the intent of other road users to mitigate unnecessary conservatism. This framing aligns with the broader CAV philosophy, in which connectivity and automation fundamentally reshape the acquisition, dissemination, and use of traffic information (Shladover, 2018). In this study, we organize the literature into four layers: single-vehicle anticipation, multi-vehicle cooperative perception (CP), robust data fusion, and human − machine collaborative awareness.

2.3.1 Single-vehicle perception

Single-vehicle perception serves as the foundation of autonomous navigation, utilizing onboard sensors (e.g., cameras, LiDAR) to interpret the immediate environment. Nevertheless, restricted by physical limits, it is evolving from reactive detection toward predictive anticipation. Standard ego-vehicle sensors are inherently constrained by geometric occlusions (e.g., intersections) and adverse weather, motivating models that infer latent conflict risks from observable motion patterns rather than relying solely on what is directly visible (Geng et al., 2023). Empirical studies using connected vehicle data indicate that instantaneous driving behaviors—such as abnormal longitudinal or lateral maneuvers—serve as reliable precursors to intersection crashes, suggesting that perception should capture dynamic risk (how traffic moves) in addition to static semantics (what objects exist) (Arvin et al., 2019).

Furthermore, single-vehicle perception capability directly influences traffic flow stability. Inefficiencies often arise when minor downstream perturbations propagate upstream as stop-and-go waves. Simulation results indicate that CAVs capable of anticipatory perception can dampen these waves, thereby improving string stability and throughput (Talebpour and Mahmassani, 2016). Complementary field experiments further show that a single autonomous vehicle, acting on anticipated rather than immediate cues, can smooth traffic flow and reduce braking cascades (Stern et al., 2018).

Beyond mere detection, perception serves as the specific input for planning by inferring intent. This capability allows the ego-vehicle to anticipate risks and reduce overly conservative maneuvers. Purely semantic perception (detecting an object) fails to resolve interaction uncertainty, often leading to overly conservative driving behavior. Recent surveys emphasize that prediction maneuvers—such as yielding or merging intentions—are critical for efficient navigation in mixed traffic (Fang et al., 2024a). By inferring low-conflict probability from subtle motions of surrounding vehicles, AI-enabled perception enables smoother operations and reduces the "fluency gap" between human and automated drivers.

2.3.2 Multi-vehicle cooperative perception

While single-vehicle perception has advanced, it remains bounded by physical viewpoints. Multi-vehicle CP addresses this by leveraging V2V, V2I, and V2X communications to share sensory information, effectively expanding the perception horizon and overcoming blind spots. Technical reviews highlight that the synergy of communication and AI enables a level of situational awareness that no single agent could achieve in isolation, particularly for protecting vulnerable road users (Adnan Yusuf et al., 2024).

Recent research further emphasizes that CP is not a naive data-broadcasting problem, but a resource-constrained perception–communication co-design task. To this end, AI-based methods have been introduced to determine what to share and when, given limited bandwidth. For example, RL–based policies have been applied to select which perception information to transmit adaptively, achieving favorable trade-offs between detection performance and communication load in connected traffic environments (Aoki et al., 2020). Similarly, informativeness-aware CP frameworks prioritize perception content that maximizes downstream utility, avoiding redundant or

low-value information exchange while maintaining situational awareness (Zhou et al., 2022; Chang et al., 2024). Beyond algorithmic designs, transportation research has also examined system-level performance and deployment realism. A representative empirical/simulation-oriented contribution evaluates decentralized CP in V2V-connected traffic, showing that CP effectiveness depends on connectivity conditions and decentralized communication behaviors—supporting the need to assess CP beyond isolated detection metrics (Yoon et al., 2022).

However, the challenge lies in resource optimization. Multi-vehicle CP is not simply about broadcasting all available data; it requires strategic information sharing under bandwidth constraints. Recent research on optimized CP demonstrates that extended visibility is achievable even with imperfect communication by prioritizing information that maximizes downstream utility (Sarlak et al., 2025). The systemic value of this shared awareness is particularly evident in early deployment scenarios. For instance, state estimation derived from CP can mitigate the limitations of low CAV penetration rates, supporting adaptive traffic signal control and stabilizing mixed traffic flows even when connected vehicles are sparse (Li et al., 2024e). Thus, CP should be evaluated not merely by detection metrics, but by its contribution to system-level control and stability.

2.3.3 Robust data fusion

Rather than replacing individual sensors, recent research increasingly focuses on exploiting their complementary characteristics. Camera, LiDAR, and radar each provide distinct advantages in semantic understanding, geometric perception, and robustness under adverse conditions, making multimodal data fusion the dominant paradigm for reliable autonomous perception. Comprehensive surveys categorize these strategies into input, feature, and decision fusion, while identifying critical challenges such as temporal alignment and uncertainty propagation (Wang et al., 2020b).

For autonomous driving, the primary fusion objective is robustness and continuity, requiring perception to remain stable under sensor dropouts, asynchronous observations, and environmental degradation. To this end, transportation research has increasingly framed fusion as an uncertainty-aware inference process. Probabilistic fusion approaches explicitly model sensor uncertainty and propagate it through semantic perception and mapping pipelines, enabling more reliable reasoning under occlusions and ambiguous observations (Berrio et al., 2022).

A representative advancement in robust fusion is the shift toward BEV-centric (bird's eye view) multi-modal representations. Frameworks such as BEVFusion demonstrate that decoupling sensor modalities and performing fusion in a unified BEV space improves tolerance to sensor degradation, particularly when individual sensors (e.g., LiDAR) partially fail or degrade (Liang et al., 2022). Complementary studies highlight that temporal misalignment and asynchronous multi-sensor streams pose fundamental challenges for maintaining fusion consistency in real-world deployments, where sensing and communication delays are unavoidable (Feng et al., 2021).

Beyond sensor-level issues, the robustness of data fusion-based perception must also account for adverse environmental conditions. Empirical evaluations indicate that different sensing modalities degrade in distinct ways under fog, rain, and snow, and that effective fusion must dynamically exploit cross-modal complementarity to sustain perception performance (Bijelic et al., 2018). Consequently, data fusion should be viewed as a pipeline that not only harmonizes heterogeneous evidence but also propagates calibrated uncertainty to downstream planning modules, ensuring that beyond-human-sight awareness remains actionable and reliable under diverse conditions.

2.3.4 Human-machine collaboration

In mixed traffic conditions with partial automation, full autonomy is not yet achievable, and human drivers are required to supervise automated systems and intervene when necessary. Under such conditions, perception plays a critical role in supporting human-machine collaboration, as it determines how system states and environmental risks are communicated between automated driving systems and human operators.

From an engineering perspective, perception is not only an internal sensing module, but also the primary channel through which automated systems convey their understanding of the driving environment to humans. Human-centered studies on collaborative driving show that effective autonomy depends on whether system perception outputs—such as detected hazards, predicted conflicts, and confidence levels—are consistent with human expectations, thereby enabling appropriate trust calibration and smooth control transitions (Xing et al., 2021).

Takeover scenarios provide a representative illustration of this collaborative process. Empirical evidence indicates that takeover performance strongly depends on the driver's situational awareness at the moment of transition, including their understanding of surrounding traffic conditions and potential risks (Gold et al., 2016). Accordingly, perception systems should not only detect beyond-human-sight hazards, but also present this information clearly and understandably, allowing drivers to recognize risks and respond appropriately quickly.

When such human-machine interaction is effectively supported, collaborative perception can lead to measurable safety and operational benefits. Studies under adverse conditions, such as foggy freeways, show that providing connected-vehicle information to drivers significantly

reduces beyond-visual-range crash risks (Ren et al., 2025). Broader reviews and meta-analyses further suggest that perception-enabled human–machine collaboration contributes to crash reduction and smoother traffic operations in mixed traffic environments (Wang et al., 2020a; Pan et al., 2024). Collectively, these findings indicate that AI-enabled perception facilitates not only sensing accuracy, but also effective collaboration between humans and machines, translating technical capabilities into system-level safety and efficiency improvements.

Overall, autonomous driving perception is evolving from improving individual perception accuracy toward holistic environmental understanding through multimodal sensing and human-machine collaboration. Future advances are expected to rely increasingly on robust perception under complex environments, efficient model deployment, and tighter integration between perception, prediction, and decision-making.

2.4 AI driving predictive and proactive traffic safety

AI has also had a transformative impact on road traffic safety, driving a fundamental shift from reactive response to a predictive and proactive paradigm.

2.4.1 Paradigm shift: From reactive to proactive safety

Traditional road transportation safety research has relied on post-incident analysis methods, including a cycle of crash, data collection, analysis, and intervention. Specifically, traffic engineers and policymakers have meticulously studied accident reports to identify locations where tragedy has struck with statistical significance (Liu et al., 2025), and then implemented countermeasures, such as redesigning intersections, improving signage, and increasing enforcement. While these evidence-based approaches have significantly improved traffic safety outcomes (Li et al., 2025c), they are constrained by a fundamental limitation: they rely on historical accident data for learning (Guo et al., 2021b). Consequently, system improvements are contingent upon the occurrence of adverse events, which often entail substantial human and economic losses. This paradigm is inherently backward-looking, unable to prevent new incidents or address risks in locations without a documented history of failure.

The advent of AI heralds a profound revolution. It catalyzes a systemic shift from a reactive posture to a predictive and proactive safety framework. This methodological evolution represents more than an incremental improvement in prediction accuracy; it reflects a fundamental shift in traffic safety management from post-event analysis toward continuous risk anticipation and intervention. It seeks to understand and mitigate risk before a collision occurs. Predictive safety is a core component of this shift (Liu et al., 2022c). Enabled by AI, this involves analyzing vast, dynamic data sets to predict adverse events. This process identifies subtle danger precursors invisible to traditional analysis. Proactive safety is the ability to act on this foresight. It deploys intelligent, real-time interventions to neutralize emerging threats. The goal is to guide the system toward a safer state.

At the heart of this paradigm shift is AI's ability to process and synthesize information at scales and speeds beyond human capability. Modern transportation systems generate an unprecedented volume of data. This data comes from a diverse sensor ecosystem. Sources include real-time video from traffic cameras and high-resolution spatial data from roadside LiDAR units. Kinematic information is gathered from millions of connected vehicles and smartphones (Shi et al., 2022). Contextual data on weather and public events is also collected (Formosa et al., 2020). Osman et al. (2019) introduced a near-crash prediction method based on observed vehicle kinematic data. Focusing on infrastructure bottlenecks, a hierarchical Bayesian logistic regression framework was constructed by Wang et al. (2015) to evaluate safety risks at expressway weaving zones, integrating multi-source inputs from RTMS sensors, geometric configurations, and meteorological records. Traditionally, much of this data was discarded or used for narrow applications. AI provides the central processing capability to fuse these disparate data streams. This fusion creates a coherent, dynamic, and holistic understanding of the traffic environment. AI can discern subtle patterns, complex correlations, and emergent behaviors, all of which are key indicators of risk.

2.4.2 Multi-scale predictive analytics in practice

This data-centric capability enables risk prediction across multiple scales, from individual interactions to network-wide phenomena. At the microscopic level, AI revolutionizes the definition of a safety-relevant event. AI systems do not wait for a crash. They are trained to recognize traffic conflicts or near-miss events (Guan et al., 2026). By analyzing data feeds, AI algorithms learn the typical movement patterns of all road users at a specific location and extrapolate them into the near future to predict safety violations. For example, Sun and Sun (2016) combined SVM with K-means clustering for crash prediction. Li et al. (2020a) proposed a crash risk prediction model using an LSTM-CNN. The system flags a predicted high-risk interaction as a conflict. In addition, Cai et al. (2025) proposed a joint model for short-term crash prediction that effectively manages data imbalance and spatiotemporal correlations, identifying speed variance as the primary risk factor in motorway accidents. While crashes are rare events, conflicts occur with a frequency that is orders of magnitude higher. This provides a rich stream of safety data (Hu et al., 2023), which can be

analyzed to learn about a location's risk without injuries. In this process, safety analysis is transformed from a study of rare failures into continuous monitoring of system performance.

At the macroscopic level, AI enables a dynamic approach to risk mapping. The traditional static hotspot maps updated annually with crash data are being replaced by living risk heat maps (Park et al., 2025). Ma et al. (2021) used a stacked sparse autoencoder to identify traffic accident hotspots. Zhang and Cheng (2020) proposed a graph deep learning model for predictive hotspot mapping of sparse spatio-temporal events on networks. These approaches ingest a wide range of information, including historical crash data, real-time traffic speeds, congestion levels, weather, and road geometry. Meanwhile, AI models learn the complex interplay between these factors and crash probability. For instance, an AI model might learn that a highway segment becomes a high-risk zone under specific conditions. These conditions could be light rain on a weekday evening with converging commuter and event traffic. This granular insight allows traffic managers to move beyond permanent, one-size-fits-all solutions. They can deploy targeted, temporary interventions when and where they are most needed, making safety management more efficient and effective.

2.4.3 From individual assessment to collaborative intervention

AI's predictive power also extends to the human element, translating individual risk assessment into system-wide proactive measures. AI brings unprecedented clarity to the most critical variable in the safety equation: the human driver. The vast majority of crashes are at least partly attributable to human error. Common errors include distraction, fatigue, or aggressive driving (Hossain and Rahman, 2023). AI provides tools to objectively and continuously quantify driver behavior. Using data from in-vehicle sensors and smartphones, algorithms can learn a driver's unique behavioral fingerprint. They can then identify deviations that signal increased risk, such as harsh braking or erratic steering. Simultaneously, in-cabin cameras with AI facial analysis can detect signs of drowsiness or distraction. A drifting gaze or a drooping head are tell-tale signs (Santos et al., 2024). Craye et al. (2016) extracted features from multi-source data to build a driver fatigue and distraction assessment system. The system can offer tailored feedback and alerts based on an individual's state, creating a personalized safety co-pilot.

At the vehicle level, this proactive capability is manifested in next-generation advanced driver-assistance systems and connected vehicle technologies (Sahnoon et al., 2025). A vehicle with an AI perception system can predict that an obscured cyclist will soon enter its path. This predictive warning gives the driver crucial extra reaction time. In the world of V2X communication, this intelligence becomes collaborative (Jalil et al., 2025). Compared with traditional driver assistance systems that operate largely at the individual vehicle level, recent AI-enabled collaborative safety frameworks increasingly exploit information sharing among vehicles, infrastructure, and cloud platforms, enabling risk mitigation at the transportation-system level rather than through isolated vehicle responses. For example, when a vehicle detects black ice, it can broadcast this information, and an AI-powered cloud platform will warn all approaching vehicles and reroute others. This creates a distributed, cooperative safety network. Meanwhile, vehicles and infrastructure share predictive insights, collectively improving the system's overall safety. According to research by Wang et al. (2020a), the adoption of CAV technology can reduce the average number of accidents by 3.4 million in the United States, the UK, Canada, India, Australia, and New Zealand.

2.4.4 The emerging frontier: LLM in safety analytics

More recently, the emergence of large-scale foundation models, particularly LLMs, is beginning to open another frontier for predictive and proactive safety. While previous AI applications focused on processing structured numerical and visual data, these new models possess an unprecedented ability to understand and reason with unstructured human language and complex, multi-modal contexts. This capability is being harnessed to mine vast, previously untapped sources of safety-relevant information (Zhang et al., 2025d). For instance, LLMs can analyze thousands of narrative-rich police crash reports, social media posts about hazardous road conditions, or public transit user feedback to identify novel risk factors and causal chains that are invisible to traditional statistical methods. By understanding the semantic content of these texts, these models can uncover recurring themes. This qualitative intelligence can then be structured and integrated into the quantitative risk models, enriching their predictive power. Furthermore, these models are becoming the nexus for human-machine interaction in safety systems. A traffic manager can now query the AI system in natural language and receive an instant and synthesized report (Xie et al., 2025). This conversational interface dramatically lowers the barrier to accessing complex safety analytics, empowering a wider range of stakeholders to participate in proactive safety management. Nevertheless, the application of LLMs in traffic safety remains at an early stage. In addition to factual reliability, LLMs may generate hallucinated explanations or recommendations that appear plausible but are not supported by traffic evidence, posing risks in safety-critical applications. Their high computational requirements also hinder deployment in latency-sensitive roadside and in-vehicle

systems. Furthermore, most existing LLMs are pretrained on general-domain corpora and require substantial domain adaptation before they can effectively understand transportation-specific terminology, regulations, and operational contexts. Developing trustworthy transportation foundation models with uncertainty estimation, efficient inference, and rigorous validation protocols therefore remains an important research direction.

Overall, AI is fundamentally reshaping road traffic safety from reactive accident investigation toward predictive and collaborative safety management. Rather than improving individual safety applications in isolation, recent advances increasingly integrate risk prediction, driver behavior analysis, connected vehicle technologies, and foundation models into a unified proactive safety framework capable of supporting system-level safety interventions.

3 Artificial intelligence in rail transportation

Rail transportation systems are inherently complex, integrating tightly coupled physical infrastructure, rolling stock, control systems, and human operations under stringent safety and reliability requirements. As illustrated in Fig. 3, modern rail systems can be viewed as a multi-layered architecture, spanning physical systems, large-scale sensing and data acquisition, intelligent modeling and optimization, system-specific applications, operational



Fig. 3 Diagram of the main areas of rail transportation.

decision-making, and overarching system-level objectives. Managing such complexity using traditional rule-based and experience-driven methods has become increasingly challenging in the face of growing demand variability, network interdependencies, and operational uncertainties. Recent advances in AI also offer new opportunities to enhance rail system intelligence across these layers by enabling data-driven perception, prediction, and decision support. More specifically, the physical layer consists of railway infrastructure, rolling stock, signaling equipment, and other operational assets that constitute the foundation of railway systems. Built upon this foundation, the sensing and data acquisition layer continuously collects heterogeneous data from onboard sensors, trackside monitoring devices, inspection systems, and operational records, providing real-time awareness of system conditions. These data are then processed within the AI and hybrid intelligent layer, where AI techniques are employed for condition assessment, traffic prediction, fault diagnosis, scheduling optimization, and decision support. The resulting capabilities are delivered through different application layers, including metro systems, high-speed railways (HSR), and conventional railways, each with distinct operational characteristics and management requirements. Finally, AI-generated insights support operational decision-making, such as maintenance scheduling, train control, and timetable optimization, ultimately contributing to higher-level objectives including safety, efficiency, reliability, sustainability, and passenger service quality.

Corresponding to the application layer in Fig. 3, the following sections review how AI technologies are deployed across three representative railway systems, i.e., metro systems, HSR, and conventional railways. Although these systems share the same underlying sensing, modeling, and decision-making pipeline, they differ substantially in operational objectives, infrastructure characteristics, and AI application priorities.

3.1 AI-driven applications in planning, operation, and maintenance for metro systems

Urbanization has intensified mobility demands, making metro systems a core of sustainable and high-capacity transport. However, growing passenger volumes, complex network interactions, and rising expectations for reliability and resilience have exposed the limitations of traditional rule-based metro network design, train timetabling, and predictive maintenance, etc. These legacy practices struggle to account for real-time variability in ridership, operational disturbances, and disruptions, resulting in crowding, delays, and limited adaptability. AI, including deep learning, RL, and hybrid learning-optimization approaches, offers new opportunities for intelligent, data-driven control. Although the greatest impact of AI lies in operations and management, its contribution expands to planning. As shown in Fig. 3, metro systems emphasize AI-enabled operational optimization and real-time decision support to accommodate high-frequency services and rapidly changing passenger demand.

3.1.1 AI enhancement in metro network planning

AI has gradually shifted metro planning from experience-driven network design toward data-driven and adaptive planning paradigms (Xiao and Xu, 2024), enabling more systematic decision-making for route optimization, station placement, and long-term system expansion. For instance, Su et al. (2024) proposed MetroGNN, a graph-based RL framework that formulates metro expansion as a Markov decision process (MDP). By modeling cities as heterogeneous graphs incorporating land use, population density, and existing transportation infrastructure, the framework sequentially selects new stations and links, achieving superior performance on benchmark data sets in terms of coverage, efficiency, and connectivity.

Beyond expansion decisions, machine learning techniques are also being leveraged to support predictive and evaluative aspects of network design. Xia et al. (2025) combined complex network theory with machine learning methods to analyze structural properties and vulnerability patterns of transportation networks, providing insights into robustness and redundancy at the planning stage. Similarly, advances in machine learning and generative AI enable planners to assess route alignment, station spacing, and multimodal integration by learning from large-scale data sets on demographics, socioeconomic factors, land use, and mobility (Da et al., 2025). These models facilitate scenario-based simulations of future demand growth, land development, and shifts in travel behavior, allowing planners to quantitatively evaluate accessibility, equity, and environmental impacts under alternative network configurations (Hadj-Mabrouk, 2024). Despite these advances, data scarcity and quality issues persist in emerging or rapidly urbanizing cities, limiting the generalizability of models. Moreover, data-driven models mainly learn from previously observed urban development patterns and may therefore provide less reliable recommendations under major policy shifts or unprecedented land-use changes.

3.1.2 Metro passenger demand prediction and flow analysis

Passenger demand prediction constitutes a foundational component of both strategic planning and real-time metro operation, as accurate ridership prediction directly affects timetable design, rolling-stock allocation, and congestion management. Recent advances in deep learning have

substantially improved the modeling of complex spatio-temporal demand patterns embedded in large-scale automated fare collection records, train operation logs, and station-level sensor data. Architectures such as LSTM, Transformers, and GNNs are particularly effective at capturing temporal dependencies, long-range correlations, and network-wide interactions among stations. For example, Zhang et al. (2023) proposed a passenger–train interaction simulation framework that captures the dynamic relationship between passenger and train flows in urban rail transit systems by integrating time-varying OD demand, train timetables, and network topology to support operational optimization and capacity evaluation. Wan et al. (2024) integrated advanced machine learning with rigorous time-series analytics and heterogeneous data fusion to enhance both short-term fluctuation prediction and longer-term demand trend estimation, establishing a prescriptive benchmark for urban rail passenger flow prediction. Hu et al. (2025) analyzed the spatiotemporal characteristics of urban rail transit passenger flow using AFC data and proposed an IPSO-SVR prediction framework that incorporates temporal, weather, and workday-related factors to improve passenger flow prediction accuracy under varying external conditions. These predictive outputs enable proactive operational decisions, including dynamic headway adjustment, rolling-stock redistribution, and reserve train activation, as demonstrated by Park et al. (2022b).

Beyond point prediction, counterfactual and causal learning methods are increasingly used to evaluate hypothetical timetable or dispatching adjustments, allowing operators to assess crowding impacts before implementation and thereby reduce simulated congestion levels (Peftitsi et al., 2021). Unlike conventional prediction models that primarily identify statistical associations, causal and counterfactual approaches are better suited to evaluating operational interventions because they disentangle the effect of a timetable or control policy from concurrent demand fluctuations. Their reliability, however, depends on strong identification assumptions and sufficiently rich observational or experimental data. In addition, real-time crowd monitoring systems leveraging computer vision, IoT sensors, and data-driven inference have improved the accuracy of detecting platform build-up and congestion propagation (Yatziv and Haddad, 2025). Despite these advances, key challenges remain, including scalability across large, dense networks, robustness to demand volatility, data privacy, and the interpretability of complex deep learning models. Hybrid machine learning-optimization frameworks, which embed learning-based predictions within constraint-based operational models, represent a promising direction to address these limitations while ensuring feasibility, transparency, and operational reliability.

3.1.3 Metro train timetabling and real-time rescheduling

Train timetabling is a core decision problem in metro operations, requiring conflict-free path allocation, feasible headways, and strict compliance with signaling, safety, and rolling-stock constraints. Recent research increasingly explores AI-enabled approaches to address the computational and adaptability limitations of traditional methods, particularly in large metro networks and disturbance-prone environments. In this context, AI provides complementary capabilities by enhancing prediction, accelerating computation, and supporting adaptive decision-making (Tang et al., 2022).

Learning-augmented exact methods, including branch-and-bound and column generation, leverage machine learning to guide node selection, variable fixing, or pricing decisions, significantly improving solver efficiency without sacrificing feasibility. RL, in particular, has shown substantial promise for real-time rescheduling under disruptions (Yin et al., 2025). By formulating rescheduling as an MDP, RL agents can learn control policies that dynamically adjust headways, reorder trains, execute short-turning strategies, or reassign rolling stock within seconds of a disturbance. For example, Ying et al. (2024) proposed a multi-agent deep RL (DRL) framework for real-time rescheduling during complete track blockages in double-track corridors, in which directional line agents coordinate recovery actions based on local observations. Trained in high-fidelity simulation environments, such RL policies demonstrate strong adaptability and scalability. Although RL enables much faster online decision-making than repeatedly solving large optimization models, this advantage is achieved through extensive offline simulation. A policy that performs well in the training environment may fail under unseen blockage patterns, demand levels, or infrastructure constraints, making generalization and safety verification central barriers to deployment. Therefore, to ensure operational safety and regulatory compliance, hybrid RL-optimization architectures embed hard constraints or feasibility checks within the decision loop. Emerging multi-agent formulations further model trains as decentralized decision-makers capable of negotiating priorities and coordinating actions, offering a promising paradigm for high-frequency operations and future virtual-coupling metro systems.

3.1.4 Metro passenger flow management and control

Passenger flow management is a core task of metro operation, influencing system safety, service reliability, and passenger experience (Gao et al., 2025). Driven by the growing availability of high-resolution data generated by automated fare collection systems, surveillance cameras, mobile devices, and IoT sensors, deep learning-based

prediction models have become effective tools for identifying potential crowding hotspots at stations, platforms, and transfer corridors. These models enable proactive operational interventions, such as dynamically adjusting dwell times, reallocating platform usage, modifying train stopping patterns, or regulating station inflow through gating strategies, rather than relying on reactive crowd control measures (Luangboriboon et al., 2025).

In parallel, abnormal demand detection methods that exploit correlations between boarding and alighting patterns use AI to identify atypical passenger surges caused by disruptions, special events, or incidents, which is particularly critical for maintaining safety on oversaturated lines and during peak periods (Cheng et al., 2025). Beyond isolated prediction tasks, integrated prediction-control frameworks are emerging as a key research direction. Such frameworks explicitly coordinate supply-side decisions, such as train dispatching, headway regulation, and rolling-stock allocation, with demand-side management measures, including access control, passenger routing guidance, and information provision, to stabilize operations under highly variable and uncertain conditions (Yoo et al., 2022). The advantage of these integrated frameworks lies in closing the gap between prediction and action: an accurate crowd prediction has limited operational value unless it can be translated into feasible train, station, and passenger-control measures. At the same time, supply-side and demand-side actions may generate feedback effects, as access restrictions or information provision can alter passenger choices and invalidate the original demand prediction. In addition, a critical future challenge lies in the deeper integration of behavioral modeling into passenger flow management. Learning-based choice and response models can capture how passengers adapt their travel decisions in response to congestion, delays, control measures, and information updates. Embedding these behavioral responses within large-scale optimization or control models allows operators to anticipate secondary effects and feedback loops, leading to more realistic and effective system-wide strategies.

3.1.5 AI applications in metro fault detection and maintenance

AI applications in metro fault detection and maintenance have become a core enabler of intelligent and resilient metro systems. Recent studies demonstrated that AI significantly improves the detection of infrastructure and rolling-stock anomalies by exploiting high-frequency, high-dimensional monitoring data from multiple subsystems, including track, traction power, signaling, and vehicles (Khajehdezfuly et al., 2025). Moving beyond conventional reactive anomaly detection, Toribio et al. (2026) developed a two-stage framework that combines time-series prediction with anomaly identification, enabling prediction of equipment faults several hours in advance and providing vital lead time for proactive maintenance interventions.

In this context, machine learning models process vibration, current, acoustic, and thermal signals to identify early-stage degradation and fault signatures, while CNN-based vision systems are increasingly applied to detect structural defects in tunnels, platforms, and other civil infrastructure components through image and video data (Saki and Soori, 2026). Meanwhile, signal-based models and vision-based models serve different maintenance contexts. Vibration, current, acoustic, and thermal signals are better suited to detecting internal degradation and early functional anomalies, whereas computer vision is more effective for visible surface defects and large-scale infrastructure inspection. Their complementary nature suggests that multimodal fusion is more informative than relying on either source alone, although sensor synchronization and heterogeneous data quality remain practical obstacles. Consequently, automated, continuous condition-monitoring systems substantially reduce reliance on labor-intensive manual inspections, improve fault-localization accuracy, and enable faster response to emerging risks. Building on these advances, predictive maintenance frameworks extend fault detection capabilities by estimating the remaining useful life (RUL) of components and predicting degradation trajectories under varying operational conditions.

3.2 AI in high-speed railway

High-speed railway (HSR) serves as the backbone of modern transportation, characterized by high operating speeds, large capacity, and stringent safety requirements. Operating in a complex environment comprising advanced rolling stock and extensive infrastructure, HSR systems face distinct challenges related to performance stability and risk management. Within the framework shown in Fig. 3, AI applications in HSR primarily focus on precise operation management, infrastructure health monitoring, and intelligent dispatching under stringent safety constraints. The integration of AI facilitates a fundamental transition from traditional reactive, manual practices to proactive, data-driven management. Therefore, this section reviews AI applications across four core domains: vehicle maintenance, infrastructure inspection, safety assurance, and operations management, highlighting the role of AI in optimization and risk mitigation.

3.2.1 AI for HSR vehicle maintenance

AI is reshaping HSR vehicle maintenance paradigms, facilitating a transition from reactive approaches to predictive and condition-based strategies. This transformation encompasses critical domains such as component

defect detection, fault diagnosis, prognostics, and intelligent decision-making for maintenance, collectively enhancing operational safety while reducing life-cycle costs. The integration of deep learning technologies has enabled enhanced processing of complex sensor data and visual information from HSR vehicles.

Vehicle component defect detection has matured significantly, with a particular focus on running gear inspection. Deep learning-based computer vision systems have demonstrated strong efficacy in identifying surface anomalies on wheelsets and pantographs. Shaikh et al. (2025) introduced the FaultSeg data set, a comprehensive benchmark comprising 829 manually annotated wheel images that capture defects including cracks, shelling, and discoloration. In a subsequent systematic evaluation of eight YOLO models (v5-v12) and an RTD Transformer, the YOLOv5-seg model achieved 91% precision, 90% recall, and real-time processing at 30 frames per second, with latency under 30 ms on edge devices. To address the challenge of low defect proportions in tread images, Zhang et al. (2022a) developed MFF-YOLOv4, which employs multiscale feature fusion to improve detection. More recently, Wen et al. (2024) optimized the YOLOv8 architecture by incorporating specialized detection layers and SPPCSPC modules, achieving 96.95% average precision while effectively mitigating interference from water stains. Similarly, Xing et al. (2022) applied an improved YOLOv3 model to rail wheel tread defect classification, maintaining real-time detection capabilities while achieving high mean average precision. These studies suggest that lightweight YOLO variants remain highly competitive for onboard or trackside real-time inspection because they balance detection accuracy and inference speed. More complex Transformer or segmentation architectures may better characterize irregular defect boundaries and contextual relationships, but their additional computational burden is not always justified when the operational task only requires rapid defect localization.

Fault diagnosis and RUL prediction represent critical research frontiers, with axle-box bearings receiving extensive attention as safety-critical components. Luo et al. (2020) proposed a simplified shallow information fusion CNN for bearing fault diagnosis, demonstrating superior accuracy and computational efficiency compared to conventional CNNs. For various operational scenarios, Gu and Huang (2020) developed a multitask learning framework that combines LSTM networks with operating-condition identification to predict bearing temperature and diagnose anomalies. A significant trend involves integrating diagnosis with prognostics. Using kernel principal component analysis for feature extraction, Sanjrani et al. (2025) proposed a dual-task LSTM model with attention mechanisms to perform fault classification and RUL prediction concurrently. Recent advances in RUL prediction also include the work by Wang et al. (2025b), who employed one-dimensional deep convolutional autoencoders combined with multilevel Bi-LSTM networks, and Jiang and Xiang (2023), who utilized ensemble deep LSTM methods to enhance prediction stability across diverse operating conditions.

The fusion of physics-based and AI approaches is emerging as a paradigm for addressing the interpretability limitations of purely deep learning methods. Chen et al. (2024b) developed a hybrid temperature model for bearing fault identification, merging the accuracy of machine learning with the physical interpretability required for safety-critical applications. This hybridization extends to comprehensive health management systems. Yang et al. (2025b) introduced the TimesNet framework for gear fault diagnosis, integrating signal acquisition, diagnosis, and decision support into a closed-loop workflow on edge-embedded platforms. Notably, this system interfaces with LLMs to intelligently map fault types to corresponding maintenance actions. At the system level, Zhang et al. (2025g) developed the "Bogie Doctor" framework, which uses deep learning to automate fault-feature extraction and diagnosis from textual maintenance logs.

In summary, the evolution of AI applications in HSR vehicle maintenance points toward integrated health management systems. These systems increasingly combine multi-source sensor fusion, hybrid physics-data modeling, and edge computing to enable autonomous, predictive maintenance.

3.2.2 AI for HSR infrastructure inspection

AI has achieved remarkable progress in detecting HSR infrastructure, addressing critical challenges in maintaining track systems, catenary networks, and civil structures. Deep learning-based methods have substantially improved detection accuracy, processing speed, and automation levels across diverse infrastructure components, enabling comprehensive condition monitoring that was previously infeasible with traditional manual inspection approaches.

Rail surface and track component defect detection represents one of the most mature AI applications in railway infrastructure monitoring. Zheng et al. (2021) proposed a multi-object detection framework combining improved YOLOv5 with Mask R-CNN, using images collected from the Shijiazhuang-Taiyuan HSR line to simultaneously localize and segment rail surface defects and fastener states. For ballastless track systems prevalent in HSR networks, Wang et al. (2021b) developed a CNN-based automatic crack severity classification method using orthogonal projection preprocessing to define severity levels, achieving over 95% accuracy with Inception-ResNet-v2. Ye et al. (2024b) introduced TrackNet, an intelligent detection method based on self-attention mechanisms and transfer learning, which addresses the

challenge of insufficient defect samples by transferring knowledge from large-scale public data sets, outperforming Swin Transformer baselines by 5.15% in average accuracy. The emergence of Transformer architectures has introduced new capabilities; Guo et al. (2024a) proposed RailFormer, a Transformer-based semantic segmentation network that integrates Criss-Cross attention modules to overcome CNN limitations in preserving hierarchical features and small-scale details. Specifically for fastener defect detection, Ye et al. (2024a) developed YOLO-Fastener, incorporating efficient channel and spatial attention mechanisms, achieving 98.33% precision with an inference time of only 10.4 ms. Ferdousi et al. (2024) introduced an ensemble learning framework with dynamic weight adaptation combining VGG-19, MobileNetV3, and ResNet50, achieving 99% validation accuracy for railway defect classification. Overall, method performance in infrastructure inspection is strongly task-dependent. CNN- and YOLO-based architectures are generally preferable for real-time localization of well-defined defects, whereas Transformer and segmentation models offer advantages when defects are small, spatially dispersed, or dependent on long-range contextual information. Ensemble learning may further improve average accuracy, but its computational and maintenance costs can restrict deployment on inspection vehicles and edge devices.

Catenary system inspection has emerged as another critical application domain due to its direct impact on power supply reliability. Tang et al. (2023) proposed RCID-YOLOv5s for railway catenary insulator defect detection, introducing object detection layers and triplet attention modules to achieve 98.0% average precision on images collected from the Zhengzhou–Xuzhou HSR line. Liu and Liu (2023) provided a comprehensive treatment of deep learning technologies for catenary support component detection, covering CNN architectures, RL, and generative adversarial networks for handling various defect types. A systematic mapping study by Chen et al. (2024b) revealed that research interest in catenary monitoring has increased significantly, with most studies focusing on inspection using dedicated vehicles equipped with high-definition cameras. Recent advances include multimodal approaches that combine visual and signal-based monitoring and the integration of domain knowledge to improve detection of small components, such as insulators (Marciniak et al., 2025). The field continues to evolve toward deploying cameras on regular operating trains and developing computer vision techniques capable of processing complex daytime backgrounds.

Track geometry degradation prediction is an advanced application that integrates spatio-temporal modeling. Wang et al. (2023d) developed a hybrid CNN-LSTM model that captures both spatial and temporal dependencies in changes in track geometry and incorporates position-error-correction methods to achieve relative position errors of 1 foot or less with 99% confidence. This approach outperforms traditional models, including multilayer perceptrons and standalone CNN or LSTM architectures for both short-term and long-term prediction. Tunnel and bridge structure inspection has similarly benefited from advances in deep learning; Dang et al. (2026) proposed SMI-YOLOv8, integrating multiscale feature fusion and mixed local channel attention for tunnel lining crack detection, achieving 93.4% precision and 95.7% mAP50. Zhu et al. (2024a) developed lightweight defect detection models for tunnel lining leveraging knowledge distillation techniques, addressing the need for real-time performance in practical mobile applications. Foreign object intrusion detection employs similar YOLO-based architectures to detect obstacles on tracks in real time during high-speed operation. These studies demonstrate that detection and degradation prediction address different maintenance needs. Visual detection is suitable for identifying current defects, whereas spatiotemporal prediction supports intervention before defects reach critical thresholds. Combining the two is more operationally meaningful than improving either task in isolation.

The integration of AI with digital twin technology represents a significant advancement in the optimization of infrastructure maintenance. Sresakoolchai and Kaewunruen (2023) combined DRL agents with railway digital twins, using track geometry and component defect data to dynamically formulate maintenance strategies via interactive learning, thereby reducing maintenance frequency and minimizing defect occurrence rates. This integration enables simulation-based optimization of maintenance schedules before real-world implementation. The overall evolution of AI applications in HSR infrastructure detection points toward comprehensive multi-component detection systems with greater automation, improved accuracy, and integration with intelligent maintenance decision-making frameworks that account for both individual component conditions and system-level optimization objectives.

3.2.3 AI for HSR safety and security

Risk prediction and early warning constitute the core components of HSR safety assurance. The key to effective assurance lies in prioritizing proactive intervention over reactive response through the advanced identification and quantitative assessment of potential hazards. The application of AI in this field is fostering an intelligent protection system that encompasses risk identification, probability prediction, early warning, and decision support.

In terms of risk probability prediction and uncertainty quantification, probabilistic graphical models are effective tools for modeling the dynamic evolution of risk. BN prediction frameworks have been widely used to model the development trajectory of railway infrastructure

defects. These approaches use N-step forward prediction and Bayesian inference to estimate future failure probability distributions, enabling quantitative projections from the current state to future risk. This methodology overcomes the limitations of traditional approaches that assess only the current state, rather than predicting future risks. Furthermore, complex fuzzy prediction systems, such as the one developed by Karakose and Yaman (2020), have achieved reliable prediction of fault time and type under incomplete data conditions through fuzzy reasoning mechanisms. This facilitates the dynamic adjustment of risk warning thresholds. By integrating expert knowledge with data-driven methods, this technical route enables systems to maintain warning accuracy and timeliness even in data-scarce scenarios.

Regarding the prediction of equipment degradation trends and the modeling of risk evolution, deep learning technologies demonstrate significant capabilities for capturing nonlinear degradation patterns. Research in this domain has systematically developed data-driven degradation-prediction methodologies, highlighting the distinct advantages of RNNs for modeling the temporal evolution of equipment performance and risk accumulation. For critical infrastructure such as turnout systems, advanced models employing sparse autoencoders and gated recurrent unit (GRU) networks have demonstrated the ability to extend warning windows from days to weeks. This extended horizon provides sufficient response time for the deployment of necessary risk control measures. Similarly, hybrid prediction models, such as the one developed by Yang et al. (2025c), have achieved millimeter-level precision in predicting tunnel surrounding rock deformation. These capabilities enable early identification of abnormal deformation patterns, providing essential technical support for proactive control of construction safety risks.

At the system level, the integration of digital twin technology and big data analytics has promoted an evolution from single-point prediction to global collaborative warning. Ghofrani et al. (2018) noted that big data analytics enables railway operators to identify risk patterns, predict risk probabilities, and optimize warning strategies based on historical data. Complementing this, Yin et al. (2020) emphasized that prognostics and health management systems construct intelligent platforms that continuously track health status and infer risk levels by integrating real-time data streams with predictive algorithms. For complex coupled systems like train-track-bridge interactions, Li et al. (2026) proposed a Bayesian optimization-based deep learning framework. This method establishes a system-level risk-prediction approach for multi-source random parameters, providing a quantitative basis for operational scheduling and dynamic risk control.

In summary, AI technology has established a multi-level technical architecture for HSR risk prediction and early warning. Probabilistic graphical models and fuzzy systems provide theoretical frameworks for uncertainty quantification; deep learning achieves accurate prediction of degradation trends; and digital twins support multi-hazard collaborative warning. The synergistic application of these technologies is driving a fundamental transformation in HSR safety management: from post-event disposal to advanced prediction, from qualitative judgment to quantitative warning, and from isolated equipment monitoring to coordinated system-level protection.

3.2.4 AI for HSR operations and management

HSR operations and management constitute a highly complex, safety-critical system in which timetable planning and real-time dispatching pose central decision-making challenges. Given that tightly coupled schedules are intrinsically vulnerable to disruptions, there is a pressing need for advanced decision-support tools that go beyond conventional optimization approaches (Ma et al., 2024a), which often prove computationally prohibitive or insufficiently flexible under uncertainty. AI contributes to this domain through two complementary pathways: predictive analytics to anticipate delays and conflicts, and learning-based control methods to compute effective actions in uncertain, time-critical environments.

Data-driven delay prediction has been extensively investigated using techniques ranging from kernel-based methods to modern deep learning architectures. Oneto et al. (2017) developed a large-scale delay prediction framework based on extreme learning machines, incorporating privacy-aware hyperparameter tuning. Although originally applied to freight, Barbour et al. (2018) demonstrated the utility of support vector regression for predicting arrival times using train, network, and conflict-related features, showing that improved estimated time of arrival predictions can mitigate uncertainty in downstream logistics and dispatch decisions.

In the domain of integrated HSR planning, AI-driven heuristics and meta-heuristics offer powerful alternatives to exact optimization. Using swarm intelligence techniques for optimization, a bi-level multiobjective mixed-integer nonlinear programming model was developed by Li et al. (2020b) to simultaneously streamline passenger assignment and train routing. Similarly, Chen et al. (2016) used a hybrid genetic algorithm for a multi-target optimization model that minimizes stopping costs while maximizing passenger travel convenience. Liu et al. (2022b) further investigated an optimization-based scheduling scheme designed to reduce both total delay time and energy consumption in the presence of unexpected disruptions.

Regarding model usability, recent research has prioritized interpretability. Huang et al. (2024) proposed a graph attention network for explainable delay propagation modeling, using attention weights to quantify the contributions of different influencing factors. This transparency is crucial, as the practical value of delay prediction is

significantly enhanced when models are interpretable, enabling operators to justify time-sensitive interventions—such as holding trains, allowing overtaking, or changing platforms—under operational pressure.

RL reformulates railway scheduling as a sequential decision-making process governed by strict operational and safety constraints. Early work by Šemrov et al. (2016) used Q-learning to address rescheduling problems on single-track railway lines, demonstrating the feasibility of learned policies in reducing delay propagation. Li and Ni (2022) subsequently developed a general multi-agent DRL environment in which objectives and constraints are distributed among agents to handle complex timetabling structures. Ying et al. (2024) proposed a multi-agent DRL framework in which individual agents manage specific trains and coordinate through centralized training to minimize both systemic delays and passenger waiting times during severe blockages. To address the challenge of generalizing across diverse disruption scenarios, Tang et al. (2025b) introduced a DRL approach that uses a quadratic assignment problem formulation to identify representative disruption tasks for efficient offline training. The resulting policy generates high-quality real-time rescheduling plans even for previously unseen situations, outperforming traditional methods. Compared with repeatedly solving optimization models, trained DRL policies can generate rescheduling actions within seconds and are therefore attractive for disruption management. However, rapid inference should not be confused with dependable decision-making: strict headway constraints, rare disruption scenarios, and distribution shifts may lead to unsafe or infeasible actions unless the learned policy is coupled with rule-based or optimization-based verification.

3.3 AI in conventional railways

In this paper, conventional railways refer to all other common rail transit modes, excluding urban rail transit and HSR. These systems operate in complex environments characterized by mixed traffic, diverse infrastructure, and frequent external disruptions. Therefore, conventional railways place greater emphasis on infrastructure inspection, predictive maintenance, and asset management, reflecting the distinct priorities of this application layer. Accordingly, data-driven, intelligent, and resilient operations are becoming a reality as embedding AI into conventional railways marks a profound paradigm transformation. To analyze this trend, this section systematizes recent AI applications from three major dimensions: infrastructure maintenance, safety and security, and operational management.

3.3.1 AI for conventional railway maintenance and inspection

AI is reshaping the conventional paradigms of railway maintenance and inspection, demonstrating a clear evolutionary trajectory in its applications. The applications of AI encompass defect identification, degradation prediction, and maintenance decision optimization across both infrastructure and rolling stock, significantly improving maintenance efficiency and safety standards.

Defect detection is a relatively mature AI application, primarily focused on the automated identification of physical anomalies on track components. For visible elements such as fasteners, sleepers, and rail surfaces, deep learning-based computer vision techniques have demonstrated considerable progress. Research predominantly employs CNNs for the automatic analysis of captured images or video streams. For instance, object detection models like the YOLO series have enabled efficient identification of defects, including wheel flats, scratches, and thermal cracks (e.g., Guo et al., 2021a; Xing et al., 2022). Zhang et al. (2022d) developed a multi-model CNN that enhanced the robustness of rail surface defect detection across varying scales. Where detailed analysis of defect morphology and location is required, semantic segmentation plays a critical role. Meng et al. (2022) proposed a multitask learning architecture that improved detection precision while maintaining processing speed. Wan et al. (2022) adopted the Swin Transformer encoder within the TSSTNet architecture to extract multi-level features, and implemented pixel-level defect segmentation and condition assessment via a multi-stream decoder.

Fault diagnosis and condition prediction focus on identifying systemic anomalies and analyzing trends. For predicting track geometry degradation, studies combine CNNs with LSTM networks to construct spatiotemporal models that learn degradation patterns from historical data (Wang et al., 2023d). Ensemble learning has also been used to integrate multiple sources of features for predicting the deterioration rate of track geometry indicators, thereby optimizing maintenance intervals (Cárdenas-Gallo et al., 2017). Maintenance planning and autonomous maintenance represent current research frontiers, extending from condition prediction to decision optimization. Sharma et al. (2018) established an integrated prediction-decision framework that uses random forests to predict defect probabilities and solves for optimal maintenance strategies via MDP. Furthermore, Sresakoolchai and Kaewunruen (2023) combined RL agents with railway digital twins, using track conditions and defect reports as inputs to dynamically formulate maintenance strategies through interactive learning, effectively reducing maintenance frequency and defect occurrence. Ejlali et al. (2024) developed a hybrid machine learning method to compute comprehensive health scores for entire train fleets, shifting focus from component-level prediction to system-level health management. These transitions from prediction to decision are important because a highly accurate deterioration

model does not automatically produce an efficient maintenance plan. To address challenges of data scarcity and generalization in visual inspection, Ferdousi (2026) proposed the DefectTwin system, which leverages generative LLMs to automatically generate defect descriptions and synthetic image data, establishing a continuous optimization loop encompassing data augmentation, multimodal analysis, and user feedback.

In summary, AI in railway maintenance has evolved from an auxiliary tool to a core decision-support system. Development trends indicate a broadening focus from fixed infrastructure to mobile equipment, a deeper analytical level from component defect identification to system health assessment, and a technical shift from single models to multimodal fusion and intelligent frameworks integrated with digital twins.

3.3.2 AI for conventional railway safety and security

Safety and security remain paramount priorities for any transportation infrastructure, as both passengers and stakeholders demand a highly protected and reliable transit environment. The application of AI in this domain is progressively constructing a comprehensive safeguard framework that encompasses real-time monitoring, incident causation analysis, and proactive prevention.

In the area of real-time risk perception and early warning, deep learning-based object detection technologies are a key research focus for addressing external threats such as trespassing on tracks. Early research primarily focused on optimizing two-stage and one-stage detection architectures. Two-stage methods emphasized accuracy by incorporating backbone networks, such as ResNet, to improve recognition of small objects in complex scenes (Wang et al., 2019a). One-stage methods prioritized real-time performance, balancing speed and accuracy through improved backbone networks, multi-scale fusion modules, and attention mechanisms (He et al., 2021). Beyond detecting known objects, methods based on image reconstruction and anomaly detection offer an alternative approach that does not rely on labeled data for specific classes, thereby addressing the challenge of unknown-class intrusions (Jahan et al., 2021). Furthermore, lightweight encoder-decoder networks have been used for real-time segmentation of track areas, enabling precise monitoring of illegal intrusions (Chen et al., 2023b). These approaches involve a clear trade-off. Two-stage detectors generally provide stronger accuracy for small or partially occluded intrusions, while one-stage and lightweight segmentation models are better suited to real-time trackside deployment. Reconstruction-based anomaly detection can identify previously unseen threats, but it often produces more false alarms because normal railway scenes themselves exhibit substantial environmental variability.

Regarding accident analysis and risk prediction, AI applications primarily follow two paths: post-incident analysis and pre-incident prevention. Post-incident analysis focuses on extracting patterns from historical events, predominantly employing natural language processing (NLP) techniques to examine unstructured textual accident logs. For example, latent Dirichlet allocation topic models and knowledge graphs are employed to automatically extract causation chains, identify risk patterns, and visualize factor correlations from unstructured text. Brown (2016) used text mining and ensemble learning to analyze reports, demonstrating the value of semantic features for improving predictive models. Subsequent studies introduced unsupervised learning for real-time dynamic classification of accident severity, aiding emergency decision-making (Shi et al., 2023). Recently, knowledge graph-based methods have become mainstream for systematically modeling complex relationships among accidents, causes, and consequences. Wang et al. (2023c) built a hazard correlation knowledge graph to analyze critical risk propagation paths and intervention points. Liu et al. (2024a) further developed a railway operation hazard knowledge graph and predictive model, enabling the identification of potential high-risk scenarios and supporting a closed loop from prediction to decision-making. Pre-incident prevention focuses on risk avoidance during system design. This includes combining rule learning with expert systems to derive potential hazardous scenarios and safety rules from documentation and expert experience, facilitating comprehensive functional safety analysis before deployment (Hadj-Mabrouk, 2019). Generative AI has the potential to provide intelligent assistance. Li et al. (2024c) constructed domain-specific data sets via prompt engineering and used techniques such as Low-Rank Adaptation to fine-tune base LLMs, thereby developing domain-specific intelligent Q&A systems and providing tools for safety training and knowledge application. Domain fine-tuning can improve terminology recognition and response relevance, but it does not eliminate hallucination or guarantee that answers remain consistent with current railway rules. The model may also inherit omissions and biases from the domain data set, particularly when accident records and operating procedures are incomplete. Railway safety Q&A systems should employ retrieval-augmented generation from version-controlled regulations, provide source traceability and abstention mechanisms, and be evaluated using expert-reviewed questions that test factual accuracy, rule consistency, and responses to ambiguous or previously unseen cases.

In conclusion, AI applications in railway safety and security have formed a multi-layered technological architecture. Computer vision enables real-time environmental monitoring and early warning. The NLP and knowledge graphs facilitate in-depth incident attribution and risk

inference. Expert systems and generative AI enhance internal risk prevention, control, and knowledge dissemination. Collectively, these technologies are driving the evolution of railway safety management from reactive response toward predictive and proactive protection.

3.3.3 AI for operations and management in conventional railway

In railway traffic operations and management, AI applications encompass core activities such as capacity management, timetabling, operational control, and resource allocation, aiming to boost the efficiency and competitiveness of transport. Data-driven AI approaches are advancing along two primary paths: developing advanced algorithms for complex, dynamic problems such as delay propagation and extracting actionable insights to support reliable decision-making.

In machine learning-based delay management, research has established an analytical chain covering pattern recognition, prediction, and decision support. Pattern recognition aims to automatically discover recurrent spatiotemporal delay patterns from historical data, providing a basis for timetable and process adjustment. Cerreto et al. (2018) identified recurrent delay patterns on high-density lines using K-means clustering. Delay prediction focuses on improving prediction accuracy and robustness. Barbour et al. (2018) proposed a data-driven approach based on support vector regression, constructing a model considering train properties, network state, and conflict characteristics to improve freight train arrival time predictions in complex networks. Oneto et al. (2017) developed a dynamic prediction framework that integrates internal operational data with external factors, employing extreme learning machines with differential privacy to balance large-scale training efficiency and model generalization robustness. Kumar et al. (2025) further proposed a hybrid model that combines GCN with LSTM and Kalman filtering, demonstrating its superiority in dynamic travel time prediction using Indian freight data. Decision support research also values model interpretability. Huang et al. (2024) employed graph attention networks for delay prediction, leveraging the attention mechanism to evaluate the impacts of diverse operational factors, thereby improving decision-making transparency. The progression from clustering and support vector regression to GCN–LSTM and attention-based models reflects the increasing need to capture delay propagation across both time and network structure. Simpler models remain competitive for corridor-level prediction with structured data, whereas graph-based models provide greater advantages in dense networks with interacting train services. Their complexity, however, can reduce transparency and complicate deployment across networks with different topologies and operating rules.

DRL provides an autonomous framework for sequential decision-making in real-time planning. The core idea is to model problems like scheduling as an MDP, learning optimal policies through environmental interaction to handle large-scale combinatorial optimization. Research covers multiple levels, from timetable optimization to real-time rescheduling (Li and Ni, 2022; Šemrov et al., 2016). In timetable optimization, Yang et al. (2023) focused on mixed-traffic single-track corridors and proposed the DRLA-eTGM method, based on DRL, that uses CNNs to extract spatiotemporal constraints to optimize weighted train dwell time. In real-time rescheduling, Liu et al. (2024b) addressed short-term rescheduling for single-track corridors with a Q-learning approach featuring a hierarchical reward mechanism, demonstrating advantages in delay reduction and computational efficiency on a UK line. Research also extends to operational control and yard optimization. Vaquero-Serrano et al. (2025) proposed a learning-based predictive control method for virtually coupled trains, achieving significant energy savings. Zhang et al. (2025c) tackled wagon routing optimization in marshalling yards using a method combining GNN with DRL, demonstrating superior performance in hump sequencing and track assignment. Yang et al. (2025a) further introduced causal RL into multi-agent collaborative scheduling for traditional single-track networks, thereby enhancing performance by modeling inter-agent interactions.

In summary, AI in railway operations and management has established a multi-layered technological system: machine learning methods focus on extracting historical patterns, predicting trends, and providing interpretable insights, while RL methods focus on autonomous, real-time decision-making in dynamic environments. Neither approach is sufficient alone. Prediction models do not prescribe feasible actions, while learned control policies may lack interpretability and guarantees. Integrating interpretable prediction, causal analysis, and optimization-verified RL is therefore a key direction for reliable intelligent railway management.

4 Artificial intelligence in maritime transportation

Maritime transportation relies on a complex global network of shipping routes, port infrastructure, and diverse vessel fleets. It acts as the cornerstone of global supply networks, sustaining roughly 90% of international trade (Park et al., 2022a). Managing this massive transportation system requires the coordination of multiple stakeholders, including shipping companies, port operators, and regulatory institutions.

The complexity and importance of maritime transportation necessitate advanced technologies to address

operational, environmental, and regulatory challenges. Recent advances in maritime sensing and communication, together with the increasing availability of large-scale data from the automatic identification system (AIS), onboard sensors, remote sensing, and port operations, make AI-driven methods increasingly viable. Accordingly, AI has emerged as a key enabler for improving efficiency, sustainability, and safety in maritime transportation. As illustrated in Fig. 4, this section focuses on four representative areas in maritime transportation: intelligent vessel navigation, port operations and maritime logistics, green shipping, and maritime safety management.

4.1 AI for intelligent and autonomous vessel navigation

According to the International Maritime Organization (IMO), a maritime autonomous surface ship (MASS) is formally designated as "a ship which, to a varying degree, can operate independently of human interaction." The multidimensional evolution of MASS is tied to a diverse spectrum of determinants, encompassing regulatory frameworks, cybersecurity protocols, human-machine factors, economic viability, ecological impacts, and ethical considerations. It also depends on the high reliability of sensors and navigation systems (Li et al., 2023a). To meet these requirements and achieve safe and efficient autonomous operation, AI has become a key enabling technology for autonomous vessel navigation.

4.1.1 Vessel trajectory prediction

As a critical technical pillar for autonomous collision avoidance and decision-making, vessel trajectory prediction has witnessed a substantial surge in research momentum in recent years. Contemporary prediction technologies rely primarily on dynamic vessel motion attributes and historical tracking logs (Gao et al., 2021; Liu et al., 2022d). AIS data have emerged as a key resource for vessel trajectory planning and optimization. Li et al. (2023a) established a benchmark using AIS data by comparing five machine learning methods and seven deep learning methods, revealing their relative performance and applicability in different maritime traffic scenarios. However, balancing prediction accuracy and computational efficiency remains challenging, particularly for real-time autonomous navigation in complex maritime traffic. To address this issue, Li et al. (2024b) proposed the deep bi-directional information-empowered model, which integrates Bi-LSTM and Bi-GRU networks with an attention mechanism to capture bidirectional temporal dependencies effectively, achieving improved prediction accuracy with enhanced computational efficiency. Beyond advances in trajectory prediction models, the safe deployment of MASS also relies on realistic and representative testing scenarios. Xin et al. (2025) developed a holistic framework for maritime traffic scenario extraction and sampling, which systematically characterizes ship motion dynamics and constructs representative real-world navigation scenarios using a hierarchical greedy sampling strategy, thereby supporting the safety assessment and validation of MASS. This line of research highlights that prediction performance alone is insufficient for autonomous navigation. A model may achieve low average trajectory error on routine AIS data while still failing in rare but safety-critical encounter situations. Representative scenario extraction is therefore essential for evaluating whether a predictor remains reliable under sharp turns,

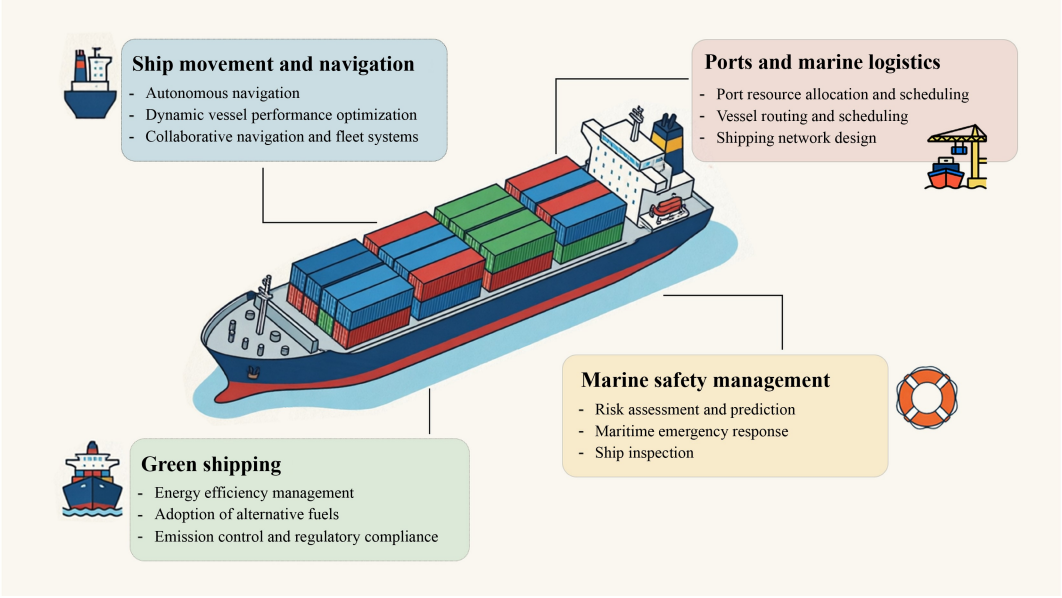


Fig. 4 Diagram of the main areas of maritime transportation.

emergency maneuvers, congested waterways, and other non-recurrent conditions.

4.1.2 Single-ship collision avoidance

DRL constitutes a dominant methodology for autonomous vessel navigation and collision mitigation, empowering artificial agents to acquire intricate control laws directly through continuous environmental feedback while instilling robust obstacle-evasion attributes. Currently, DRL methods for autonomous ship collision avoidance are divided into value-based approaches (e.g., deep Q-network (DQN), double deep Q-network (DDQN)) for discrete action spaces and policy-gradient approaches (e.g., deep deterministic policy gradient (DDPG), proximal policy optimization (PPO)) for continuous action spaces and non-deterministic policies (Wang and Zhao, 2025). The choice between value-based and policy-gradient methods is closely related to the vessel-control setting. For example, Zhao and Roh (2019) proposed a policy-gradient-based DRL approach in which a deep neural network maps observed ship states directly to rudder angle commands for autonomous collision avoidance. Yang et al. (2024) engineered an anthropomorphic collision avoidance approach rooted in DRL and velocity obstacle theories, fusing a DDQN framework with a fuzzy-set-derived expert navigation weight. The aforementioned methods achieve collision avoidance either by a global assessment of the surrounding environment or by sequentially evaluating the risk of individual encounters. Additional strategies are employed to strengthen the resilience of the learning process and extend the approach's applicability across diverse MASS and environmental scenarios. To address limitations of rule-based systems, Sonntag et al. (2025) proposed a DRL method that ensures COLREGs compliance by incorporating a tailored reward function to promote smooth action transitions and reduce human cognitive bias in path-following and collision avoidance tasks, demonstrating effective performance across varied static and dynamic encounter scenarios. Inspired by meta-learning, Jia et al. (2025) applied meta-RL with a two-layer recurrent model, enabling agents to assess risks and dynamically optimize collision-avoidance policies. These studies demonstrate that DRL can outperform static rule-based strategies when vessel encounters evolve dynamically and cannot be fully enumerated in advance.

4.1.3 Collaborative multi-ship collision avoidance

Despite the demonstrated effectiveness of DRL in ship collision avoidance, it struggles to capture collaborative interactions and environmental complexity in multi-ship scenarios, limiting the effectiveness of cooperative strategies. Multi-agent DRL (MADRL) has therefore emerged as a promising approach for enabling coordinated behaviors in multi-ship scenarios, with recent advancements providing new insights for handling increasingly crowded maritime environments. Niu et al. (2023) proposed a data-driven, multi-ship autonomous collision-avoidance decision-making framework based on MADRL, introducing a non-coordination factor to model collaborative collision-avoidance behaviors among multiple vessels. Focusing on cooperation under information constraints, Wang and Zhao (2025) used the multi-agent DDPG algorithm to address cooperative navigation with partial observability. Their study shows that agents capable of learning communication protocols can compensate for missing information, significantly outperforming single-agent algorithms in cooperative collision-avoidance tasks. Further extending collaborative decision-making capability, Wang et al. (2025g) developed an MADRL approach that leverages a deep recurrent Q-network and a decentralized partially observable MDP framework to enable collaborative decision-making in multi-ship scenarios. Experimental results demonstrated that the artificial potential field approaches can achieve safe, rational, and effective collision avoidance. Collectively, these studies suggest that the principal advantage of MADRL lies not merely in improving individual collision-avoidance performance, but in learning coordinated responses among interacting vessels. At the same time, most existing evaluations rely on simplified simulations with homogeneous agents and reliable communication, leaving substantial uncertainty regarding scalability, mixed-autonomy interaction, and compliance with heterogeneous human navigation behavior.

4.2 AI-empowered port operations and maritime logistics

Ports serve as pivotal nodes in the end-to-end maritime transportation chain. The concept of a "smart port" emerged from Industry 4.0 and represents an advanced generation of port development, in which smart-technology-based solutions enhance the efficiency and operations of ports, port users, and the workforce, thereby benefiting both the ports and the broader supply chain (Li et al., 2023b). AI functions as a core driver in smart port operations and maritime logistics by facilitating data-centric decision-making that streamlines asset allocation, operational synchronization, and logistical efficiency.

4.2.1 AI for smart port operations

The emergence of smart ports has ushered in an era of abundant data, enabling the deployment of advanced AI-driven methodologies to address complex operational challenges in ports. The berth allocation (BA) problem is central to port operation optimization, as it determines

vessel berthing times and locations and underpins downstream operational coordination (Zhen et al., 2024). Considering uncertainties in vessel arrivals and container handling times, Lv et al. (2024) formulated the BA problem as an MDP to minimize the mean vessel waiting time. Their model incorporates a tailored state space, a rule-based action space, and a carefully designed reward function, and implements a DQN to learn berthing policies. Extending BA studies to include integrated quay crane scheduling, Jo and Moon (2025) introduced a hierarchical RL framework with three cooperative agents: an upper-level agent that manages vessel release and two lower-level agents that coordinate berth and crane assignments in real time.

Furthermore, due to the high complexity and dynamic interactions of automated container terminal (ACT) systems, operating an ACT yard with a large fleet of automated guided vehicles (AGVs) also presents significant challenges. Scheduling AGVs and ensuring safe, stable transportation paths are critical tasks for smart port management. To address this issue, Gong et al. (2024) formulated a hybrid multi-AGV dispatching architecture designed to mitigate energy dissipation and minimize cumulative makespan. In this methodology, the AGV dispatching procedure is initially formulated as an MDP, followed by the deployment of an innovative multi-agent DDPG algorithm to achieve instantaneous online scheduling. Chen et al. (2024c) developed an AGV path-optimization model for port environments based on an artificial potential field (APF) and a twin delayed DDPG (TD3) framework. The APF generates attractive and repulsive forces based on container locations and obstacles, which are used as input for TD3 to iteratively select optimal actions and generate smooth, safe AGV paths from start to destination. Besides AGVs, intelligent transportation equipment, such as AI robots for transportation (ART), has been gradually adopted in ACTs and offers greater autonomy and distributed decision-making capabilities. Zhang et al. (2024b) developed an MARL framework to optimize ART speed regulation and task sequencing in ACTs, thereby reducing waiting times at the quay and improving the efficiency and coordination of loading operations.

Taken together, these studies indicate a shift from static, independently optimized port tasks toward dynamic coordination among berths, quay cranes, AGVs, and other terminal equipment. AI is particularly valuable when decisions must be updated rapidly in response to operational changes, whereas optimization remains indispensable for enforcing complex resource and safety constraints.

4.2.2 AI for maritime logistics

Beyond terminal-level operational optimization, AI-based approaches have been increasingly applied to enhance coordination at the port-shipping interface, which is critical to maritime logistics performance. Deviations between vessel-reported estimated times of arrival and their actual times of arrival frequently lead to anchorage overcrowding, inefficient berth utilization, and cascading delays across the maritime supply chain. Therefore, accurate prediction of vessel arrival time (VAT) and proactive arrival management are essential for mitigating these impacts and enhancing overall maritime logistics efficiency. Leveraging large-scale AIS and port operation data, recent studies have employed machine learning techniques to support dynamic arrival management. For example, Lei et al. (2024) investigated VAT prediction in inland waterways based on a tree-based machine learning model. The model integrates vessel characteristics with waterway conditions, such as water depth and traffic flow, and demonstrates high prediction accuracy using AIS data from the Yangtze River. Building on data-driven VAT prediction in more complex maritime environments, Evmides et al. (2024) extended the analysis to international shipping routes using AIS data collected in the Eastern Mediterranean Sea. Their study systematically evaluates the performance of diverse machine learning paradigms—encompassing deep neural network structures and tree-based ensemble frameworks—to refine VAT estimation metrics within modern maritime supply chain environments.

Traditional VAT prediction frameworks predominantly rely on either static port call records or dynamic AIS trajectories, often falling short of fully synthesizing both data streams for holistic estimation. To address this limitation, Chu et al. (2025) synthesized static port call registries with dynamic AIS data using a temporal interpolation scheme and a tree-based stacking architecture, substantially reducing prediction errors and highlighting the value of synchronizing real-time vessel movements with scheduled port operations to improve arrival management and port resource planning. This improvement indicates that data integration may be more consequential than replacing one prediction algorithm with another. While the critical impact of vessel arrival stochasticity on berth planning has gained broad consensus, the prevailing literature treats VAT estimation and BA scheduling as decoupled tasks, thereby falling short of creating a seamless, data-driven bridge between VAT forecasting and downstream BA decisions. Motivated by this gap, Chu et al. (2026) developed a two-stage predict-then-optimize framework that embeds improved VAT prediction into discrete and continuous BA models, enabling data-driven berth scheduling and a quantitative evaluation of the resulting operational benefits. From a future research perspective, integrated prediction and optimization, in which predictive models are trained end-to-end with explicit consideration of downstream decision

objectives, may constitute a promising direction in maritime logistics.

4.3 AI enabling green shipping

The IMO has implemented various regulations to reduce greenhouse gas emissions and promote green shipping, including the energy efficiency design index, the ship energy efficiency management plan, the energy efficiency existing ship index (EEXI), and the carbon intensity indicator (CII). To meet these requirements, shipping companies are leveraging AI technologies and operational solutions to enhance energy efficiency and reduce emissions.

4.3.1 Energy-efficient ship operation optimization

AI-based intelligent optimization techniques for ship operations focus on strategies such as speed, route, and trim optimization to achieve operational energy savings and emission reductions. Ship fuel consumption and carbon emissions are highly sensitive to sailing speed, making speed optimization across varying conditions crucial to achieving both economic and environmental sustainability in ship operations. Yan et al. (2020) developed a random forest-based method that combines ship noon reports with meteorological data from the European Centre for medium-range weather forecasts to form a speed optimization model aimed at minimizing total voyage consumption while ensuring on-time arrival. Building on this work, Luo et al. (2023) conducted a comparative study of ensemble versus deterministic meteorological prediction for speed optimization and demonstrated that ensemble-based strategies offer greater potential for fuel savings than their deterministic counterparts. Further considering dynamic meteorological conditions, Luo et al. (2024) formulated a sailing speed optimization framework that couples an artificial neural network (ANN) driven fuel consumption prediction model with a rolling multistage graph optimization scheme. To address data privacy concerns, Wang et al. (2023a) integrated federated learning (FL)-based fuel consumption prediction with downstream optimization models for selecting sailing speeds. The two-stage FL framework reduced fuel consumption compared to individual-data-based models and facilitated collaborative information sharing among shipping companies. These studies show that the principal contribution of AI lies in learning nonlinear fuel-consumption responses to speed, weather, loading, and sea conditions that are difficult to capture with fixed empirical formulas.

The navigational environments along different routes vary in complexity, especially due to dynamic weather conditions. Some studies have focused on combining route and speed optimization to tackle these challenges. For instance, Guo et al. (2026) developed an enhanced learning network that incorporates constraint mechanisms tailored to route and speed optimization. The framework captured beneficial evolutionary patterns to guide efficient optimization of candidate solutions while ensuring the generated sailing plans remain feasible for long-distance transoceanic voyages. Zhou et al. (2026) developed an RL framework that links an extreme gradient boosting model for fuel consumption forecasting with an advanced deep Q-network to co-optimize the route and speed of a gate-rudder-equipped cargo vessel. Beyond speed and route planning, dynamic trim optimization synergistically enriches these paradigms by uplifting the vessel's hull hydrodynamic properties. By regulating the fore-and-aft draft differential, trim control suppresses wave-making resistance and curbs energy dissipation induced by environmental perturbations, thereby yielding substantial fuel savings. Han et al. (2026) formulated a two-stage framework for the co-optimization of weather-routing, velocity, and trim configurations tailored for dual ocean-going vessels. In this setup, fuel consumption rates are initially evaluated using a privacy-preserving personalized FL scheme, after which discrete heading selections and continuous speed-trim corrections are optimized via a hybrid-action multi-agent PPO paradigm. Blending speed, path, and trim optimization vectors yields a holistic strategy for bolstering sustainable maritime navigation. However, the enlarged action space substantially increases computational complexity and makes solution quality more sensitive to forecast errors in weather, fuel consumption, and arrival requirements. The strongest reported savings should therefore be interpreted cautiously when they are derived from idealized simulations or vessel-specific models.

4.3.2 Ship emission prediction and monitoring

With the emergence of massive ship operational data, machine learning models have become increasingly important in emission prediction and monitoring. These models enable the accurate prediction and assessment of greenhouse gas and pollutant emissions, allowing ship operators to implement data-driven strategies for emission reduction and ensure compliance with strict environmental regulations. Since fuel consumption is a major determinant of greenhouse gas emissions, many studies have focused on developing fuel consumption rate (FCR) prediction models using machine learning techniques that integrate knowledge from the shipping industry. Yan et al. (2024b) proposed an ANN-based FCR prediction model that explicitly incorporates shipping-domain knowledge by optimizing its structure and parameters, and rigorously validated its effectiveness. To address the trade-off between model interpretability and prediction accuracy in ship FCR, Wang et al. (2023b) incorporated domain knowledge into two FCR methods: a physics-informed

neural network that improves black-box interpretability without sacrificing accuracy, and a mixed-integer quadratic optimization model that extends feature-variable expressions within an additive white-box framework.

Ship emission surveillance represents a highly interdisciplinary paradigm, integrating atmospheric physics, transportation, telecommunications, and advanced computer science. Within this domain, maritime regulatory bodies and shipping enterprises constitute the core stakeholders. However, effectively organizing ship emission monitoring data, particularly for implementing expansion policies for emission control areas, faces significant obstacles in data acquisition, transmission, analysis, and information services (Zhuge et al., 2024). To address these challenges, Elsisi et al. (2024) conceptualized an Internet of Things (IoT) architecture for monitoring ship emissions in the port area. This architecture synthesizes essential building blocks, including IoT-driven industrial sensor nodes, real-time data tracking, edge-based online processing, and customized information services for port authorities. Expanding on the drone monitoring model, Du and Wu (2025) formulated the rolling-horizon control team orientation challenge, introducing a dynamic optimization framework for base station allocation and drone routing. For scalability in large-scale scenarios, they devised three enhanced variants of DRL models, along with four heuristic drone search tactics, to improve monitoring performance.

4.4 AI driving maritime safety

Maritime safety is a critical aspect of the shipping industry, encompassing the prevention of accidents, protection of lives, and safeguarding of marine environments. Traditional safety measures often rely on reactive approaches that address incidents after they occur. However, with the integration of AI, the industry is shifting toward predictive and proactive solutions. By leveraging advanced data analytics, machine learning algorithms, and real-time monitoring systems, AI enables early identification of potential risks, supports timely decision-making, and enhances operational safety.

4.4.1 AI for maritime predictive maintenance

Breakthroughs in AI and sensory architectures are catalyzing the transition toward condition-centered and prognostic maintenance paradigms within the shipping sector. Data-driven models enable accurate health assessments and failure predictions, facilitating proactive maintenance decisions. However, limited data availability, diverse system information, and privacy concerns pose challenges to collaborative data sharing among maritime stakeholders. FL is a decentralized, privacy-preserving machine learning approach that offers a promising solution to these challenges. Llasag Rosero et al. (2025) introduced an FL algorithm designed to synchronize multidimensional labels for collaborative predictive maintenance. Their approach demonstrated significant improvements in prediction and classification tasks for turbofan and maritime engines, effectively addressing challenges related to non-independent and identically distributed data. Kalafatelis et al. (2025) proposed a model-agnostic FL framework to tackle system heterogeneity and communication overhead in predictive maintenance. By integrating client clustering, structured pruning, and knowledge distillation, this method delivers highly optimized, privacy-enhanced solutions for heterogeneous maritime fleets. These advancements highlight the transformative potential of FL in addressing critical barriers such as data heterogeneity, privacy preservation, and the need for collaborative learning among maritime stakeholders.

4.4.2 AI for port state control

Port authorities have adopted port state control (PSC) as the last line of defense against non-compliant foreign vessels. During inspections, vessels found to violate relevant conventions are identified as defective, and severe deficiencies may result in detention until corrective actions are taken (Guan et al., 2025). Most studies on PSC leverage machine learning techniques and PSC data to design inspection strategies, improve the efficiency of PSC implementation, and evaluate its effectiveness (Tian et al., 2023). Among these methods, the smart predict-then-optimize (SPO) framework has attracted significant attention for its ability to link predictive models to downstream optimization tasks directly. For example, Yan et al. (2023) addressed the optimization of ship inspection planning by integrating risk prediction with resource allocation. They proposed integrated decision trees that unify prediction and decision-making processes, introducing the concept of "similar sets" to enhance model performance and streamline inspection efficiency. Tian et al. (2023) mined PSC inspection records to formulate vessel maintenance strategies that minimize operational expenditures for ship operators, encompassing inspection, rectification, and risk-associated penalties. Their framework introduces an SPO paradigm that leverages an ensemble of SPO decision trees, calibrated via a loss function that explicitly maps predictive variations to downstream operational impacts.

Further advancements in PSC research have focused on addressing challenges such as data uncertainty and imbalances in inspection data sets. Yan et al. (2024a) developed a prescriptive analytics approach that combines regression and classification features in random forests, refining predictions of discrete quantitative targets to support more effective inspection strategies. Integrating domain

knowledge into PSC inspection models enhances both accuracy and trustworthiness. Yan et al. (2025) proposed a monotonic regression decision tree model to predict ship risk levels. By refining a conventional decision tree with an optimization model that minimizes prediction error subject to monotonicity constraints, the method ensures that the outputs align with domain knowledge while preserving the tree structure. Leveraging LLMs to process unstructured data and extract meaningful features, Jin et al. (2025) combined autoencoder-based deep learning and dynamic thresholding techniques to address data imbalance and improve ship detention prediction accuracy, outperforming traditional approaches in both predictive performance and robustness. Overall, LLM-assisted feature extraction can enrich PSC models by exploiting unstructured inspection narratives, but its contribution depends on factual consistency and domain alignment. Text-derived features should therefore be validated against inspection rules and structured records to avoid introducing semantic noise or unsupported risk signals into detention decisions.

4.4.3 AI for maritime transportation risk assessment

Maritime transportation risk assessment (MTRA) involves a systematic evaluation of potential hazards, accident probabilities, and safety vulnerabilities in maritime operations. It integrates analytical methods to predict, quantify, and mitigate risks, ensuring a safer and more resilient maritime transportation system. Given the increasing complexity of maritime activities, advanced methodologies are essential to improve real-time risk prediction and proactive decision-making. Machine learning enhances MTRA by analyzing large data sets, identifying patterns, and improving predictive accuracy (Lin et al., 2025). As a key machine learning technique, BNs have broad applications in maritime risk assessment, owing to their ability to capture causal relationships between risk factors and incidents. Specifically, BNs are used to examine human and environmental factors, pinpoint the root causes of accidents, assess severity, and support data-informed maritime safety decisions. A large body of research has adopted BN models built on machine learning to improve the effectiveness and precision of maritime risk evaluation. For example, Ma et al. (2024b) developed a machine learning-based BN model to analyze the effects of influential factors on maritime accident types, severity, and losses. The model used the tree-augmented network learning algorithm and expectation-maximization algorithm, along with techniques such as influence strength assessment, sensitivity analysis, scenario simulation, and model validation. Given the challenges posed by inconsistent data in maritime risk assessment, Fan et al. (2025b) proposed a framework to address outliers and missing data, thereby building a comprehensive database for BN modeling. They introduce a Fisher optimization method and novel learning techniques to improve the accuracy of severity prediction.

5 Artificial intelligence in air transportation

Air transportation constitutes one of the most complex and safety-critical components of the global mobility system, encompassing airports, airlines, air traffic management (ATM), and emerging low-altitude airspace. These subsystems operate across multiple spatial and temporal scales and involve tightly coupled planning, operational, and control processes that must cope with demand uncertainty, environmental disturbances, and strict regulatory constraints. With the continued growth of air transportation and increasing operational complexity, traditional rule-based and optimization-driven approaches are increasingly challenged by system scale, uncertainty, and the need for real-time decision-making.

Recent advances in AI provide new opportunities to enhance adaptability and resilience across air transportation systems. By enabling data-driven prediction, learning-based decision support, and adaptive control, AI supports more flexible resource utilization, improved disruption management, and enhanced situational awareness under dynamic conditions. Importantly, the influence of AI extends across the aviation ecosystem, from airline and airport operations to airspace management and low-altitude air transportation. Accordingly, as shown in Fig. 5, this section reviews AI applications in four representative domains—airline operations, airport operations, ATM, and low-altitude air transportation—highlighting their distinct roles and challenges within an integrated air transportation system.

5.1 AI in airline operations

Airline operations encompass a complex array of interconnected activities ranging from strategic network planning and crew scheduling to real-time revenue management and maintenance execution. These operations are inherently challenging due to their large scale, high dimensionality, and sensitivity to external disruptions such as weather events and mechanical failures. Traditional OR methods, while foundational, often struggle to handle the stochastic nature of aviation environments and the sheer volume of high-velocity data. AI, particularly through advancements in machine learning, deep learning, and RL, is transforming this landscape. By shifting from static, rule-based models to dynamic, data-driven frameworks, AI enables airlines to optimize resource utilization, enhance demand prediction accuracy, automate disruption recovery, and transition toward predictive maintenance strategies, ultimately driving greater

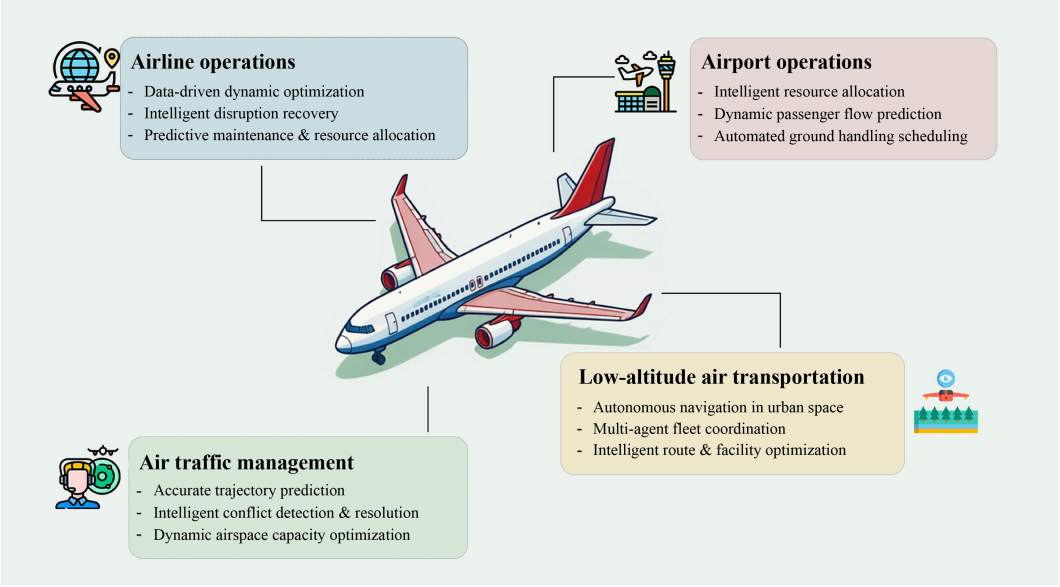


Fig. 5 Diagram of the main areas of air transportation.

operational efficiency and economic resilience.

5.1.1 AI-empowered scheduling, planning, and assignment

The emergence of AI has enabled decision-making frameworks to leverage large volumes of historical operational data more effectively, opening new avenues for addressing complex airline planning problems. Within the strategic planning phase of airline operations, core problems encompassing fleet planning, aircraft routing, and crew scheduling are inherently large-scale, highly constrained, and computationally intensive. This combinatorial complexity catalyzes the hybridization of data-driven heuristics with conventional mathematical optimization frameworks.

From a methodological perspective, existing studies can be broadly classified into two categories based on the role AI plays. In the first category, AI is embedded within classical OR frameworks to improve computational efficiency, while the underlying optimization models and decomposition structures remain unchanged. In the context of crew pairing, Yaakoubi et al. (2020) and Tahir et al. (2021) both used historical data to identify flight connections that frequently appear in high-quality solutions. Yaakoubi et al. (2020) identified groups of flights likely to form pairings and used this information to obtain effective initial clusters for dynamic constraint aggregation, thereby improving the structure of the restricted master problem. In contrast, Tahir et al. (2021) focused on the pricing stage by predicting promising flight-to-flight connections and using these predictions to accelerate the search within the subproblems. Moving beyond crew pairing, Quesnel et al. (2022) considered personalized crew rostering, predicted compatibility between individual crew members and candidate pairings, and used these predictions to restrict the pairing set explored in the pricing process. A more direct integration of learning arises in aircraft routing, where Thakkar and Palaniappan (2024) replaced the dynamic programming-based pricing procedure with an RL approach to construct maintenance-feasible aircraft routes in large-scale settings. These studies indicate that AI is particularly effective when used to identify promising variables, connections, or search regions within large-scale optimization models. Compared with replacing the entire optimization process, this learning-augmented strategy retains feasibility guarantees while reducing the computational burden of crew pairing, rostering, and aircraft routing.

In the second category, the optimization problems are modeled as sequential decision processes, naturally represented as MDPs, and RL is employed to learn effective policies directly. For example, Geursen et al. (2023) formulated the multi-stage airline fleet planning problem under uncertain demand and fuel prices as an MDP and proposed an advantage actor-critic (A2C) RL approach. Their results indicated that, particularly in highly uncertain environments, the learned policy achieved competitive solution quality with substantially reduced computational effort compared with deterministic and DQN-based baselines. Ruan et al. (2021) applied a similar paradigm to aircraft maintenance routing by modeling the problem as a sequential aircraft-to-flight assignment process and learning a policy that incrementally constructs feasible routings. In these settings, RL enables rapid solution construction without repeatedly solving large-scale optimization models. Compared with learning-assisted optimization, direct RL provides faster online solution

construction and is better suited to sequential planning under uncertainty. However, its performance depends strongly on the fidelity of the training environment, and operational constraints that are not fully represented during training may lead to infeasible or unreliable decisions.

5.1.2 AI enabling more powerful disruption management and recovery

Air transportation operations are frequently disrupted by factors such as adverse weather conditions, mechanical failures, and crew shortages, which affect the planned schedules of aircraft, crew members, and passengers. An effective recovery system must be able to generate feasible solutions quickly to mitigate delays and cancellations, thereby reducing associated economic losses and service quality degradation. In recent years, AI techniques have been increasingly applied to disruption management in the aviation sector, owing to their advantages in pattern recognition and complex decision-making. These methods have demonstrated significant potential to improve prediction accuracy and accelerate optimization processes (Hu et al., 2024).

Current related research can be classified into three categories. The first category comprises data-driven methods that integrate intelligent prediction with real-time optimization. Kim et al. (2022) developed a machine learning-based model that improves the spatial and temporal resolution of weather prediction through wind-field regression and convective-weather clustering, and couples these predictions with a graph-based routing algorithm to enable automated in-flight re-routing under dynamic conditions. Similarly, Haider et al. (2024) proposed a subnetwork prediction-optimization method for aircraft schedule recovery. By leveraging historical disruption logs and machine learning classifiers to identify key aircraft and narrow the search space for a column generation algorithm, this method reduces the computational time without compromising solution quality. Both studies demonstrate that the primary value of AI lies in identifying disruption-relevant states and reducing the search space before optimization. This is particularly useful in airline recovery, where solution speed is critical, but the final plan must still satisfy aircraft, crew, passenger, and airport constraints.

The second category includes deep learning-based historical data modeling methods. Herekoğlu and Kabak (2024) developed a framework that integrates deep learning with a column generation optimizer to solve airline crew recovery problems under operational disruptions. The deep learning model, trained on historical recovery data, predicts effective recovery actions to guide the optimization process, enabling faster computation without sacrificing solution quality. Applied to a major European airline, the method demonstrated improved efficiency and highlighted the potential of AI for sustainable and resilient airline operations. Nevertheless, these methods learn from historical recovery actions and may reproduce past operational preferences rather than identify fundamentally better recovery strategies. Their effectiveness may therefore decline when disruption patterns differ substantially from those represented in the training data.

The third category covers RL–based collaborative optimization frameworks. Wang et al. (2025c) proposed an attention-based DRL model for integrated recovery of flights, aircraft, and crew, formulating the task as an MDP to learn optimal recovery policies under operational constraints. The method rapidly produces high-quality solutions across multiple disruption types, outperforming traditional sequential and heuristic approaches. In contrast, Ding et al. (2023) developed a DRL-guided variable neighborhood search for the joint recovery of aircraft, crew, and passengers, integrating actions such as rerouting, re-accommodation, and cruise-speed control into a single model. Using PPO, the framework dynamically selects neighborhood operations, enhancing efficiency and scalability for large-scale disruption recovery.

In summary, these AI-based approaches have demonstrated strong potential for prediction, decision-making, and resource optimization, enabling the aviation industry to achieve faster, more accurate, and more scalable management and recovery in response to diverse disruptions.

5.1.3 AI makes aircraft maintenance smart

The aviation industry is undergoing a paradigm shift from traditional corrective and preventive strategies toward smart, predictive maintenance. This change is driven by the utilization of big data and AI, which empower airlines to manage operational uncertainties and optimize complex scheduling problems (Ma et al., 2022).

The foundation of smart maintenance lies in accurate aircraft prognostics. Deep learning techniques are increasingly employed to extract degradation patterns from historical sensor data for component failure prediction. For instance, Nguyen and Medjaher (2019) utilized LSTM to estimate the probability of system failure over future time windows. Such predictions enable planners to make maintenance or inventory decisions based on real-time aircraft health monitoring. Similarly, Lee and Mitici (2023) utilized a CNN combined with Monte Carlo dropout to generate probabilistic estimates of RUL for aircraft engines. Unlike traditional methods that rely on fixed degradation rates, this approach embeds probabilistic health states into maintenance scheduling optimization, enabling more risk-aware scheduling.

While predictive machine learning models focus on prediction, RL techniques have been utilized for aircraft

routing and maintenance decision-making. RL agents learn optimal policies by interacting with the environment to maximize cumulative rewards, such as minimizing maintenance cost or maximizing fleet availability. Hu et al. (2021) developed an RL-driven strategy leveraging an extreme learning machine-integrated Q-learning algorithm that provided optimal maintenance decisions based on prognostic information and spare part availability. Their results demonstrated that RL techniques can identify high-quality time windows for maintenance and spare part ordering, thereby effectively balancing costs. Furthermore, Ruan et al. (2021) developed an RL-based algorithm for the operational aircraft maintenance routing problem. Their method efficiently generates maintenance-feasible routes that comply with strict workforce and regulatory constraints, outperforming traditional heuristic methods in computational efficiency.

Moreover, recent advancements have integrated DRL to optimize decisions within uncertain environments. Lee and Mitici (2023) used a DRL agent to schedule aircraft engine replacements adaptively. Their findings demonstrated that AI-driven policies could reduce total maintenance costs by nearly 30% and eliminate over 95% of unscheduled maintenance events compared to traditional baselines. Additionally, Tseremoglou and Santos (2024) formulated a partially observable MDP based on predicted component RUL, deploying a DQN to schedule tasks under 4M (i.e., Manpower, Material, Machinery, and Method) constraints. Taken together, these studies show that AI delivers the greatest benefit when prognostics and maintenance scheduling are connected rather than treated as separate tasks. Accurate health prediction alone is insufficient unless it can be translated into feasible maintenance actions under workforce, material, and fleet constraints.

In conclusion, AI technologies redefine maintenance by directly linking predictive analytics to operational decisions. This paradigm not only offers superior foresight into future asset health but also enables dynamic responses in uncertain environments. Ultimately, these adaptive policies allow airlines to autonomously navigate trade-offs among safety, reliability, and cost efficiency, moving beyond reactive measures toward a truly proactive maintenance strategy.

5.1.4 AI enhancement in revenue management and pricing

Revenue management (RM) and pricing are central to airline profitability, as they determine how limited seat capacity is allocated across fare products over time. Classical RM methods, including dynamic programming and mathematical programming, generally rely on estimated demand models or predefined assumptions about customer arrivals, willingness to pay, cancellations, and no-show behavior. These assumptions become restrictive when passenger behavior is nonlinear, demand is non-stationary, and airlines face competition from alternative transportation modes. Recent advances in deep learning and RL have therefore extended airline RM in two related directions: improving the predictive layer of RM and learning adaptive pricing or inventory-control policies through interaction with simulated or operational environments.

Accurate prediction of demand and fares is an important prerequisite for effective RM decisions. Conventional time-series models, such as ARIMA, are often inadequate for capturing the nonlinear interrelationships among multiple factors and the volatility of airfare dynamics. To address this, Zhao et al. (2022) proposed a multi-attribute dual-stage attention model based on a Seq2Seq architecture with LSTM units. By synthesizing high-dimensional attributes—including booking horizons, temporal characteristics, and route-specific features—this deep learning approach significantly outperforms traditional statistical and machine learning benchmarks, providing accurate fare prediction for downstream inventory decisions.

Beyond predictive accuracy, AI enables the modeling of complex passenger behavior and intermodal competition. Contemporary travelers often exhibit "patient" behavior, monitoring price trajectories to optimize purchase timing. Jo et al. (2024) demonstrated that by embedding historical price states within an MDP, RL agents can identify these strategic patterns and derive non-monotonic pricing policies that yield superior revenue compared to traditional monotonic policies. For the multi-flight dynamic pricing problem with high-speed rail (HSR) competition, Zhu et al. (2024b) introduced an extended multinomial logit (MNL) utility function that jointly accounts for travel time, reference fares, and competition. They also developed multiple DRL algorithms and found that trust region policy optimization (TRPO) achieves superior stability and adaptability, reaching up to 99% of the theoretical optimal revenue. These studies suggest that RL is most useful when pricing decisions influence future customer behavior and market states, making the problem inherently sequential. In contrast, conventional optimization remains competitive when demand distributions are stable and can be estimated reliably, whereas RL gains importance under non-stationary demand and intermodal competition.

AI-driven dynamic pricing represents an adaptive extension of RM under uncertain market conditions. Bondoux et al. (2020) demonstrated that DRL can effectively balance short-term revenue loss and long-term policy improvement through active exploration, and further proposed initializing DQN using estimates from existing RM systems to accelerate convergence. Shihab and Wei (2022) demonstrated that DRL agents can autonomously learn seat-inventory control policies

through interaction with the environment, reducing reliance on explicit demand modeling while matching the performance of exact dynamic methods. AI is transforming airline RM from forecast-driven optimization toward more adaptive, data-driven decision systems.

5.2 AI in airport operations

Airports serve as vital hubs in the global air transportation network, where the efficient synchronization of airside and landside activities is paramount for maintaining system throughput and service quality. As passenger traffic continues to grow, airport operators face increasing pressure to optimize limited resources, such as runways, gates, and ground support equipment, while managing complex passenger flows and ensuring safety. Conventional manual or heuristic-based management approaches often lack the flexibility to respond to real-time fluctuations and uncertainties. The integration of AI technologies offers a robust solution, empowering airports to predict capacity constraints, automate resource allocation, and manage passenger dynamics with unprecedented precision. From intelligent gate assignment and ground handling to predictive crowd control, AI-driven systems are fostering a more agile, data-informed, and passenger-centric operational environment.

5.2.1 AI-powered resource assignment

The daily operational scheduling of an airport can be characterized as a multi-level resource assignment optimization problem. Given the heavy traffic and high frequency of arrivals and departures, the effectiveness of assigning critical resources, such as runways, taxiways, and gates, significantly impacts the airport's throughput capacity and the propagation of flight delays. Recent research increasingly leverages AI to learn and predict the states and real-time demand variations of these resources. This AI-driven approach improves decision accuracy and enhances the robustness of assignment plans under dynamic operating conditions, thereby significantly elevating the airport's overall operational efficiency.

Accurate prediction of airport capacity is critical for efficient ATM, as it directly impacts runway utilization, delay reduction, and airspace efficiency. Wang and Zhang (2021c) proposed a multi-CNN deep learning framework to simultaneously predict runway configurations and airport acceptance rates for multi-airport systems. It uses gridded weather prediction data to capture spatial interdependencies, achieving higher accuracy than existing single-airport models, as validated across the New York Metroplex airports. After airport capacity is determined, runway operations require precise sequencing of takeoffs and landings, in which uncertainty in individual aircraft's runway occupancy becomes a pivotal factor. Herrema et al. (2019) developed a gradient boosting–based model to identify whether landing aircraft will use procedural or non-procedural runway exits, enabling early identification of flights associated with extended runway occupancy. Similarly, a machine learning model was developed by Gao et al. (2023) to predict the runway occupancy time of arriving aircraft based on high-resolution operational and meteorological data. By providing early, aircraft-specific insights, these methodologies support safer and more robust runway sequencing and spacing decisions.

Gates are among the most heavily occupied airport surface resources, and improving their utilization is essential for enhancing airport turnaround efficiency. Although gate assignment has been widely studied, its effectiveness is often undermined by uncertainty in actual gate occupancy durations. Recent advances in deep learning enable such uncertainty to be better captured and incorporated into gate scheduling decisions. A bi-objective gate assignment model was embedded within a predict-then-optimize framework by Cao et al. (2024), which ingests deep learning–based arrival time predictions as a core component, where treating these predicted arrival times as deterministic inputs serves to minimize potential gate conflicts. Shadman et al. (2025) focused on an estimate-then-optimize framework for gate assignment under arrival-time uncertainty, where machine learning is used to estimate arrival time distributions and embed them into a two-stage stochastic programming model to support robust gate scheduling. Zhang et al. (2025a) addressed robustness to gate assignment by explicitly modeling uncertainties in taxi-in and taxi-out times. Classical machine learning regressors are employed to predict taxi delays, from which uncertainty sets are constructed and embedded into a robust bi-objective gate assignment model. The comparison among deterministic, stochastic, and robust formulations highlights that the best prediction model does not automatically produce the best gate plan. Deterministic predict-then-optimize methods are computationally efficient but may underestimate disruption risk, whereas stochastic and robust models provide stronger protection against uncertainty at the cost of greater computational complexity.

Once runways and gates are designated, taxiway planning aims to generate conflict-free routes between the runways and gates with minimal taxiing distance. AI-based prediction of intersection states enables early identification of potential congestion and supports fast, near-optimal taxi route assignment in real time (Wang et al., 2024a).

5.2.2 AI involved in task assignment and rostering

Airport ground handling comprises a series of closely

coordinated activities. Two critical scheduling decisions related to these activities are rostering and task assignment. The former determines workforce availability over time, while the latter allocates operational tasks to qualified resources. Traditional deterministic optimization models rely on fixed flight schedules and standard service times, which often fail to capture operational uncertainties arising from flight delays, turnaround variability, and stochastic passenger flows. Recent advances in machine learning and data-driven prediction provide new opportunities to incorporate predictive information into real-time and tactical decision-making frameworks.

Accurate flight volume and task volume prediction form the foundation of rostering and task assignment. Precise predictions of flight arrivals and their corresponding service demands enable automated scheduling and dispatch to better align with actual operations, thereby reducing the need for manual adjustments. Rebollo and Balakrishnan (2014) developed a data-driven approach for arrival delay prediction using historical flight and weather information, demonstrating substantial improvements over schedule-based baselines. More recently, Kim et al. (2016) employed gradient boosting and ensemble learning techniques to model nonlinear interactions between air traffic congestion, meteorological factors, and airport capacity constraints, achieving robust short-horizon delay prediction. Deep learning architectures have further enhanced predictive performance. Li et al. (2022b) integrated attention mechanisms into recurrent networks to dynamically weight influential features, such as upstream network disruptions and local runway congestion.

These predictive outputs are increasingly embedded into task assignment and rostering decisions. Bertsimas and Kallus (2020) introduced the predictive-prescriptive optimization paradigm, which systematically integrates machine learning-based prediction into optimization models, enabling scheduling decisions that explicitly account for uncertainty distributions. Wu et al. (2023) modeled airport ground handling as a multi-fleet vehicle routing problem with various constraints and proposed a deep learning-driven construction heuristic trained via RL that outperforms classical heuristics and metaheuristics on benchmarks, demonstrating scalability and adaptability under stochastic flight arrivals. Zhou et al. (2023a) proposed a learning-assisted large neighborhood search for airport ground vehicle routing and scheduling, in which a GCN is trained on historical operational data to improve the destroy/repair operators, thereby outperforming state-of-the-art heuristics in real airport scenarios. AI has also been applied to support data-driven staff rostering and shift allocation under stochastic demand. Brun et al. (2025) integrated deep neural network-based passenger flow prediction with optimization-based checkpoint scheduling at major international airports, enabling demand-aware staffing plans that significantly reduce passenger waiting times and workforce overstaffing. Collectively, these studies indicate that AI improves ground handling not simply by predicting demand more accurately, but by connecting forecasts with task assignment and rostering decisions. Learning-assisted heuristics are especially useful for large, stochastic problems, while mathematical optimization remains necessary to enforce qualifications, temporal precedence, and labor constraints.

Overall, AI is driving a paradigm shift in airport ground handling operations. The resulting prediction-optimization frameworks enable proactive, adaptive, and uncertainty-aware task assignment and rostering, thereby supporting greater service robustness and more efficient resource utilization.

5.2.3 AI technologies for passenger flow management

Passenger flow management is a core operational challenge in airport terminals, where stochastic passenger arrivals and limited capacity jointly shape congestion level and service quality. Uncertainty in passenger demand constitutes a major driver of operational inefficiency, affecting staffing levels, checkpoint utilization, and the reliability of downstream processes such as boarding and flight connections. Due to the complex interactions among passengers, infrastructure, and operational resources, airport passenger flow management has increasingly become a natural application domain for AI and data-driven DSSs. Recent studies have focused on applying AI approaches to improve prediction accuracy, enhance congestion management, and support real-time operational decision-making.

A primary area of AI application is passenger flow prediction. To estimate airport transfer passenger flows, data-driven machine learning models were trained on real-time streams by Guo et al. (2022), which highlights how computational intelligence can optimize resource allocation and alleviate congestion. Similarly, traditional time series models were benchmarked against neural networks by Hopfe et al. (2024) to evaluate short-term prediction performance under volatile conditions. Their findings highlight that neural network models offer superior adaptability to fluctuating demand, suggesting AI's advantage in dynamic, uncertain operational environments. Beyond flow prediction, AI contributes to understanding passenger behavior and queue management. Rodríguez-Sanz et al. (2021) applied machine learning techniques to identify behavioral patterns in airport terminal queues. By analyzing large-scale passenger movement data, they modeled congestion hotspots and informed terminal design and staffing strategies. These approaches underscore the value of AI in simultaneously optimizing passenger experience and operational efficiency.

Another emerging research direction involves recognizing mobility patterns within transportation hubs. Wang et al. (2025h) explored AI-based prediction of individual mobility trajectories by analyzing indoor movement patterns. Such capability may support proactive crowd management, personalized guidance systems, and enhanced safety protocols, particularly in complex or high-traffic hubs. AI also enhances safety and surface operations. Zhang et al. (2022c) applied spatio-temporal GCNs to predict airport surface movements and assess safety risks. By capturing temporal and spatial correlations, AI models can identify potential conflicts among aircraft and ground vehicles, providing predictive insights to reduce accidents and improve coordination.

As air traffic grows, AI-driven systems are increasingly critical to developing safer, more efficient, and passenger-focused airport operations. Key research opportunities may lie in deeper integration of passenger behavior models, fusion of multimodal data streams, and enhanced coordination across terminal networks. These directions will further enable proactive management of airport systems, ensuring that AI not only responds to dynamic conditions but also anticipates and shapes future operational environments.

5.3 AI in air traffic management

ATM is the backbone of aviation safety and efficiency, responsible for coordinating the movement of aircraft through complex airspace sectors and airport terminals. With the rapid expansion of global air traffic, traditional ATM systems rely heavily on human cognitive capabilities and rigid airspace structures, which are becoming increasingly saturated. This bottleneck necessitates a shift toward greater automation and decision support. In modern ATM systems, AI has emerged as a pivotal driver, enhancing capabilities in trajectory prediction, conflict detection, and airspace capacity management. By deploying deep learning for accurate state prediction, combined with RL for strategic conflict resolution, AI augments human controllers' situational awareness and decision-making, thereby accelerating the transition toward scalable, resilient airspace management under the next-generation trajectory-based operations (TBO) paradigm.

5.3.1 AI enabling traffic prediction

AI has become a pivotal enabler in air traffic prediction, advancing weather prediction, sector capacity estimation, and trajectory prediction.

In meteorological prediction, deep learning architectures have proven particularly effective at modeling complex atmospheric dynamics to ensure flight safety. For instance, Wang et al. (2024b) employed a supervised deep learning approach to develop a short-term convective weather prediction model based on a CNN-Transformer. The model demonstrated optimal performance for 2- to 6-h prediction horizons. Its capability to learn complex weather patterns from global historical data provides critical lead time for route adjustments. Building on these convective prediction capabilities, Wang et al. (2025f) developed a hybrid CNN-Transformer model for the spatiotemporal nowcasting of echo top (ET) height, a critical vertical parameter for convective weather. Through the fusion of Doppler radar records and ERA5 reanalysis data, CNN modules within this framework extract spatial features, while Transformers capture the underlying temporal dynamics. The model significantly outperforms traditional LSTM and CNN-based methods, enabling accurate severe weather prediction up to 6 h in advance to support altitude-based flight rerouting.

In parallel with weather prediction, AI-driven predictive analytics have revolutionized the estimation of airspace capacity and controller workload, providing essential tools for balancing demand and resources with high precision. In the prediction sector, Zhou et al. (2023b) proposed AirFusion, which uses temporal fusion Transformers to predict traffic demand and airspace sector capacity with a 4-h look-ahead window. By integrating interpretable multi-horizon predictions with dynamic airspace sectorization, the model effectively balances airspace resources. When predicted demand exceeds capacity, it uses graph-based partitioning to split sectors, achieving high-precision prediction with a coefficient of determination exceeding 0.9. Xu et al. (2024b) proposed a framework that integrates an attention-based WP-ConvLSTM deep learning model for dynamic airspace sectorization. This framework effectively supports dynamic sector management by accurately predicting controller workload and providing a reliable, AI-driven solution for the refined management of high-density airspace. These studies demonstrate that AI is useful not only for predicting demand but also for representing controller workload and dynamic capacity, which are difficult to describe through fixed analytical rules. Nevertheless, capacity estimates depend on controller behavior, sector configuration, and procedural context, limiting direct transfer across airspaces.

Beyond weather and sector capacity prediction, the integration of AI technologies is critical for precisely predicting individual aircraft trajectories, enabling the high-fidelity synchronization required for modern ATM. Mondoloni and Rozen (2020) noted that the most critical prerequisite for realizing the TBO paradigm is obtaining accurate, synchronized trajectory information across the entire system. The core challenge lies in managing prediction uncertainties and integrating heterogeneous flight data. To address these uncertainties, particularly within complex terminal airspaces, Zeng et al. (2020) employed a sequence-to-sequence deep LSTM network

to develop a data-driven 4D trajectory prediction model.

In conclusion, AI-driven prediction models have significantly enhanced the predictive capabilities of ATM systems, transforming how weather, capacity, and trajectories are managed. However, despite its potential, the practical deployment of AI in air traffic prediction is constrained by principal challenges: a prevailing lack of explainability and transparency, limited human trust, and persistent technological accessibility gaps (Abdillah et al., 2024).

5.3.2 AI-aided traffic control

As a cornerstone of modern aviation infrastructure, air traffic control functions, with the primary mandate of maintaining the safe, efficient, and orderly movement of aircraft both within terminal airspaces and across airport surfaces. The application of AI in this domain is progressively enhancing situational awareness, predicting operational risks, and supporting decision-making in ATM.

In risk identification, data-driven learning paradigms have become a dominant approach for conflict detection and prediction. Early studies leveraged aircraft surveillance data to build learning-based conflict identification systems. Ortner et al. (2022) developed an augmented air traffic control system that employed LSTM networks to automatically detect and classify potential conflicts in traffic data streams. Xu and Luo (2021) integrated association rule mining and random forest algorithms to predict and provide early warnings for air traffic controllers' unsafe acts, thereby supporting the identification of human-factor-related conflict risks in air traffic control. Recently, hybrid deep learning frameworks integrating recurrent networks, GCNs, and convolutional architectures have been proposed to jointly capture temporal evolution, spatial interactions, and trajectory-level features (Zhong et al., 2025). These models improve predictive performance and provide more accurate, interpretable insights into key operational factors, such as airport congestion, thereby supporting more proactive operational decision-making in ATM.

Research on risk resolution examines how AI can recommend or execute conflict mitigation actions in coordination with human controllers. RL and DRL are particularly suitable for this task, as air traffic control can be formulated as a sequential decision-making problem under uncertainty. A DRL-based approach has been applied to conflict detection and resolution, demonstrating substantial improvements in computational efficiency while maintaining high conflict-resolution performance (Wang et al., 2019b). More recently, a hybrid methodology that couples RL with geometric algorithms was proposed by Wang et al. (2025a), achieving a substantial decline in conflict rates, maintaining high-fidelity trajectory adherence with minimal deviations, mitigating redundant computational overhead, and robustly adapting to dynamic environmental conditions.

Recently, human-AI interaction has also received increasing attention. NLP technology offers a new approach to improving the efficiency and safety of interactions between air traffic controllers (ATCOs) and AI systems. Sarhan et al. (2025) developed an intelligent air traffic control communication system that integrates automatic speech recognition, natural language understanding and generation, aiming to automate the comprehension and response generation of instructions. The study demonstrates that an NLP-based automated communication framework can effectively support ATCOs in making rapid, accurate conflict decisions in high-pressure environments, providing a technical foundation for constructing a human-centric, AI-assisted collaborative conflict resolution system.

In conclusion, AI is becoming a key enabling technology for air traffic control. Research trajectories have shifted from data-driven conflict detection and risk prediction toward deep learning-based spatio-temporal modeling, facilitating a tactical transition from reactive maneuvers to proactive scheduling. Meanwhile, RL and multi-agent approaches are applied to decision-making for conflict resolution, with increasing emphasis on human-AI collaboration and natural language interaction to enhance safety and operational efficiency.

5.3.3 AI provides controller decision support

ATM is a safety-critical and cognitively demanding domain, in which controllers must continuously make time-sensitive decisions under uncertainty, high traffic density, and complex operational constraints. These decisions directly affect system safety, efficiency, and resilience. As traffic demand continues to grow, traditional ATM is reaching its limits, posing significant problems such as congestion, higher costs, longer delays, and greater emissions. In this context, AI-enabled decision support systems (DSSs) have been proposed to help ATCOs make efficient, high-quality decisions under complex traffic conditions and to alleviate their cognitive workload.

The key challenge in implementing these support systems is ensuring high acceptance and adoption of the proposed advisories (Renkhoff et al., 2025). One major factor underlying this challenge is the limited transparency of many AI models. To build operational trust, research has focused on improving the transparency and interpretability of AI reasoning. One promising approach is integrating high-performance predictive models with post-hoc explanation techniques. For example, Xie et al. (2021) combined the XGBoost machine learning algorithm with XAI tools such as SHAP for real-time operational risk prediction. This framework not only predicts

meteorological hazards but also explains the contribution of specific features (e.g., wind speed, and humidity), allowing controllers to verify the system's logic. Beyond post-hoc analysis, recent studies have explored the use of LLMs as embodied agents for conflict resolution. These agents can generate conflict-resolution actions while simultaneously providing human-level textual explanations, thereby bridging the gap between machine decision-making processes and human understanding (Andriuškevičius and Sun, 2024). However, natural-language fluency does not establish operational correctness. An LLM may hallucinate aircraft states, overlook separation requirements, or provide an explanation that is inconsistent with its recommended maneuver. Therefore, LLM-based agents should presently be regarded as advisory interfaces grounded in verified surveillance data and rule-based conflict-resolution tools, rather than autonomous controllers.

Building on the need to improve trust in and acceptance of AI-assisted decision-making, a parallel research stream investigates "strategic conformance," in which AI adapts its problem-solving style to individual ATCOs. For example, Regtuit et al. (2018) proposed a two-stage method that applies K-means clustering to identify a controller's dominant conflict resolution strategies from historical data, followed by training a model-free RL agent to replicate the personalized strategy. Experimental results indicate that advisory acceptance rates vary significantly with the degree of conformance: controllers accepted 77.8% of advisories under conformal conditions, compared to 66.7% under non-conformal conditions, highlighting the effectiveness of personalized decision support.

At the system level, the design of human–AI interactive systems focuses on coordinated interaction and shared situational awareness between controllers and AI-enabled DSSs. Gerdes et al. (2025) proposed a digital ATCO as an AI-enabled team partner for human ATCOs, aiming to alleviate workload and controller shortages. The digital ATCO relies on data-driven and machine-learning-based situation assessment to construct digital situational awareness and shared mental models, and interacts with human ATCOs through integrated interfaces.

In summary, AI in ATM has evolved from an auxiliary tool to a core decision-support system. By enhancing interpretability, personalizing advisories, and improving the efficiency of human-AI interaction, AI-enabled DSS can effectively assist ATCOs in making timely, high-quality decisions while reducing their workload.

5.4 AI in low-altitude air transportation

Low-altitude air transportation, characterized by the proliferation of unmanned aerial vehicles (UAVs) and urban air mobility (UAM) concepts, represents a rapidly emerging frontier in the aviation sector. Unlike structured high-altitude airspace, the low-altitude domain is often unstructured, obstacle-rich, and highly dynamic, posing unique challenges for navigation, safety, and fleet management. The successful scaling of low-altitude operations requires autonomy levels that surpass traditional remote control or pre-programmed flight paths. AI is instrumental in addressing these challenges, enabling autonomous navigation in complex urban environments, optimizing large-scale logistics routing, and facilitating data-driven facility location planning. Through computer vision, multi-agent coordination, and intelligent optimization, AI provides the technological foundation for safe, efficient, and economically viable low-altitude air transportation networks.

5.4.1 Navigation and path planning with AI

Navigation and path planning in the low-altitude domain differ fundamentally from high-altitude operations due to the presence of complex, unstructured environments and the requirement for high-frequency control loops. A comprehensive review by Kumar et al. (2026) highlighted that while traditional heuristic and mathematical methods provide a foundation, they struggle with the dynamic and unstructured nature of low-altitude urban environments, necessitating the adoption of learning-based approaches. While traditional methods rely on global navigation satellite systems and precomputed waypoints, they often fail in urban canyons, where signal degradation and dynamic obstacles are prevalent. DRL algorithms are enabling a shift from automated to fully autonomous flight by allowing UAVs to learn robust control policies and obstacle avoidance strategies directly from sensor inputs.

At the level of flight dynamics and stability, neural networks are increasingly replacing or augmenting classical PID controllers to handle nonlinear aerodynamic effects. O'Connell et al. (2022) introduced Neural-Fly, a deep-learning-based control architecture that enables UAVs to adapt online to rapidly changing wind conditions. By leveraging domain-adversarially invariant meta-learning to learn a shared representation of aerodynamics, the system achieves precise flight control in turbulent environments that would destabilize conventional controllers. Pushing the limits of agility, Kaufmann et al. (2023) developed Swift, an autonomous system that combines DRL with onboard perception to race drones at champion-level speeds. By integrating a policy network trained in simulation with a visual-inertial perception system that estimates the drone's state directly from onboard sensors, their system outperforms human world champions. It optimizes time-optimal trajectories in real time, effectively bridging the "sim-to-real" gap and demonstrating that AI can better master the physical limits of aerial platforms than human pilots.

Beyond low-level control, AI is critical for micro-level path planning and dynamic obstacle avoidance in cluttered urban environments. Navigating through urban flows requires adaptive planning that accounts for environmental dynamics, as wind gusts and building wakes create turbulent conditions. Tonti et al. (2025) used DRL combined with LSTM cells to enable UAVs to navigate simplified urban flows, learning to exploit flow structures to find energy-efficient paths while avoiding collisions. To address the challenge of real-time collision resolution in high-density airspace, Zhang et al. (2021b) proposed a fusion scheme that integrates 3D voxel-based jump point search for static path planning with an MDP for dynamic conflict resolution. Their approach effectively resolves conflicts with intruder drones while maintaining trajectory smoothness, a critical requirement for UAM.

In scenarios requiring sustained autonomy under uncertainty, such as border patrolling, stochastic frameworks are essential. Biskin et al. (2025) developed a stochastic navigation strategy for UAVs in border patrol missions, using simulation-based optimization methods such as simulated annealing and stochastic Nelder-Mead to discover optimal movement strategies that maximize detection probability against unpredictable intruders. Furthermore, enabling autonomy in unstructured environments remains a key challenge. Loquercio et al. (2021) demonstrated a fully autonomous system capable of high-speed flight in previously unseen complex environments by training a sensorimotor policy entirely in simulation. Their approach maps noisy sensory observations directly to collision-free trajectories in a receding-horizon fashion, enabling zero-shot transfer to challenging real-world environments like dense forests and collapsed buildings without relying on external positioning infrastructure.

In summary, AI empowers UAVs to perceive, decide, and act in real time, transforming them from remotely piloted machines into intelligent autonomous agents capable of navigating the complex, dynamic low-altitude airspace.

5.4.2 AI helps logistics and routing

Logistics routing constitutes a core operational layer of the low-altitude air transportation systems, determining how delivery tasks are assigned, sequenced, and coordinated across fleets of UAVs and supporting ground assets. At the system level, routing decisions encompass task-vehicle assignment, service order determination, delivery-area partitioning, and time-energy trade-off management. As UAVs are increasingly deployed for last-mile delivery, emergency response, and urban distribution, such routing decisions must be performed at scale and under highly dynamic operational conditions, thereby motivating the adoption of AI in low-altitude logistics routing.

Classical formulations such as the VRP and the traveling salesman problem (TSP) provide the theoretical foundation for logistics routing, with numerous extensions incorporating capacity limits, time windows, pickup-and-delivery constraints, and multi-depot structures (Shuaibu et al., 2025). In low-altitude air transportation systems, these problems are further complicated by UAV-specific constraints, including limited battery endurance, heterogeneous vehicle capabilities, restricted takeoff and landing locations, weather sensitivity, and airspace availability. The resulting problem scale and uncertainty substantially undermine the computational efficiency of classical exact optimization approaches in real-time operations, motivating the adoption of AI-based, data-driven routing methods that enable adaptive decision-making under complex, dynamic conditions.

Machine learning techniques enable routing systems to exploit large volumes of heterogeneous data, including historical delivery records, real-time traffic conditions, meteorological information, and customer demand patterns (Li et al., 2025a). By learning predictive models of travel time, energy consumption, and service reliability, machine learning-based routing frameworks can move beyond static delivery plans toward dynamic optimization strategies that support continuous route adjustment. Such learning-enhanced routing approaches significantly improve system responsiveness to fluctuating demand and environmental uncertainty.

Recent studies demonstrate the effectiveness of machine learning-based routing optimization in complex urban environments. Learning-assisted routing models integrate real-time information to reconfigure delivery networks and update service sequences dynamically. Ramírez-Villamil et al. (2023) developed a machine learning-assisted two-echelon parcel distribution system that combines delivery-area clustering with routing optimization, achieving significant reductions in travel distance and delivery time through joint spatial partitioning and route planning. These clustering-based routing strategies improve operational efficiency, mitigate congestion, and reduce environmental impact in densely populated cities.

AI-enabled routing is particularly valuable in multimodal logistics systems that involve heterogeneous fleets of trucks, drones, and other delivery vehicles. In such systems, UAVs operate in close coordination with ground vehicles, with trucks serving as mobile depots and drones executing short-range aerial deliveries. Bi et al. (2024) investigated truck-drone delivery coordination using MARL, demonstrating that learning-based strategies can effectively balance drone battery consumption against delivery time while improving overall system performance.

Beyond static route construction, AI also supports dynamic and autonomous routing under uncertainty. Logistics operations are frequently affected by unexpected disruptions such as demand surges, order cancellations,

traffic incidents, or adverse weather. Learning-based routing systems can perform online re-optimization and task reassignment in response to such events, improving resource utilization and operational robustness. Bruni et al. (2023) showed that machine learning-driven routing and fleet allocation models significantly reduce risk amid demand variability, while recent studies further explore the integration of routing with dynamic scheduling and fulfillment decisions across the logistics chain (Raj et al., 2024; Hong et al., 2023). Overall, these studies show that the main advantage of AI lies in online adaptation rather than static route quality alone. Frequent re-optimization may reduce operational stability and user predictability, suggesting that responsiveness should be balanced against schedule consistency.

In conclusion, AI-driven logistics routing transforms low-altitude UAV operations from offline planning problems into adaptive, real-time decision-making systems. By enabling large-scale task coordination, dynamic routing, and multimodal fleet cooperation, AI plays a central role in enhancing the efficiency, resilience, and scalability of emerging low-altitude air transportation networks.

5.4.3 AI applications in facility location

Facility location represents a fundamental planning problem in low-altitude air transportation systems, encompassing the deployment of drone depots, micro-hubs, charging stations, emergency hangars, and supporting infrastructure nodes. Such decisions directly influence service coverage, response performance, energy consumption, and overall operational reliability. Compared with conventional ground-based networks, drone systems are subject to tighter onboard energy constraints, evolving airspace regulations, and greater exposure to weather and environmental uncertainty. Consequently, AI-related techniques and data-driven methods have been increasingly incorporated into location-planning frameworks to improve demand estimation, risk representation, computational scalability, and solution robustness.

A related stream of research first examined how learning components can be embedded in classical optimization pipelines. Khalil et al. (2016) demonstrated that learning-based branching strategies can improve the performance of mixed-integer programming solvers, which constitute the computational backbone of many facility location formulations. Subsequently, representation learning approaches that exploit graph structures have attracted increasing attention in combinatorial optimization research. Cappart et al. (2021) provided a comprehensive review of GNN-based reasoning methods and discussed their applicability to combinatorial optimization problems with relational and topological structures, emphasizing their ability to encode spatial and network relationships within structured optimization tasks.

With the growing availability of high-resolution spatial and operational data, research attention gradually expanded toward data-driven planning. In drone facility deployment, machine learning has been applied to infer fine-grained demand patterns, service hotspots, and risk profiles from heterogeneous data sources. Braßel et al. (2023) combined georeferenced hotspot information, restricted-airspace data, and robust UAV hangar location optimization for emergency service deployment under restricted airspace, battery, and wind-related constraints. In logistics applications, Dukkanci et al. (2024) synthesized recent drone facility location models and highlighted the growing emphasis on facility-type classification, drone-specific modeling assumptions, vehicle interactions, and future data-rich planning directions. Taken together, this line of work indicates that AI and data-driven methods are most valuable not as replacements for optimization, but as mechanisms for constructing richer inputs, predicting dynamic demand and risk, and supporting scalable solution procedures.

In parallel, facility deployment has expanded from two-dimensional ground layouts to three-dimensional, communication-oriented infrastructure placement. Al-Hourani et al. (2014) analyzed altitude-dependent coverage characteristics of aerial platforms under air-to-ground channel models. Bor-Yaliniz et al. (2016) subsequently formulated a three-dimensional placement problem for aerial base stations, explicitly accounting for air-to-ground channel characteristics and network-service objectives. More recently, Elnabty et al. (2022) surveyed UAV placement optimization approaches for UAV-assisted communication in 5G and beyond networks, covering deployment scenarios, optimization objectives, solution techniques, and operational issues such as energy limitations and interference.

In summary, AI applications in facility location have progressed from solver-level acceleration to data-driven, learning-assisted infrastructure planning. For low-altitude transportation networks, these methods primarily contribute by integrating predictive analytics, spatial risk modeling, and optimization-based decision-making to support more adaptive, scalable, and reliable deployment decisions.

6 Key technological components and challenges

6.1 Road transportation

Road transportation has advanced rapidly with the advent of advanced AI models, yet intertwined challenges and emerging opportunities increasingly shape its evolution.

Regarding traffic prediction, modern road networks are becoming both more data-rich and more heterogeneous,

driven by the proliferation of connected vehicles, mobile sensing, and infrastructure intelligence. While this creates unprecedented opportunities for fine-grained prediction, it also exposes fundamental limitations in current data-driven paradigms, particularly in terms of generalization, robustness, and interpretability. One prominent opportunity lies in exploring foundation models and large-scale pretraining for traffic prediction. Instead of training task-specific models for individual cities or networks, researchers are increasingly investigating whether a unified "traffic foundation model" can be pretrained on large, diverse mobility data sets and then adapted to new urban contexts through lightweight fine-tuning. Such models promise improved transferability, reduced data requirements, and faster deployment across cities. However, large-scale pretraining does not automatically yield reliable cross-city transfer: differences in topology, sensor definitions, temporal resolution, travel behavior, and local policies may cause substantial negative transfer. Pretraining and inference costs may also outweigh the benefits for smaller networks or real-time edge deployment. In addition, there is growing recognition that correlation-driven prediction alone is insufficient for decision-critical applications. Causal inference offers a pathway to move beyond pattern recognition toward understanding how exogenous events—such as policy interventions, incidents, or weather extremes—actively shape traffic dynamics. Integrating causal reasoning into AI-based predictors enables more reliable counterfactual analysis and supports scenario-based traffic management. Another emerging direction is the fusion of physical traffic knowledge with data-driven learning. Embedding traffic flow theory, conservation laws, and behavioral constraints into AI models can improve stability, interpretability, and extrapolation under unseen conditions. This physics-informed perspective aligns predictive accuracy with scientific consistency and enhances robustness in sparse or disrupted data environments. Together, these directions signal a transition from isolated prediction models toward adaptive, transferable, and decision-aware traffic prediction systems.

Regarding shared mobility, despite significant progress from AI-driven systems, their future trajectory is shaped by structural challenges that extend beyond algorithmic performance. A critical concern is fairness, as dispatching, matching, and pricing strategies may inadvertently reinforce spatial inequities by creating service gaps or disadvantaging specific user groups (Zhou et al., 2025). Embedding fairness-aware constraints into efficiency-oriented optimization frameworks remains a nontrivial task, particularly when demand is highly uneven. These challenges are further amplified by the transition toward SAVs, which require large-scale, real-time fleet coordination under uncertainty (Shaygan et al., 2025). Managing robotic fleets introduces new demands for fault tolerance, resilience, and ethical decision-making in complex urban environments. In parallel, achieving truly seamless mobility depends on deep multimodal integration within a mobility-as-a-service ecosystem. This raises substantial technical barriers, including fragmented data ownership, interoperability between public and private operators, and the combinatorial complexity of real-time cross-modal journey planning.

Regarding autonomous driving, road networks are becoming more information-rich but also more operationally heterogeneous, driven by mixed traffic, uneven sensing coverage, and rapidly evolving bottlenecks. While this creates new opportunities to anticipate occluded conflicts and dampen the propagation of disturbances earlier, it also exposes fundamental limitations in today's perception-to-traffic paradigm, particularly in generalization, robustness, and outcome alignment. A central challenge is that expanded perception does not directly map to safer and more efficient traffic (Ran et al., 2025), because transportation benefits are mediated by interaction dynamics at merges, lane changes, and intersections, where small miscalibration in uncertainty or intent inference can shift driving toward either smoother coordination or unnecessary conservatism, with measurable impacts on bottleneck discharge and corridor reliability. Another structural challenge lies in evaluation: crashes are rare, and mixed-traffic safety is often inferred from surrogate safety measures, yet conventional indicators and thresholds may no longer be valid as vehicles react faster, plan ahead, and exchange information, creating a gap between benchmarked gains in perception and the true evolution of traffic risk. (Do et al., 2025) This motivates an emerging opportunity to rethink safety and efficiency assessment around scenario-complete, traffic-consistent indicators that remain meaningful under CAV behaviors, rather than relying solely on object-level detection scores. More broadly, the surrogate-safety literature has highlighted both the necessity and the limitations of current SSM-based (surrogate safety measures-based) evaluation in the CAV era, underscoring the need for uncertainty-aware, interaction-centric, and system-level validation frameworks (Wang et al., 2021a).

Regarding traffic safety, while AI holds immense promise for enabling predictive and proactive traffic safety, translating research advances into large-scale deployment presents multifaceted challenges spanning data, technology, and governance. Data-related issues underpin these challenges. Traffic crashes are statistically rare, leading to severe class imbalance during model training, while the use of fine-grained behavioral and trajectory data raises significant privacy concerns (Zhu et al., 2026). Practical solutions increasingly rely on surrogate safety indicators for richer supervision and privacy-preserving learning paradigms such as FL. Beyond data, the complexity and opacity of AI models pose obstacles to trust, validation, and regulatory acceptance. The black-box nature of many safety models

complicates verifying decision logic, especially in rare or extreme scenarios. To address this, explainable AI techniques are being combined with digital twin platforms to test and validate model behavior across large-scale simulated environments before real-world deployment (Li et al., 2024d). System integration and deployment introduce further engineering challenges. Real-time safety interventions require ultra-low latency, which can conflict with the computational demands of complex models, while limited interoperability constrains cooperative safety applications such as V2X. These issues are gradually being addressed through edge computing architectures and the standardization of communication protocols. Overarching these technical challenges are critical human and ethical considerations, including alert fatigue, ambiguity in legal liability, and the risk of embedding historical biases into safety systems (Wang and Xu, 2026). Addressing these concerns requires coordinated progress in human–machine interface design, regulatory frameworks, algorithmic auditing, and system-level governance that spans model development, deployment, monitoring, and continuous updating throughout the operational lifecycle.

6.2 Rail transportation

Regarding AI-based metro operations and management, the future will increasingly center on developing large-scale, integrated decision models that unify strategic, real-time control, and disruption management within a single analytical framework. From a modeling perspective, future research should move beyond isolated operational layers and instead develop multi-resolution formulations that explicitly link station-level passenger flow dynamics, train-level control decisions (e.g., headway regulation, dwell time adjustment, and train ordering), and line- or network-level performance objectives. Such integrated models will enable consistent decision-making across temporal and spatial scales while improving responsiveness under fluctuating demand and operational disturbances. Distributed control architectures based on multi-agent AI represent a promising approach to addressing system complexity, enabling trains, platforms, and junctions to coordinate locally using partial information while maintaining system-level feasibility and performance through coordination constraints and shared objectives. As automation levels rise, human-AI collaboration will remain essential; transparent and interpretable decision-support interfaces should be embedded within operational systems to enable human oversight, override, and compliance with safety and regulatory requirements. Overall, AI-driven operational intelligence will underpin the next generation of metro systems, enabling adaptive scheduling, proactive crowd management, fault anticipation, and more resilient service delivery. As metro operations become increasingly adaptive and data-driven, future models must also explicitly account for uncertainty, rare disruptions, and cascading failures. In particular, multi-agent and distributed control frameworks warrant deeper theoretical investigation, including convergence guarantees, stability properties, and system-level optimality under partial observability. Beyond control and scheduling, AI provides a powerful foundation for integrating demand prediction, real-time optimization, anomaly detection, and predictive maintenance into unified decision-support platforms, often supported by digital twins. Through advances in RL, deep learning, and hybrid optimization-learning architectures, future metro networks can achieve substantially higher levels of reliability, efficiency, and resilience in complex and uncertain operating environments.

Regarding AI-based HSR operation and management, while RL-based methods are attractive for real-time control due to their rapid inference, they face significant challenges, including strict constraint satisfaction (particularly safety headways), generalization to novel disruptions, and rigorous validation required for safety certification. AI is transforming HSR operations by integrating predictive analytics with advanced learning-based control. Delay prediction models, evolving from conventional machine learning to interpretable deep architectures, provide accurate predictions and explainable insights that support informed human decision-making. Concurrently, RL approaches, particularly multi-agent and multi-task frameworks, offer scalable solutions for real-time rescheduling under uncertainty. However, the large-scale adoption of these techniques requires overcoming hurdles related to constraint enforcement and safety validation. Future research is expected to focus on hybrid prediction-optimization frameworks that combine the adaptability of learning methods with the rigor of mathematical optimization to achieve broader applicability and regulatory acceptance.

Regarding AI-based conventional railways, the examination of maintenance, safety, and operations reveals a consistent paradigm shift driven by AI. Systems are advancing from sense-and-respond reactive models toward predict-prevent-optimize proactive approaches, with further progression toward coordinated intelligent operations. Looking forward, several cross-cutting research frontiers emerge. First, addressing data-related challenges remains critical, including developing standardized, open data sets for benchmarking, advancing FL for privacy-preserving collaboration across operators, and improving techniques for learning from limited or imperfect data, particularly for rare safety-critical events. Second, enhancing the explainability and trustworthiness of AI-driven decisions, especially for safety and real-time control applications, is paramount for regulatory acceptance and operational adoption. Finally, generative AI may expand beyond synthetic data generation to automated reporting, scenario simulation, and interactive knowledge

systems. However, generated defect samples, incident narratives, or operating scenarios may contain physically unrealistic details or reproduce biases in historical records. Textual outputs may also become outdated when maintenance standards and safety rules change. Railway applications therefore require domain-grounded generation, version-controlled knowledge retrieval, expert verification, and evaluation on real operational cases; generative quality or linguistic fluency alone is insufficient evidence of safety or practical value.

Beyond methodological advances, the large-scale deployment of AI in railway systems also faces significant implementation and governance challenges. Railway operations involve long asset lifecycles, strict safety certification procedures, and highly standardized operational processes, making the integration of AI into legacy signaling, maintenance, and traffic management systems considerably more difficult than laboratory validation. Furthermore, railway operators require AI systems that are interpretable, auditable, and capable of supporting human dispatchers and maintenance engineers rather than replacing them. Future research should therefore place greater emphasis on lifecycle management, digital twin-enabled validation, interoperability across heterogeneous railway assets, and governance frameworks that support safety certification, accountability, and continuous model monitoring.

6.3 Maritime transportation

The deployment of AI within maritime transportation offers substantial opportunities to overhaul the sector through advancements in operational efficiency, safety, and environmental sustainability; nevertheless, translating these advantages into practice requires overcoming a variety of intricate challenges. One pressing issue is the heterogeneity of maritime data. These data often vary in format, quality, and completeness, making their integration into AI systems more challenging. The absence of unified standards for data collection and sharing further exacerbates this fragmentation, limiting the reliability and scalability of AI applications. Addressing this requires establishing standardized protocols across the industry to ensure data interoperability. Advanced preprocessing techniques, such as anomaly detection and data fusion, can be deployed to improve data quality and consistency, thereby creating a more robust foundation for AI-driven solutions. LLMs may assist by extracting structured information from unstructured maritime reports and mapping heterogeneous records into standardized formats. However, automated standardization is vulnerable to hallucinated fields, terminology ambiguity, and inconsistent interpretations across shipping companies, ports, and regulatory jurisdictions. These errors may remain hidden after conversion into structured databases and subsequently contaminate prediction or optimization models. LLM-generated records should therefore retain links to their source documents, support human verification and abstention, and be evaluated through field-level extraction accuracy, cross-jurisdiction consistency, and downstream decision impact.

Maritime transportation operates in a data- and security-sensitive setting where privacy and cybersecurity cannot be overlooked. The involvement of multiple stakeholders, such as shipping companies, port authorities, and regulatory agencies, requires sharing large volumes of operational data to enable collaborative AI applications. However, concerns over data breaches, unauthorized access, and misuse can hinder cooperation and limit the availability of high-quality data sets for AI training and deployment. Protecting confidential data necessitates the deployment of robust privacy-preserving measures, such as advanced encryption, secure data transmission protocols, and strict access control mechanisms. Furthermore, decentralized AI frameworks, which enable local data processing without exchanging raw data, offer a viable solution for fostering collaboration while preserving data integrity.

The diversity of maritime systems introduces complexity in applying AI technologies. Ships differ significantly in size, design, technological capabilities, and operational contexts, making it challenging to develop universal AI solutions for such a heterogeneous sector. Moreover, the dynamic and unpredictable maritime environments further complicate the deployment of standardized systems. Adaptive AI models that adjust to different scenarios and data sets are crucial. Techniques such as transfer learning, domain adaptation, and meta-learning enhance AI's robustness and flexibility, enabling generalization across diverse environments. However, AI's predictive capabilities alone may not suffice for real-time decision-making in such operational settings. By integrating AI with OR, optimization frameworks can translate AI predictions into actionable, real-time decisions. For instance, AI can predict risks like weather disruptions or vessel collisions, while OR provides interpretable optimization models to adaptively determine the best routes or resource allocations under specific constraints. This synergy ensures both efficiency and transparency in decision-making, particularly in high-stakes maritime operations.

The maritime sector faces growing pressure to adopt sustainable practices in line with international environmental regulations, such as EEXI and CII. AI technologies offer significant opportunities to improve energy efficiency and reduce emissions through applications such as speed optimization, weather routing, and fuel consumption modeling. However, high retrofitting costs and the long lifespans of ships often limit the integration of these technologies. The dynamic nature of maritime operations, influenced by environmental and logistical uncertainties, further complicates optimization efforts. Here, integrating

AI with OR can play a pivotal role in achieving sustainable, efficient operations. For instance, AI can predict fuel consumption and emission patterns under varying operational conditions, while OR can provide multi-objective optimization models that balance operational efficiency with environmental goals. These models help stakeholders navigate trade-offs, such as reducing emissions while maintaining profitability, and offering actionable solutions for meeting sustainability standards.

Furthermore, maritime AI deployment faces an underdeveloped regulatory and ethical framework. While international organizations such as the IMO have begun to establish guidelines for autonomous technologies, the lack of globally harmonized regulations creates uncertainty for stakeholders. This regulatory ambiguity complicates compliance efforts and slows investment in AI-driven maritime solutions. Unresolved ethical issues, such as accountability for system failures or AI-driven accidents, further raise concerns about liability and trust. Global coordination among regulators, with industry input, is essential to establish clear frameworks for liability, compliance, and safety. Pilot initiatives and large-scale simulations can serve as testing grounds for these technologies, demonstrating their reliability and fostering trust among stakeholders.

Moreover, from an implementation perspective, maritime AI systems must operate across highly heterogeneous vessels, ports, and regulatory jurisdictions, posing challenges beyond algorithmic development. Differences in onboard sensing capabilities, communication standards, and international operational regulations complicate large-scale deployment and interoperability. Moreover, autonomous navigation and intelligent port management require clear governance mechanisms regarding responsibility allocation, cybersecurity, and compliance with international maritime regulations. Future research should therefore emphasize standardized data sharing, interoperable AI platforms, and governance frameworks that support trustworthy autonomous maritime operations among multiple stakeholders.

In summary, realizing AI's potential in maritime transportation requires addressing data inconsistencies, system diversity, privacy concerns, sustainability challenges, and regulatory uncertainty. Integrating AI with OR enhances efficiency and adaptability through optimization frameworks, while LLMs support data standardization and transparency. Backed by standardized practices, strong privacy safeguards, and global regulations, these advancements will drive a safer, more efficient, and sustainable maritime future.

6.4 Air transportation

In terms of AI-assisted airline operations, the future of AI will likely converge toward holistic, integrated decision-making systems that break down the traditional silos between planning, scheduling, and execution. One critical research frontier is the development of end-to-end learning frameworks that simultaneously optimize recovery of crew, aircraft, and passengers during disruptions, moving beyond sequential or decomposed optimization approaches. This requires advancing MARL capabilities to handle the immense state-action spaces of network-wide recovery. Another pivotal direction involves the seamless integration of predictive maintenance data into day-of-operations scheduling. Future research must focus on closing the loop between prognostics and logistics, enabling self-healing schedules that proactively adjust routing to accommodate component health status without service interruption. Furthermore, as AI systems assume greater autonomy in dispatch and control centers, research into XAI and human-centric AI will be paramount. Developing interfaces that not only recommend actions but also provide causal reasoning and confidence intervals is essential for fostering trust and ensuring effective collaboration between human dispatchers and AI agents, particularly in safety-critical scenarios. Ultimately, the industry is trending toward "Airline Digital Twins," in which high-fidelity virtual replicas of the airline network enable risk-free training of AI agents and robust scenario testing before implementation.

In terms of AI-driven airport operations, as airports evolve into hyper-connected smart hubs, the role of AI will expand from isolated point solutions to the backbone of total airport management (TAM). Future research is expected to prioritize developing privacy-preserving collaborative learning frameworks, such as FL, to overcome data-sharing barriers among competing stakeholders (airlines, ground handlers, and airport authorities). This will enable system-wide optimization of airport collaborative decision-making processes without compromising sensitive commercial data. Additionally, integrating computer vision and biometric technologies with flow management systems will enable "seamless travel," where passenger processing is continuous and non-intrusive. Research will also increasingly focus on the energy-efficient operation of airports, leveraging AI to optimize charging schedules for electric ground support equipment and electric aircraft in coordination with renewable energy generation. Finally, the concept of the cognitive airport will emerge, where AI systems not only predict operational states but also autonomously negotiate resource allocation among stakeholders to maximize global efficiency and resilience against severe disruptions.

In terms of AI-based ATM, AI is driving ATM toward complete TBO and, eventually, toward a unified team model that combines human and machine intelligence. A primary avenue for future research is the certification and safety assurance of AI models in safety-critical airspace environments. Developing formal verification methods and robustness guarantees for neural networks is a

prerequisite for their deployment in separation assurance and tactical control. Concurrently, research will delve into high-fidelity human–AI teaming, exploring how adaptive automation can dynamically adjust its level of support based on controller workload and fatigue states to maintain optimal situational awareness. Scalability remains another core challenge; future AI architectures must demonstrate the ability to handle the combinatorial complexity of high-density traffic scenarios, including the integration of supersonic and hypersonic vehicles. Moreover, the environmental impact of aviation will drive research into "Green AI" for ATM, where trajectory optimization algorithms are explicitly designed to minimize contrail formation, noise, and fuel burn, balancing capacity demands with sustainability goals.

In the context of AI in the low-altitude economy, the absence of legacy infrastructure makes this emerging domain a greenfield for "AI-native" system design. Future research will heavily concentrate on the development of decentralized, autonomous unmanned aircraft system traffic management architectures. In these systems, AI agents onboard UAVs will negotiate right-of-way and resolve conflicts peer-to-peer, reducing reliance on centralized ground control. Significant attention will also be directed toward AI-enabled urban airspace management, specifically the safe integration of aerial vehicles into complex urban landscapes. This involves advancing perception algorithms that can operate reliably under GPS-denied conditions and in dynamic weather, as well as semantic understanding of urban topology for safe selection of emergency landing sites. Furthermore, as drone swarms become operationally viable for logistics and surveillance, research into swarm intelligence and control of collective behavior will be critical to ensuring scalable, collision-free operations. Finally, ethical and regulatory frameworks for AI in low-altitude flight that address noise pollution, privacy concerns, and liability in autonomous accidents will be an essential interdisciplinary research focus to ensure public acceptance and societal integration.

In terms of implementation and engineering management, the future deployment of AI in aviation will depend not only on algorithmic performance but also on certification, human supervision, and operational integration. Because aviation remains one of the most safety-critical transportation domains, AI systems must demonstrate reliability, traceability, and regulatory compliance before supporting operational decision-making. Future research should therefore prioritize human–AI collaborative decision support, standardized validation under operational scenarios, integration with existing air traffic management infrastructure, and certification frameworks for both conventional aviation and emerging low-altitude transportation systems.

7 Discussion and conclusions

This review presents a unified synthesis of AI research across the four major transportation domains (road, rail, air, and maritime), moving beyond domain-specific surveys to identify common methodological paradigms, transferable insights, and shared research challenges. By identifying representative tasks and functionalities within each domain, the study evaluates how diverse AI methodologies—including deep learning, graph-based models, RL, and emerging foundation models—are specifically adapted to handle domain-specific operational logic and physical constraints. Meanwhile, this paper analyzes the critical transition from reactive to predictive system management, examining the transition across diverse infrastructure and regulatory environments. Consequently, synthesizing evidence across different transportation modes reveals several common evolutionary patterns that are difficult to identify within single-domain reviews. Specifically, AI applications are consistently shifting (i) from reactive analysis toward predictive and proactive decision-making, (ii) from isolated task-specific models toward unified and transferable learning frameworks, and (iii) from perception and prediction toward integrated decision support that combines learning, optimization, and domain knowledge. These shared patterns provide a unified perspective for understanding the future evolution of AI-enabled transportation systems.

The theoretical and practical significance of this work lies in its ability to highlight the broad applicability and transformative value of AI across the entire transportation landscape. Theoretically, this research establishes that while AI techniques offer broad utility, their ultimate effectiveness remains strictly contingent upon their alignment with domain-specific characteristics and system-level requirements. From a practical perspective, AI plays fundamentally different roles across transportation modes. In road transportation, AI primarily supports real-time perception, traffic prediction, and decentralized decision-making under highly dynamic environments. Rail transportation places greater emphasis on operational reliability, predictive maintenance, and optimization under tightly coupled infrastructure constraints. Maritime applications focus more on vessel interaction modeling, long-horizon navigation, and risk-aware decision-making in relatively sparse but uncertain environments, whereas aviation relies heavily on integrating AI with optimization and human supervision to support safety-critical operational decisions. Collectively, these advancements demonstrate AI's capacity to improve efficiency, safety, and resilience across heterogeneous systems, providing a strategic roadmap for practitioners to bridge the gap between methodological innovation and real-world deployment. At the same time, these differences indicate that there is no universally optimal AI methodology.

Instead, the suitability of different AI techniques is largely determined by operational objectives, physical constraints, data characteristics, and human involvement within each transportation domain. Beyond these domain-specific applications, an important finding of this review is that the effectiveness of AI is determined less by the choice of individual algorithms than by how well they are aligned with transportation-specific operational objectives, physical constraints, and human decision-making processes. Consequently, successful AI deployment increasingly relies on integrating data-driven learning with transportation knowledge rather than pursuing more complex models alone.

Despite the progress documented, this study identifies several cross-cutting challenges that remain critical to the advancement of the field. From a data perspective, issues such as data sparsity, abnormality, and the need for heterogeneous data fusion must be addressed before constructing reliable prediction models. From a modeling perspective, the requirements for real-time model updates and interpretable decision-making are as important as high prediction accuracy. These challenges encourage the exploration of emerging methods, such as transfer learning, few-shot learning, and causal inference, to address complex and evolving traffic environments. Moreover, researchers must increasingly focus on improving the service quality of intelligent transportation systems through AI-driven route planning, ATM, and decision-making.

Beyond advances in AI algorithms, the next generation of intelligent transportation systems will increasingly depend on interdisciplinary collaboration across transportation planning, operations research, computer science, behavioral science, and public policy. Transportation planning provides long-term perspectives on infrastructure development, multimodal integration, accessibility, and sustainability, enabling AI to support strategic planning rather than merely improving short-term operational efficiency. Operations research complements data-driven learning by offering mathematically rigorous optimization, uncertainty modeling, and constraint handling, thereby ensuring that AI-generated solutions remain operationally feasible in complex transportation systems. At the same time, behavioral science can help AI models better capture human decision-making processes, including travel choices, risk perception, passenger responses, and human-AI interaction, improving both interpretability and realism. Finally, as AI becomes increasingly embedded in transportation planning and operations, public policy and governance will play an essential role in addressing broader societal issues such as safety certification, transparency, fairness, privacy protection, accountability, and regulatory compliance. Future breakthroughs are therefore likely to arise not only from more powerful AI models, but also from closer collaboration among these complementary disciplines to develop transportation systems that are intelligent, trustworthy, human-centered, and socially sustainable.

In summary, the provided insights offer researchers a clearer understanding of the current landscape of AI-enabled transportation and help them identify promising future research directions, including trustworthy and domain-grounded foundation models, physics-informed learning, and continual adaptation. One limitation of this review is that the selection and organization of the literature may be influenced by subjective judgment, and certain subdomains or rapidly emerging topics may not be fully covered. Additionally, while this study emphasizes methodological and application-level insights, the analysis regarding the practicalities of real-world deployment—including economic costs and specific operational constraints—remains limited. Overall, this review provides a systematic framework for understanding AI in transportation and suggests that future efforts must move beyond isolated applications toward more integrated, scalable, and adaptive AI-driven transportation architectures.

Competing Interests The authors declare that they have no competing interests.

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References

Abdillah R E, Moenaf H, Rasyid L F, Achmad S, Sutoyo R (2024). Implementation of artificial intelligence on air traffic control — A systematic literature review. In: Proceedings of 2024 18th International Conference on Ubiquitous Information Management and Communication (IMCOM), January, Kuala Lumpur: Malaysia, 1–7

Al-Hourani A, Kandeepan S, Lardner S (2014). Optimal LAP altitude for maximum coverage. IEEE Wireless Communications Letters, 3(6): 569–572

Andriuškevičius J, Sun J (2024). Automatic control with human-like reasoning: Exploring language model embodied air traffic agents. arXiv preprint arXiv:2409.09717

Aoki S, Higuchi T, Altintas O (2020). Cooperative perception with deep reinforcement learning for connected vehicles. In: Proceedings of 2020 IEEE Intelligent Vehicles Symposium (IV), Las Vegas: USA, IEEE, 328–334.

Arvin R, Kamrani M, Khattak A J (2019). How instantaneous driving

behavior contributes to crashes at intersections: Extracting useful information from connected vehicle message data. Accident Analysis and Prevention, 127: 118–133

Barbour W, Martinez Mori J C M, Kuppa S, Work D B (2018). Prediction of arrival times of freight traffic on US railroads using support vector regression. Transportation Research Part C, Emerging Technologies, 93: 211–227

Barros J, Araujo M, Rossetti R J (2015). Short-term real-time traffic prediction methods: A survey. In: Proceedings of 2015 International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS), September, Luxembourg: Luxembourg, IEEE, 132–139

Berrio J S, Shan M, Worrall S, Nebot E (2022). Camera–LiDAR integration: Probabilistic sensor fusion for semantic mapping. IEEE Transactions on Intelligent Transportation Systems, 23(7): 7637–7652

Bertsimas D, Kallus N (2020). From predictive to prescriptive analytics. Management Science, 66(3): 1025–1044

Bharadiya J P (2023). Artificial intelligence in transportation systems a critical review. American Journal of Computing and Engineering, 6(1): 34–45

Bi Z, Guo X, Wang J, Qin S, Liu G (2024). Truck-drone delivery optimization based on multi-agent reinforcement learning. Drones (Basel), 8(1): 27

Bijelic M, Gruber T, Ritter W (2018). Benchmarking image sensors under adverse weather conditions for autonomous driving. In: 2018 IEEE Intelligent Vehicles Symposium (IV), IEEE, Changshu: China, 1773–1779

Biskin B, Fliege J, Martinez-Sykora A (2025). Autonomous navigation of unmanned aerial vehicles (UAVs) for border patrolling: A stochastic framework. IMA Journal of Management Mathematics, 36(2): 231–254

Bondoux N, Nguyen A Q, Fiig T, Acuna-Agost R (2020). Reinforcement learning applied to airline revenue management. Journal of Revenue and Pricing Management, 19(5): 332–348

Bor-Yaliniz R I, El-Keyi A, Yanikomeroglu H (2016). Efficient 3-D placement of an aerial base station in next generation cellular networks. In: Proceedings of 2016 IEEE International Conference on Communications, July, Kuala Lumpur: Malaysia, 1–5.

Braßel H, Zeh T, Fricke H, Eltner A (2023). Optimal UAV hangar locations for emergency services considering restricted areas. Drones (Basel), 7(3): 203

Brown D E (2016). Text mining the contributors to rail accidents. IEEE Transactions on Intelligent Transportation Systems, 17(2): 346–355

Brun A, Feron E, Alam S, Delahaye D (2025). Schedule optimization and staff allocation for airport security checkpoints using guided simulated annealing and integer linear programming. Journal of Air Transport Management, 124: 102746

Bruni M E, Fadda E, Fedorov S, Perboli G (2023). A machine learning optimization approach for last-mile delivery and third-party logistics. Computers & Operations Research, 157: 106262

Cai B, Camarcat L, Shang W L, Quddus M (2025). A new spatiotemporal convolutional neural network model for short-term crash prediction. Frontiers of Engineering Management, 12(1): 86–98

Cao F, Tang T, Gao Y, Michler O, Schultz M (2024). Predicting flight arrival times with deep learning: A strategy for minimizing potential conflicts in gate assignment. Transportation Research Part C, Emerging Technologies, 169: 104866

Cappart Q, Chételat D, Khalil E B, Lodi A, Morris C, Veličković P (2021). Combinatorial optimization and reasoning with graph neural networks. Journal of Machine Learning Research, 22(1): 1–61

Cárdenas-Gallo I, Sarmiento C A, Morales G A, Bolivar M A, Akhavan-Tabatabaei R (2017). An ensemble classifier to predict track geometry degradation. Reliability Engineering & System Safety, 161: 53–60

Cerreto F, Nielsen B F, Nielsen O A, Harrod S S (2018). Application of data clustering to railway delay pattern recognition. Journal of Advanced Transportation, 2018(1): 6164534

Chang C, Zhang J, Zhang K, Zheng Y, Shi M, Hu J, Li S, Li L (2024). CAV driving safety monitoring and warning via V2X-based edge computing system. Frontiers of Engineering Management, 11(1): 107–127

Chen C, Yang H, Zhai C, Chen X M, Mo D (2024a). Competitive pricing for ride-sourcing platforms with MARL. Transportation Research Part C, Emerging Technologies, 165: 104697

Chen D J, Ni S Q, Xu C A, Lv H X, Wang S M (2016). High-speed train stop-schedule optimization based on passenger travel convenience. Mathematical Problems in Engineering, 2016(1): 8763589

Chen L, Wu Q (2026). Spatiotemporal-decoupled interactive learning for traffic flow prediction. Scientific Reports, 16(1): 9050

Chen S Y, Frøseth G T, Derosa S, Lau A, Rönnquist A (2024b). Railway catenary condition monitoring: A systematic mapping of recent research. Sensors (Basel), 24(3): 1023

Chen X, Liu S, Zhao J, Wu H, Xian J, Montewka J (2024c). Autonomous port management based AGV path planning and optimization via an ensemble reinforcement learning framework. Ocean and Coastal Management, 251: 107087

Chen X, Ma D, Liu R W (2024d). Application of artificial intelligence in maritime transportation. Journal of Marine Science and Engineering, 12(3): 439

Chen X, Zhang S, Li L (2019). Multi-model ensemble for short-term traffic flow prediction under normal and abnormal conditions. IET Intelligent Transport Systems, 13(2): 260–268

Chen Y, Chen X M (2022). A novel reinforced dynamic graph convolutional network model with data imputation for network-wide traffic flow prediction. Transportation Research Part C, Emerging Technologies, 143: 103820

Chen Y, Wang W, Chen X M (2023a). Bibliometric methods in traffic flow prediction based on artificial intelligence. Expert Systems with Applications, 228: 120421

Chen Y, Xie N, Xu H, Chen X, Lee D H (2024e). A multi-context aware human mobility prediction model based on motif-preserving travel preference learning. IEEE Transactions on Intelligent Transportation Systems, 25(2): 2139–2152

Chen Y, Zhang H, Li C, Chi B, Chen X, Wu J (2025). Large language model empowered smart city mobility. Frontiers of Engineering Management, 12(1): 201–207

Chen Z C, Yang J, Chen L F, Feng Z C, Jia L M (2023b). Efficient

railway track region segmentation algorithm based on lightweight neural network and cross-fusion decoder. Automation in Construction, 155: 105069

Cheng Z H, Wang J W, Trépanier M, Sun L J (2025). Abnormal metro passenger demand is predictable from alighting and boarding correlation. Transportation Research Part C, Emerging Technologies, 178: 105239

Chu Z, Yan R, Wang S (2025). Vessel arrival time to port prediction via a stacked ensemble approach: Fusing port call records and AIS data. Transportation Research Part C, Emerging Technologies, 176: 105128

Chu Z, Yan R, Yang X, Pang K W, Wang S (2026). Integrating vessel arrival time forecasting into berth allocation decisions: A predictive-operational framework. Advanced Engineering Informatics, 69: 104010

Coppola P, Silvestri F, Pastorelli L (2025). Mobility as a Service (MaaS) for university communities: Modeling preferences for integrated public transport bundles. Travel Behaviour & Society, 38: 100890

Craye C, Rashwan A, Kamel M S, Karray F (2016). A multi-modal driver fatigue and distraction assessment system. International Journal of Intelligent Transportation Systems Research, 14(3): 173–194

Da L C, Chen T J, Li Z H, Bachiraju S, Yao H Y, Li L, Dong Y S, Hu X Y, Tu Z Z, Wang D J, Zhao Y, Zhou B, Pendyala R, Stabler B, Yang Y Z, Zhou X S, Wei H (2025). Generative AI in transportation planning: A survey. arXiv preprint arXiv:2503.07158

Dang D D, Gong L, Jin C L, Cui X N, Yang T T, Qin J (2026). SMI-YOLOv8: Intelligent detection of tunnel lining cracks via multiscale feature attention fusion. Measurement, 257: 118833

Ding Y, Wandelt S, Wu G, Xu Y, Sun X (2023). Towards efficient airline disruption recovery with reinforcement learning. Transportation Research Part E, Logistics and Transportation Review, 179: 103295

Do W, Saunier N, Miranda-Moreno L (2025). Evaluation of conventional surrogate indicators of safety for connected and automated vehicles in car following at signalized intersections. Transportation Research Record: Journal of the Transportation Research Board, 2679(2): 1118–1133

Du J, Wu P (2025). Deep reinforcement learning for UAVs rolling horizon team orienteering problem under ECA. Ocean Engineering, 326: 120781

Dukkanci O, Campbell J F, Kara B Y (2024). Facility location decisions for drone delivery: A literature review. European Journal of Operational Research, 316(2): 397–418

Durlik I, Miller T, Kostecka E, Tuński T (2024). Artificial intelligence in maritime transportation: A comprehensive review of safety and risk management applications. Applied Sciences. 14(18): 8420

Ejlali M, Arian E, Taghiyeh S, Chambers K, Sadeghi A H, Taghiye E, Cakdi D, Handfield R B (2024). Developing hybrid machine learning models to assign health score to railcar fleets for optimal decision making. Expert Systems with Applications, 250: 123931

Elnabty I A, Fahmy Y, Kafafy M (2022). A survey on UAV placement optimization for UAV-assisted communication networks in 5G and beyond networks. Physical Communication, 51: 101564

Elsisi M, Yu J, Lai C, Su C (2024). A drone-assisted deep learning-based IoT system for monitoring ship emissions in ports considering adversarial attacks. IEEE Transactions on Instrumentation and Measurement, 73: 9506111

Evmides N, Aslam S, Ramez T T, Michaelides M P, Herodotou H (2024). Enhancing prediction accuracy of vessel arrival times using machine learning. Journal of Marine Science and Engineering, 12(8): 1362

Fan G, Sabri A Q M, Rahman S S A, Pan L, Rahardja S (2025a). Emerging trends in graph neural networks for traffic flow prediction: A survey. Archives of Computational Methods in Engineering, 32(8): 4811–4855

Fan H, Wang J, Chang Z, Lyu J, Jia H (2025b). Embracing imperfect data: A novel data-driven Bayesian network framework for maritime accidents severity risk assessment. Ocean Engineering, 329: 121212

Fang J, Wang F, Xue J, Chua T S (2024a). Behavioral intention prediction in driving scenes: A survey. IEEE Transactions on Intelligent Transportation Systems, 25(8): 8334–8355

Fang W, Li X, Lin Z, Zhou J, Zhou T (2024b). Mixture correntropy with variable center LSTM network for traffic flow forecasting. Digital Transportation and Safety, 3(4): 264–270

Feng D, Haase-Schutz C, Rosenbaum L, Hertlein H, Gläser C, Timm F, Wiesbeck W, Dietmayer K (2021). Deep multi-modal object detection and semantic segmentation for autonomous driving: Datasets, methods, and challenges. IEEE Transactions on Intelligent Transportation Systems, 22(3): 1341–1360

Ferdousi R, Hossain M A, Yang C, Saddik A E (2026). Defecttwin: When LLM meets digital twin for railway defect inspection. IEEE Access, 2026.3681818

Ferdousi R, Laamarti F, Yang C S, Saddik A E (2024). A reusable AI-enabled defect detection system for railway using ensembled CNN. Applied Intelligence, 54(20): 9723–9740

Ficzere P (2023). The role of artificial intelligence in the development of rail transport. Cognitive Sustainability, 2(4): 10.55343/CogSust.81

Fondevila-Gascón J F, Gutiérrez-Aragón Ó, Lopez-Lopez D, Curiel-Barrios G, Alabart-Algueró J (2025). Passenger perceptions of Artificial Intelligence in airline operations: Implications for air transport management. Journal of Air Transport Management, 129: 102874

Formosa N, Quddus M, Ison S, Abdel-Aty M, Yuan J (2020). Predicting real-time traffic conflicts using deep learning. Accident Analysis and Prevention, 136: 105429

Gao D, Zhu Y, Zhang J, He Y, Yan K, Yan B (2021). A novel MP-LSTM method for ship trajectory prediction based on AIS data. Ocean Engineering, 228: 108956

Gao H, Xie Y, Yuan C, He X, Niu T (2023). Prediction of aircraft arrival runway occupancy time based on machine learning. International Journal of Computational Intelligence Systems, 16(1): 150

Gao Y, Wang P P, Zhang Y, Wang J W, Wang C Y (2025). Platform-based passenger flow prediction in metro systems: A novel CNN-BILSTM-attention approach. IET Intelligent Transport Systems, 19(1): e70069

Geng M, Cai Z, Zhu Y, Chen X, Lee D H (2023). Multimodal vehicular trajectory prediction with inverse reinforcement learning and risk aversion at urban unsignalized intersections. IEEE Transactions on

Intelligent Transportation Systems, 24(11): 12227–12240

Gerdes I, Jameel M, Materne L J, Bruder C (2025). Synergies in the skies: Situation awareness and shared mental model in digital-human air traffic control teams. Aerospace (Basel, Switzerland), 12(6): 472

Geursen I L, Santos B F, Yorke-Smith N (2023). Fleet planning under demand and fuel price uncertainty using actor–critic reinforcement learning. Journal of Air Transport Management, 109: 102397

Ghofrani F, He Q, Goverde R M, Liu X (2018). Recent applications of big data analytics in railway transportation systems: A survey. Transportation Research Part C, Emerging Technologies, 90: 226–246

Gold C, Körber M, Lechner D, Bengler K J (2016). Taking over control from highly automated vehicles in complex traffic situations: The role of traffic density. Human Factors, 58(4): 642–652

Gong L, Huang Z, Xiang X, Liu X (2024). Real-time AGV scheduling optimisation method with deep reinforcement learning for energy-efficiency in the container terminal yard. International Journal of Production Research, 62(21): 7722–7742

Gu J, Huang M (2020). Fault diagnosis method for bearing of high-speed train based on multitask deep learning. Shock and Vibration, 2020(1): 8873504

Guan K, Zhang J, Ye W, Jiang Y (2026). Solution to data imbalance and complex interactions in traffic conflict modeling: a hypergraph and generative AI approach. Accident Analysis and Prevention, 226: 108338

Guan Y, Tian X, Wu Y, Wang S (2025). Equitable port state control in maritime transportation: A data-driven optimization approach. Transportation Research Part C, Emerging Technologies, 180: 105303

Guo F, Liu J, Qian Y, Xie Q Y (2024a). Rail surface defect detection using a transformer-based network. Journal of Industrial Information Integration, 38: 100584

Guo F, Qian Y, Shi Y F (2021a). Real-time railroad track components inspection based on the improved YOLOv4 framework. Automation in Construction, 125: 103596

Guo M, Zhao X, Yao Y, Yan P, Su Y, Bi C, Wu D (2021b). A study of freeway crash risk prediction and interpretation based on risky driving behavior and traffic flow data. Accident Analysis and Prevention, 160: 106328

Guo X, Grushka-Cockayne Y, De Reyck B (2022). Forecasting airport transfer passenger flow using real-time data and machine learning. Manufacturing & Service Operations Management, 24(6): 3193–3214

Guo X, Zhang Q, Jiang J, Peng M, Zhu M, Yang H F (2024b). Towards explainable traffic flow prediction with large language models. Communications in Transportation Research, 4: 100150

Guo Y, Wang Y, Zhang L, Wu L, Chen X (2026). Towards sustainable shipping: A learning-aided route-speed joint optimization considering energy efficiency and punctual arrival. Transportation Research Part E, Logistics and Transportation Review, 205: 104489

Hadj-Mabrouk H (2019). Contribution of artificial intelligence to risk assessment of railway accidents. Urban Rail Transit, 5(2): 104–122

Hadj-Mabrouk H (2024). A literature review on the applications of artificial intelligence to European rail transport safety. IET Intelligent Transport Systems, 18(12): 2291–2324

Haider I, Sen G, Arsalan M, Das A K (2024). Subnetwork prediction approach for aircraft schedule recovery. Engineering Applications of Artificial Intelligence, 133: 108472

Han P, Wang Y, Liu Z, Zhong Y, Yan C (2026). A tailored multi-agent reinforcement learning based approach for enhancing collaborative twin ocean-going ships energy efficiency. Ocean Engineering, 347: 124032

He D Q, Zou Z H, Chen Y J, Liu B, Miao J (2021). Rail transit obstacle detection based on improved CNN. IEEE Transactions on Instrumentation and Measurement, 70: 1–14

Herekoğlu A, Kabak Ö (2024). Crew recovery optimization with deep learning and column generation for sustainable airline operation management. Annals of Operations Research, 342(1): 399–427

Herrema F, Curran R, Hartjes S, Ellejmi M, Bancroft S, Schultz M (2019). A machine learning model to predict runway exit at Vienna airport. Transportation Research Part E, Logistics and Transportation Review, 131: 329–342

Hong F, Wu G, Luo Q, Liu H, Fang X, Pedrycz W (2023). Logistics in the sky: A two-phase optimization approach for the drone package pickup and delivery system. IEEE Transactions on Intelligent Transportation Systems, 24(9): 9175–9190

Hopfe D H, Lee K, Yu C (2024). Short-term forecasting airport passenger flow during periods of volatility: Comparative investigation of time series vs. neural network models. Journal of Air Transport Management, 115: 102525

Hossain M M, Rahman M A (2023). Understanding the potential key risk factors associated with teen driver crashes in the United States: A literature review. Digital Transportation and Safety, 2(4): 268–277

Hu S, Ji M, Chang Z, Wang H, Kong X (2025). An improved particle swarm optimization algorithm based urban rail passenger flow prediction model: A case study in Beijing, China. Digital Transportation and Safety, 4(2): 101–107

Hu Y, Li Y, Huang H (2023). Spatio-temporal dynamic change mechanism analysis of traffic conflict risk based on trajectory data. Accident Analysis and Prevention, 191: 107203

Hu Y, Miao X, Zhang J, Liu J, Pan E (2021). Reinforcement learning-driven maintenance strategy: A novel solution for long-term aircraft maintenance decision optimization. Computers & Industrial Engineering, 153: 107056

Hu Y, Wang S, Zhang S, Li Z (2024). Review of optimization problems, models and methods for airline disruption management from 2010 to 2024. Digital Transportation and Safety, 3(4): 246–263

Huang P, Guo J W, Liu S, Corman F (2024). Explainable train delay propagation: A graph attention network approach. Transportation Research Part E, Logistics and Transportation Review, 184: 103457

Huang Z, Sheng Z, Qu Y, You J, Chen S (2025). Vlm-RL: A unified vision language models and reinforcement learning framework for safe autonomous driving. Transportation Research Part C, Emerging Technologies, 180: 105321

Jahan K, Umesh J P, Roth M (2021). Anomaly detection on the rail lines using semantic segmentation and self-supervised learning. In: Proceedings of 2021 IEEE Symposium Series on Computational Intelligence (SSCI), December, Orlando: USA, IEEE, 1–7

Jalil K, Xia Y, Zhao J (2025). Advancements in collision avoidance techniques for internet-connected vehicles: A comprehensive review of methods and challenges. Engineering Applications of Artificial Intelligence, 160: 111836

Jia X, Gao S, He W (2025). Meta-reinforcement learning-based collision avoidance for autonomous ship. Ocean Engineering, 339: 122064

Jiang M, Xiang Y (2023). Prediction on the remaining useful life of rolling bearings using ensemble DLSTM. Shock and Vibration, 2023(1): 3742912

Jin J, Fu X, Gao X, Cheng T, Yan R (2025). MSD-LLM: Predicting ship detention in port state control inspections with large language model. arXiv:2505.19568

Jo S, Lee G M, Moon I (2024). Airline dynamic pricing with patient customers using deep exploration-based reinforcement learning. Engineering Applications of Artificial Intelligence, 133: 108073

Jo S, Moon I (2025). A hierarchical reinforcement learning approach for real-time berth allocation and quay crane scheduling. International Journal of Production Research, 63(24): 10027–10052

Kalafatelis A S, Pitsiakou A, Nomikos N, Tsoulakos N, Syriopoulos T, Trakadas P (2025). FLUID: Dynamic model-agnostic federated learning with pruning and knowledge distillation for maritime predictive maintenance. Journal of Marine Science and Engineering, 13(8): 1569

Karakose M, Yaman O (2020). Complex fuzzy system based predictive maintenance approach in railways. IEEE Transactions on Industrial Informatics, 16(9): 6023–6032

Karim A A, Nower N (2024). Probabilistic spatio-temporal graph convolutional network for traffic forecasting. Applied Intelligence, 54: 7070–7085

Kaufmann E, Bauersfeld L, Loquercio A, Müller M, Koltun V, Scaramuzza D (2023). Champion-level drone racing using deep reinforcement learning. Nature, 620(7976): 982–987

Khajehdezfuly A, Azizipour H, Kaewunruen S (2025). A review of applications of AI in monitoring, inspection, and maintenance of railway tracks. Journal of Industrial Information Integration, 48: 101005

Khalil E B, Le Bodic P, Song L, Nemhauser G L, Dilkina B (2016). Learning to branch in mixed integer programming. Proceedings of the AAAI Conference on Artificial Intelligence, 30(1): 724–731

Kim J, Justin C, Mavris D, Briceno S (2022). Data-driven approach using machine learning for real-time flight path optimization. Journal of Aerospace Information Systems, 19(1): 3–21

Kim Y, Choi S, Briceno S, Mavris D (2016). A deep learning approach to flight delay prediction. In: Proceedings of 2016 IEEE/AIAA 35th Digital Avionics Systems Conference (DASC), Sacramento: USA, 1–6

Kumar P, Pal K, Govil M C (2026). Comprehensive review of path planning techniques for unmanned aerial vehicles (UAVs). ACM Computing Surveys, 58(3): 1–44

Kumar S, Sharma A, Kumar G (2025). Data-driven predictive model for dynamic expected travel time estimation in rail freight networks: A case study. Transportation Research Part E, Logistics and Transportation Review, 200: 104201

Lee J, Mitici M (2023). Deep reinforcement learning for predictive aircraft maintenance using probabilistic remaining-useful-life prognostics. Reliability Engineering & System Safety, 230: 108908

Lei J, Chu Z, Wu Y, Liu X, Luo M, He W, Liu C (2024). Predicting vessel arrival times on inland waterways: A tree-based stacking approach. Ocean Engineering, 294: 116838

Li C, Geng M, Chen Y, Cai Z, Zhu Z, Chen X M (2024a). Demand forecasting and predictability identification of ride-sourcing via bidirectional spatial-temporal transformer neural processes. Transportation Research Part C, Emerging Technologies, 158: 104427

Li C, Liu W (2024). Multimodal transport demand forecasting via federated learning. IEEE Transactions on Intelligent Transportation Systems, 25(5): 4009–4020

Li H, Jiao H, Yang Z (2023a). AIS data-driven ship trajectory prediction modelling and analysis based on machine learning and deep learning methods. Transportation Research Part E, Logistics and Transportation Review, 175: 103152

Li H, Xing W, Jiao H, Yang Z, Li Y (2024b). Deep bi-directional information-empowered ship trajectory prediction for maritime autonomous surface ships. Transportation Research Part E, Logistics and Transportation Review, 181: 103367

Li J, Liao C, Hu S, Chen X, Lee D H (2024d). Physics-guided multi-source transfer learning for network-scale traffic flow prediction. IEEE Transactions on Intelligent Transportation Systems, 25(11): 17533–17546

Li J, Liu S, Huang W, Yan B (2025a). Artificial intelligence in low-altitude flight: Developmental opportunity or ethical challenge? Aeronautical Journal, 129(1336): 1683–1701

Li J, Xie N, Zhang K, Guo F, Hu S, Chen X M (2022a). Network-scale traffic prediction via knowledge transfer and regional MFD analysis. Transportation Research Part C, Emerging Technologies, 141: 103719

Li J Y, Li C, Niu S, Dai B (2024c). RSChat: Intelligent question answering model for railway safety knowledge. In: Proceedings of 24th International Conference on Computer and Information Science (ICIS), September, Shanghai: China, IEEE, 55–60

Li K X, Li M, Zhu Y, Yuen K F, Tong H, Zhou H (2023b). Smart port: A bibliometric review and future research directions. Transportation Research Part E, Logistics and Transportation Review, 174: 103098

Li L (2025). A review of data science and artificial intelligence applications in air transportation systems. Artificial Intelligence for Transportation, 2: 100023

Li M, Jiang G, Lo H K (2023c). Optimal cancellation penalty for competing ride-sourcing platforms under waiting time uncertainty. Transportation Research Part E, Logistics and Transportation Review, 174: 103107

Li P, Abdel-Aty M, Yuan J (2020a). Real-time crash risk prediction on arterials based on LSTM-CNN. Accident Analysis and Prevention, 135: 105371

Li W, Zhu T, Feng Y (2024e). A cooperative perception based adaptive signal control under early deployment of connected and automated vehicles. Transportation Research Part C, Emerging Technologies, 169: 104860

Li W Q, Ni S Q (2022). Train timetabling with the general learning environment and multi-agent deep reinforcement learning. Transportation Research Part B: Methodological, 157: 230–251

Li X, Wang Y, Zhang H (2022b). An attention-based deep learning

framework for flight delay prediction. Aerospace Science and Technology, 124: 107540

Li X J, Li D W, Hu X T, Yan Z Y, Wang Y S (2020b). Optimizing train frequencies and train routing with simultaneous passenger assignment in high-speed railway network. Computers & Industrial Engineering, 148: 106650

Li Y, Bai F, Lyu C, Qu X, Liu Y (2025b). A systematic review of generative adversarial networks for traffic state prediction: Overview, taxonomy, and future prospects. Information Fusion, 117: 102915

Li Y, Virakvichetra L, Zhang J, Li H, Lu Y (2025c). Jointly modeling the dependence of injury severity and crash size involved in motorcycle crashes in Cambodia using a copula-based approach. Frontiers of Engineering Management, 12(2): 394–413

Li Z, Mao J F, Yu Z W (2026). Deep learning-driven efficient running safety assessment and reliability analysis for the stochastic train-track-bridge system. Reliability Engineering & System Safety, 266: 111822

Liang T, Xie H, Yu K, Xia Z, Lin Z, Wang Y, Tang T, Wang B, Tang Z (2022). BEVFusion: A simple and robust LiDAR-camera fusion framework. Advances in Neural Information Processing Systems, 35: 10421–10434

Lin X, Lu Q, Zhao P, Chen L, Tang J, Guan D, Broyd T (2026). Field-theory inspired physics-informed graph neural network for reliable traffic flow prediction under urban flooding. Reliability Engineering & System Safety, 265: 111487

Lin Y, Li X, Yuen K (2025). Machine learning applications for risk assessment in maritime transport: Current status and future directions. Engineering Applications of Artificial Intelligence, 155: 110959

Liu J, Lin Z Y, Liu R H (2024b). A reinforcement learning approach to solving very-short term train rescheduling problem for a single-track rail corridor. Journal of Rail Transport Planning & Management, 32: 100483

Liu J, Ong G P, Chen X (2022a). GraphSAGE-based traffic speed forecasting for segment network with sparse data. IEEE Transactions on Intelligent Transportation Systems, 23(3): 1755–1766

Liu J J, Zhao H, Dai X W (2022b). An improved adaptive particle swarm optimization method for high-speed train scheduling in unexpected events. In: Proceedings of IEEE 17th International Conference on Control & Automation (ICCA), June, Naples, Italy, IEEE, 130–134

Liu J T, Chen K Y, Duan H Y, Li C L (2024a). A knowledge graph-based hazard prediction approach for preventing railway operational accidents. Reliability Engineering & System Safety, 247: 110126

Liu Q, Li C, Jiang H, Nie S, Chen L (2022c). Transfer learning-based highway crash risk evaluation considering manifold characteristics of traffic flow. Accident Analysis and Prevention, 168: 106598

Liu R, Liang M, Nie J, Lim W, Zhang Y, Guizani M (2022d). Deep learning-powered vessel trajectory prediction for improving smart traffic services in maritime Internet of Things. IEEE Transactions on Network Science and Engineering, 9(5): 3080–3094

Liu S, Kang L, Sun H, Wu J, Amihere S (2025). Exploring the factors of major road traffic accidents: A case study of China. Frontiers of Engineering Management, 12(2): 414–424

Liu Z, Liu W (2023). Deep learning-based detection of catenary support component defect and fault in high-speed railways. Advances in High-speed Rail Technology, Springer, Singapore, 163–201

Loquercio A, Kaufmann E, Ranftl R, Müller M, Koltun V, Scaramuzza D (2021). Learning high-speed flight in the wild. Science Robotics, 6(59): eabg5810

Luangboriboon N, Samà M, D'Ariano A, Fujiyama T (2025). Assessment of passenger management strategies within major railway terminals. Journal of Rail Transport Planning & Management, 36: 100540

Luo H L, Bo L, Peng C, Hou D (2020). Fault diagnosis for high-speed train axle-box bearing using simplified shallow information fusion convolutional neural network. Sensors (Basel), 20(17): 4930

Luo X, Yan R, Wang S (2023). Comparison of deterministic and ensemble weather forecasts on ship sailing speed optimization. Transportation Research Part D, Transport and Environment, 121: 103801

Luo X, Yan R, Wang S (2024). Ship sailing speed optimization considering dynamic meteorological conditions. Transportation Research Part C, Emerging Technologies, 167: 104827

Lv Y, Zou M, Li J, Liu J (2024). Dynamic berth allocation under uncertainties based on deep reinforcement learning towards resilient ports. Ocean and Coastal Management, 252: 107113

Ma H L, Sun Y, Chung S H, Chan H K (2022). Tackling uncertainties in aircraft maintenance routing: A review of emerging technologies. Transportation Research Part E, Logistics and Transportation Review, 164: 102805

Ma J, Tang C, Xu W, Ma S, Wu H (2024a). An algorithm for train delay propagation on double-track railway lines under FCFS management. Frontiers of Engineering Management, 11(4): 721–733

Ma L, Ma X, Chen L (2024b). A data-driven Bayesian network model for pattern recognition of maritime accidents: A case study of Liaoning Sea area. Process Safety and Environmental Protection, 189: 115–133

Ma Z, Mei G, Cuomo S (2021). An analytic framework using deep learning for prediction of traffic accident injury severity based on contributing factors. Accident Analysis and Prevention, 160: 106322

Mallick T, Macfarlane J, Balaprakash P (2024). Uncertainty quantification for traffic forecasting using deep-ensemble-based spatiotemporal graph neural networks. IEEE Transactions on Intelligent Transportation Systems, 25(8): 9141–9152

Mao C, Liu Y, Shen Z J M (2020). Dispatch of autonomous vehicles for taxi services: A deep reinforcement learning approach. Transportation Research Part C, Emerging Technologies, 115: 102626

Marciniak K, Majewski P, Reiner J (2025). Inspection of railway catenary systems using machine learning with domain knowledge integration. Scientific Reports, 15(1): 29426

Meng S J, Kuang S Y, Ma Z, Wu Y L (2022). MtlrNet: An effective deep multitask learning architecture for rail crack detection. IEEE Transactions on Instrumentation and Measurement, 71: 1–10

Mondoloni S, Rozen N (2020). Aircraft trajectory prediction and synchronization for air traffic management applications. Progress in

Aerospace Sciences, 119: 100640

Mostafa A M, Aldughayfiq B, Tarek M, Alaerjan A S, Allahem H, Elbashir M K, Ezz M, Hamouda E (2025). AI-based prediction of traffic crash severity for improving road safety and transportation efficiency. Scientific Reports, 15(1): 27468

Nguyen K T P, Medjaher K (2019). A new dynamic predictive maintenance framework using deep learning for failure prognostics. Reliability Engineering & System Safety, 188: 251–262

Niu Y, Zhu F, Wei M, Du Y, Zhai P (2023). A multi-ship collision avoidance algorithm using data-driven multi-agent deep reinforcement learning. Journal of Marine Science and Engineering, 11(11): 2101

O'Connell M, Shi G, Shi X, Azizzadenesheli K, Anandkumar A, Yue Y, Chung S J (2022). Neural-fly enables rapid learning for agile flight in strong winds. Science Robotics, 7(66): eabm6597

Olugbade S, Ojo S, Imoize A L, Isabona J, Alaba M O (2022). A review of artificial intelligence and machine learning for incident detectors in road transport systems. Mathematical & Computational Applications, 27(5): 77

Oneto L, Fumeo E, Clerico G, Canepa R, Papa F, Dambra C, Mazzino N, Anguita D (2017). Dynamic delay predictions for large-scale railway networks: Deep and shallow extreme learning machines tuned via thresholdout. IEEE Transactions on Systems, Man, and Cybernetics. Systems, 47(10): 2754–2767

Ortner P, Steinhöfler R, Leitgeb E, Flühr H (2022). Augmented air traffic control system—artificial intelligence as digital assistance system to predict air traffic conflicts. AI, 3(3): 623–644

Osman O A, Hajij M, Bakhit P R, Ishak S (2019). Prediction of near-crashes from observed vehicle kinematics using machine learning. Transportation Research Record: Journal of the Transportation Research Board, 2673(12): 463–473

Pan Y, Wu Y, Xu L, Xia C, Olson D L (2024). The impacts of connected autonomous vehicles on mixed traffic flow: A comprehensive review. Physica A, 635: 129454

Pan Z, Zhang W, Liang Y, Zhang W, Yu Y, Zhang J, Zheng Y (2022). Spatio-temporal meta learning for urban traffic prediction. IEEE Transactions on Knowledge and Data Engineering, 34(3): 1462–1476

Park H, Blanco C C, Bendoly E (2022a). Vessel sharing and its impact on maritime operations and carbon emissions. Production and Operations Management, 31(7): 2925–2942

Park N, Park J, Joo Y J, Abdel-Aty M (2025). Micro-level hotspot identification at intersections using traffic conflict analysis. Accident Analysis and Prevention, 220: 108167

Park Y, Choi Y, Kim K, Yoo J K (2022b). Machine learning approach for study on subway passenger flow. Scientific Reports, 12(1): 2754

Peftitsi S, Jenelius E, Cats O (2021). Evaluating crowding in individual train cars using a dynamic transit assignment model. Transportmetrica. B, Transport Dynamics, 9(1): 693–711

Quesnel F, Wu A, Desaulniers G, Soumis F (2022). Deep-learning-based partial pricing in a branch-and-price algorithm for personalized crew rostering. Computers & Operations Research, 138: 105554

Raj G, Roy D, de Koster R, Bansal V (2024). Stochastic modeling of integrated order fulfillment processes with delivery time promise: Order picking, batching, and last-mile delivery. European Journal of Operational Research, 316(3): 1114–1128

Ramírez-Villamil A, Montoya-Torres J R, Jaegler A, Cuevas-Torres J M (2023). Reconfiguration of last-mile supply chain for parcel delivery using machine learning and routing optimization. Computers & Industrial Engineering, 184: 109604

Ran Q, Liang C, Liu P (2025). A safe lane-changing strategy for autonomous vehicles based on deep Q-networks and prioritized experience replay. Digital Transportation and Safety, 4(3): 170–174

Rebollo J J, Balakrishnan H (2014). Characterization and prediction of air traffic delays. Transportation Research Part C, Emerging Technologies, 44: 231–241

Regtuit R, Borst C, Van Kampen E J (2018). Building strategic conformal automation for air traffic control using machine learning. In: Proceedings of 2018 AIAA Information Systems-AIAA Infotech@ Aerospace, January, Kissimmee, Florida, 1–22

Ren W, Zhao X, Yao Y, Chen C, Fu Q, Zhang Y (2025). Does connected vehicle information reduce beyond-visual-range crash risk in foggy freeway conditions? A study based on extreme value theory. Accident Analysis and Prevention, 217: 108060

Renkhoff J, Ternus S, Guleria Y (2025). A Survey on personalized conflict resolution approaches in air traffic control. Aerospace (Basel, Switzerland), 12(9): 751

Rodríguez-Sanz Á, Fernández de Marcos A, Pérez-Castán J A, Comendador F G, Arnaldo Valdés R, París Loreiro Á (2021). Queue behavioural patterns for passengers at airport terminals: A machine learning approach. Journal of Air Transport Management, 90: 101940

Rong R, Ma S, Ren N, Lin Q, Jia N (2025). Generative artificial intelligence in intelligent transportation systems: A systematic review of applications. Frontiers of Engineering Management, 12(4): 1020–1036

Rose M H, Seely B E, Barrett P F (2006). The best transportation system in the world: Railroads, trucks, airlines, and American public policy in the twentieth century. Ohio State University Press

Llasag Rosero R, Silva C, Ribeiro B, Albisser M, Brutsche M, Arias Chao M (2025). Label synchronization strategies for hybrid federated learning. Reliability Engineering & System Safety, 256: 110751

Ruan J H, Wang Z X, Chan F T S, Patnaik S, Tiwari M K (2021). A reinforcement learning-based algorithm for the aircraft maintenance routing problem. Expert Systems with Applications, 169: 114399

Sadek A W (2007). Artificial intelligence applications in transportation. Transportation Research Circular, 1–7

Sahnoon I, de Barros A G, Kattan L (2025). Measuring safety benefits of a connected cruise control–equipped vehicle in a connected road environment. Canadian Journal of Civil Engineering, 52(5): 843–859

Saki S, Soori M (2026). Artificial intelligence, machine learning and deep learning in advanced transportation systems, a review. Multimodal Transportation, 5(1): 100242

Sanjrani A N, Huang H Z, Shah S A, Narejo A, Bhagat K, Ali B (2025). High-speed train bearing health assessment based on degradation stages through diagnosis and prognosis by using dual-task LSTM with attention mechanism. Quality and Reliability Engineering International, 41(5): 1735–1750

Santos M, Coelho P J, Pires I M, Gonçalves P, Dias G P (2024). An overview of machine learning algorithms to reduce driver fatigue and distraction-related traffic accidents. Procedia Computer Science, 238: 97–102

Sarhan A M, Fathy R, Ali H A (2025). Intelligent air traffic control using NLP-enhanced speech recognition and natural language generation. Journal of Electrical Systems and Information Technology, 12(1): 41

Sarlak A, Amin R, Razi A (2025). Extended visibility of autonomous vehicles via optimized cooperative perception under imperfect communication. Transportation Research Part C, Emerging Technologies, 180: 105350

Sayed S A, Abdel-Hamid Y, Hefny H A (2023). Artificial intelligence-based traffic flow prediction: A comprehensive review. Journal of Electrical Systems and Information Technology, 10(1): 13

Šemrov D, Marsetič R, Žura M, Todorovski L, Srdic A (2016). Reinforcement learning approach for train rescheduling on a single-track railway. Transportation Research Part B: Methodological, 86: 250–267

Shadman M, Kordani A A, Akbaripour H (2025). A machine learning approach to address robust bi-objective gate assignment under aircraft's taxi delay uncertainties. Expert Systems with Applications, 285: 128055

Shaikh M Z, Jatoi S, Baro E N, Das B, Hussain S, Chowdhry B S (2025). FaultSeg: A dataset for train wheel defect detection. Scientific Data, 12(1): 309

Sharma S, Cui Y, He Q, Mohammadi R, Li Z G (2018). Data-driven optimization of railway maintenance for track geometry. Transportation Research Part C, Emerging Technologies, 90: 34–58

Shaygan M, Ardecani F B, Nejad M (2025). Optimizing mixed traffic environments with shared and private autonomous vehicles: An equilibrium analysis of entrance permit and tradable credit strategies. Transportation Research Part E, Logistics and Transportation Review, 194: 103897

Shaygan M, Meese C, Li W, Zhao X G, Nejad M (2022). Traffic prediction using artificial intelligence: Review of recent advances and emerging opportunities. Transportation Research Part C, Emerging Technologies, 145: 103921

Shen L, Li J, Chen Y, Li C, Chen X, Lee D H (2024). Short-term metro origin-destination passenger flow prediction via spatio-temporal dynamic attentive multi-hypergraph network. IEEE Transactions on Intelligent Transportation Systems, 25(8): 9945–9957

Shi L, Qian C, Guo F (2022). Real-time driving risk assessment using deep learning with XGBoost. Accident Analysis and Prevention, 178: 106836

Shi L Y, Yang X, Chang X M, Wu J J, Sun H J (2023). An improved density peaks clustering algorithm based on k nearest neighbors and turning point for evaluating the severity of railway accidents. Reliability Engineering & System Safety, 233: 109132

Shihab S A, Wei P (2022). A deep reinforcement learning approach to seat inventory control for airline revenue management. Journal of Revenue and Pricing Management, 21(2): 183–199

Shladover S E (2018). Connected and automated vehicle systems: Introduction and overview. Journal of Intelligent Transport Systems, 22(3): 190–200

Shuaibu A S, Mahmoud A S, Sheltami T R (2025). A review of last-mile delivery optimization: Strategies, technologies, drone integration, and future trends. Drones (Basel), 9(3): 158

Sonntag V, Perrusquia A, Tsourdos A, Guo W (2025). A COLREGs compliance reinforcement learning approach for USV manoeuvring in track-following and collision avoidance problems. Ocean Engineering, 316: 119907

Sresakoolchai J, Kaewunruen S (2023). Railway infrastructure maintenance efficiency improvement using deep reinforcement learning integrated with digital twin based on track geometry and component defects. Scientific Reports, 13(1): 2439

Stern R E, Cui S, Delle Monache M L, Bhadani R, Bunting M, Churchill M, Hamilton N, Haulcy R, Pohlmann H, Wu F, Piccoli B, Seibold B, Sprinkle J, Work D (2018). Dissipation of stop-and-go waves via control of autonomous vehicles: Field experiments. Transportation Research Part C, Emerging Technologies, 89: 205–221

Su H, Zheng Y, Ding J, Jin D, Li Y (2024). MetroGNN: Metro network expansion with reinforcement learning. In: Proceedings of the ACM Web Conference, May, Singapore, 650–653

Sun J, Sun J (2016). Real-time crash prediction on urban expressways: identification of key variables and a hybrid support vector machine model. IET Intelligent Transport Systems, 10(5): 331–337

Sun Z, Jia X, Cai Y, Ji A, Lin X, Liu L, Wang W, Tu Y (2025). Joint control of traffic signal phase sequence and timing: A deep reinforcement learning method. Digital Transportation and Safety, 4(2): 118–126

Tahir A, Quesnel F, Desaulniers G, El Hallaoui I, Yaakoubi Y (2021). An improved integral column generation algorithm using machine learning for aircrew pairing. Transportation Science, 55(6): 1411–1429

Talebpour A, Mahmassani H S (2016). Influence of connected and autonomous vehicles on traffic flow stability and throughput. Transportation Research Part C, Emerging Technologies, 71: 143–163

Talpur K, Hasan R, Gocer I, Ahmad S, Bhuiyan Z (2025). AI in maritime security: Applications, challenges, future directions, and key data sources. Information (Basel), 16(8): 658

Tang J, Yu M H, Wu M H (2023). Detection of railway catenary insulator defects based on improved YOLOv5s. PeerJ. Computer Science, 9: e1474

Tang J, Zhu R, Wu F, He X, Huang J, Zhou X, Sun Y (2025a). Deep spatio-temporal dependent convolutional LSTM network for traffic flow prediction. Scientific Reports, 15(1): 11743

Tang R F, De Donato L, Besinović N, Flammini F, Goverde R M, Lin Z Y, Liu R, Tang T, Vittorini V, Wang Z (2022). A literature review of artificial intelligence applications in railway systems. Transportation Research Part C, Emerging Technologies, 140: 103679

Tang T, Chai S M, Wu W, Yin J T, D'Ariano A (2025b). A multi-task deep reinforcement learning approach to real-time railway train rescheduling. Transportation Research Part E, Logistics and Transportation Review, 194: 103900

Thakkar D, Palaniappan B (2024). Aircraft routing using dynamic programming and reinforcement learning: A customer-centric

approach. Journal of the Air Transport Research Society, 2: 100018

Tian X, Yan R, Liu Y, Wang S (2023). A smart predict-then-optimize method for targeted and cost-effective maritime transportation. Transportation Research Part B: Methodological, 172: 32–52

Tonti F, Rabault J, Vinuesa R (2025). Navigation in a simplified urban flow through deep reinforcement learning. Journal of Computational Physics, 538: 114194

Toribio L, Veloso B, Gama J, Zafra A (2026). A two-stage framework for early failure detection in predictive maintenance: A case study on metro train. Neurocomputing, 670: 132506

Tseremoglou I, Santos B F (2024). Condition-based maintenance scheduling of an aircraft fleet under partial observability: A deep reinforcement learning approach. Reliability Engineering & System Safety, 241: 109582

Tsigdinos S, Nikitas A, Bakogiannis E (2025). Contextualizing urban road network hierarchy and its role for sustainable transport futures: A systematic literature review using bibliometric analysis and content analysis tools. Frontiers of Engineering Management, 12(2): 361–393

Urata J, Xu Z, Ke J, Yin Y, Wu G, Yang H, Ye J (2021). Learning ride-sourcing drivers' customer-searching behavior: A dynamic discrete choice approach. Transportation Research Part C, Emerging Technologies, 130: 103293

Vaquero-Serrano M A, Borrelli F, Felez J (2025). A learning model predictive control for virtual coupling in intelligent train control systems. Computer-Aided Civil and Infrastructure Engineering, 40(31): 6279–6304

Wan C, Ma S, Song K C (2022). TSSTNet: A two-stream Swin transformer network for salient object detection of no-service rail surface defects. Coatings, 12(11): 1730

Wan L, Cheng W Z, Yang J (2024). Optimizing metro passenger flow prediction: Integrating machine learning and time-series analysis with multimodal data fusion. IET Circuits, Devices & Systems, 2024(1): 5259452

Wang C, Xie Y, Huang H, Liu P (2021a). A review of surrogate safety measures and their applications in connected and automated vehicles safety modeling. Accident Analysis and Prevention, 157: 106157

Wang C Y, Jiang W L, Shi L, Zhang L (2025b). Rolling bearing remaining useful life prediction using deep learning based on high-quality representation. Scientific Reports, 15(1): 8228

Wang F, Bi J, Xie D, Zhao X (2024a). Quick taxi route assignment via real-time intersection state prediction with a spatial-temporal graph neural network. Transportation Research Part C, Emerging Technologies, 158: 104414

Wang H, Yan R, Au M H, Wang S, Jin Y J (2023a). Federated learning for green shipping optimization and management. Advanced Engineering Informatics, 56: 101994

Wang H, Yan R, Wang S, Zhen L (2023b). Innovative approaches to addressing the tradeoff between interpretability and accuracy in ship fuel consumption prediction. Transportation Research Part C, Emerging Technologies, 157: 104361

Wang L, Abdel-Aty M, Shi Q, Park J (2015). Real-time crash prediction for expressway weaving segments. Transportation Research Part C, Emerging Technologies, 61: 1–10

Wang L, Yang H, Han Y, Yin S, Wu Y (2025a). Taming deep reinforcement learning-based conflict resolution in air traffic control using geometric technique. Expert Systems with Applications, 281: 127579

Wang L, Zhong H, Ma W, Abdel-Aty M, Park J (2020a). How many crashes can connected vehicle and automated vehicle technologies prevent: A meta-analysis. Accident Analysis and Prevention, 136: 105299

Wang N, Guo J (2022). Multi-task dispatch of shared autonomous electric vehicles for mobility-on-demand services–combination of deep reinforcement learning and combinatorial optimization method. Heliyon, 8(11): e11319

Wang N, Yang X, Chen J H, Wang H W, Wu J J (2023c). Hazards correlation analysis of railway accidents: A real-world case study based on the decade-long UK railway accident data. Safety Science, 166: 106238

Wang Q, Mao J, Wen X, Wallace S W, Deveci M (2025c). Flight, aircraft, and crew integrated recovery policies for airlines—A deep reinforcement learning approach. Transport Policy, 160: 245–258

Wang R, Xi L, Ye J, Zhang F, Yu X, Xu L (2025d). Adaptive spatio-temporal relation based transformer for traffic flow prediction. IEEE Transactions on Vehicular Technology, 74(2): 2220–2230

Wang S, Dong C, Shao C, Luo S, Zhang J, Meng M (2025e). Traffic state estimation incorporating heterogeneous vehicle composition: A high-dimensional fuzzy model. Frontiers of Engineering Management, 12(4): 952–970

Wang S, Li Y, Yang B, Duan R (2024b). Short-term forecasting of convective weather affecting civil aviation operations using deep learning. IEEE Access: Practical Innovations, Open Solutions, 12: 166011–166030

Wang S, Sun M, Li Y (2025f). Nowcasting echo top for aviation operations using CNN-Transformer. IEEE Transactions on Intelligent Transportation Systems, 26(12): 21724–21733

Wang W D, Hu W B, Wang W J, Xu X Y, Wang M D, Shi Y Y, Qiu S, Tutumluer E (2021b). Automated crack severity level detection and classification for ballastless track slab using deep convolutional neural network. Automation in Construction, 124: 103484

Wang X, Bai Y, Liu X (2023d). Prediction of railroad track geometry change using a hybrid CNN-LSTM spatial-temporal model. Advanced Engineering Informatics, 58: 102235

Wang X, Xu J (2026). Secure traffic accident warning system with privacy support for autonomous driving. Reliability Engineering & System Safety, 266: 111803

Wang Y, Wang L D, Hu Y H, Qiu J (2019a). RailNet: A segmentation network for railroad detection. IEEE Access: Practical Innovations, Open Solutions, 7: 143772–143779

Wang Y, Zhang Y (2021c). Prediction of runway configurations and airport acceptance rates for multi-airport system using gridded weather forecast. Transportation Research Part C, Emerging Technologies, 125: 103049

Wang Y, Zhao Y (2025). Multiple ships cooperative navigation and collision avoidance using multi-agent reinforcement learning with communication. Ocean Engineering, 320: 120244

Wang Z, Chen P, Chen L, Mou J (2025g). Collaborative collision avoidance approach for USVs based on multi-agent deep reinforcement learning. IEEE Transactions on Intelligent Transportation

Systems, 26(4): 4780–4794

Wang Z, Li H, Wang J, Shen F (2019b). Deep reinforcement learning based conflict detection and resolution in air traffic control. IET Intelligent Transport Systems, 13(6): 1041–1047

Wang Z, Su X, Ding Z (2021d). Long-term traffic prediction based on LSTM encoder-decoder architecture. IEEE Transactions on Intelligent Transportation Systems, 22(10): 6561–6571

Wang Z, Wu Y, Niu Q (2020b). Multi-sensor fusion in automated driving: A survey. IEEE Access: Practical Innovations, Open Solutions, 8: 2847–2868

Wang Z A, Jiang Z, Huang A, Zhang X, Luo Q, Guan W (2025h). Predicting individual mobility pattern by identifying indoor trajectories in transport hub. IEEE Transactions on Intelligent Transportation Systems, 26(10): 15529–15545

Wen Y, Gao X R, Luo L, Li J L (2024). Improved YOLOv8-based target precision detection algorithm for train wheel tread defects. Sensors (Basel), 24(11): 3477

Wu Y, Zhou J, Xia Y, Zhang X, Cao Z, Zhang J (2023). Neural airport ground handling. IEEE Transactions on Intelligent Transportation Systems, 24(12): 15652–15666

Xia Y Q, Wang K W, Tanirat P, Lee B, Moulitsas I, Li J (2025). Machine learning driven complex network analysis of transport systems. Journal of Transport Geography, 127: 104270

Xiao L, Xu W (2024). Urban spatial cluster structure in metro travel networks: An explorative study of Wuhan using big and open data. Frontiers of Engineering Management, 11(2): 231–246

Xie J, Liu Y, Chen N (2023). Two-sided deep reinforcement learning for dynamic mobility-on-demand management with mixed autonomy. Transportation Science, 57(4): 1019–1046

Xie J, Zhang Y, Li K, Wang B, Qin Y, Lu G, Xia Y (2026). Inspiration in human reasoning logic: Automating the inference and analysis of traffic accident information via macro-micro integration. Traffic Injury Prevention, 27(1): 50–60

Xie N, Chen Y, Tang W, Chen X M (2025). Multi-agent reinforcement learning with causal communication for ride-sourcing pricing in mixed autonomy mobility. Transportation Research Part C, Emerging Technologies, 176: 105164

Xie Y, Pongsakornsathien N, Gardi A, Sabatini R (2021). Explanation of machine-learning solutions in air-traffic management. Aerospace (Basel, Switzerland), 8(8): 224

Xin X, Liu K, Yu Y, Yang Z (2025). Developing robust traffic navigation scenarios for autonomous ship testing: an integrated approach to scenario extraction, characterization, and sampling in complex waters. Transportation Research Part C, Emerging Technologies, 178: 105246

Xing Y, Lv C, Cao D, Hang P (2021). Toward human-vehicle collaboration: Review and perspectives on human-centered collaborative automated driving. Transportation Research Part C, Emerging Technologies, 128: 103199

Xing Z Y, Zhang Z Y, Yao X W, Qin Y, Jia L M (2022). Rail wheel tread defect detection using improved YOLOv3. Measurement, 203: 111959

Xu D, Tang Y, Ju J, Yu Z, Zheng J, Gu T, Guo H (2025). Cross-city traffic state prediction based on knowledge transfer framework. Expert Systems with Applications, 272: 126747

Xu H, Chen Y, Li C, Chen X M (2024a). Space-time adaptive network for origin-destination passenger demand prediction. Transportation Research Part C, Emerging Technologies, 167: 104842

Xu H, Zou T, Liu M, Qiao Y, Wang J, Li X (2022). Adaptive spatiotemporal dependence learning for multi-mode transportation demand prediction. IEEE Transactions on Intelligent Transportation Systems, 23(10): 18632–18642

Xu M, Di Y, Ding H, Zhu Z, Chen X, Yang H (2023b). AGNP: Network-wide short-term probabilistic traffic speed prediction and imputation. Communications in Transportation Research, 3: 100099

Xu M, Di Y, Yang H, Chen X, Zhu Z (2023a). Multi-task supply-demand prediction and reliability analysis for docked bike-sharing systems via transformer-encoder-based neural processes. Transportation Research Part C, Emerging Technologies, 147: 104015

Xu Q, Pang Y, Liu Y (2024b). Dynamic airspace sectorization with machine learning enhanced workload prediction and clustering. Journal of Air Transport Management, 121: 102683

Xu R, Luo F (2021). Risk prediction and early warning for air traffic controllers' unsafe acts using association rule mining and random forest. Safety Science, 135: 105125

Yaakoubi Y, Soumis F, Lacoste-Julien S (2020). Machine learning in airline crew pairing to construct initial clusters for dynamic constraint aggregation. EURO Journal on Transportation and Logistics, 9(4): 100020

Yan R, Jiang S, Angeloudis P, Cao X, Wang J, Wang S (2025). Prediction of ship risk by a monotonic decision tree. Transportation Research Part C, Emerging Technologies, 180: 105317

Yan R, Wang S, Du Y (2020). Development of a two-stage ship fuel consumption prediction and reduction model for a dry bulk ship. Transportation Research Part E, Logistics and Transportation Review, 138: 101930

Yan R, Wang S, Zhen L (2023). An extended smart predict, and optimize (SPO) framework based on similar sets for ship inspection planning. Transportation Research Part E, Logistics and Transportation Review, 173: 103109

Yan R, Wang S, Zhen L, Jiang S (2024a). Classification and regression in non-linear prescriptive analytics: Development of hybrid models. Computers & Operations Research, 163: 106517

Yan R, Yang D, Wang T, Mo H, Wang S (2024b). Improving ship energy efficiency: Models, methods, and applications. Applied Energy, 368: 123132

Yan Y, Wang K, Qu X (2024c). Urban air mobility (UAM) and ground transportation integration: A survey. Frontiers of Engineering Management, 11(4): 734–758

Yang F Y, Liu J X, Li J Y, Liu L, Wang S J, Li W Q, Ni S Q (2025a). Causal reinforcement learning for train scheduling on single-track railway networks. Transportation Research Part C, Emerging Technologies, 178: 105215

Yang F Y, Yang Y H, Ni S Q, Liu S, Xu C G, Chen D J, Zhang Q P (2023). Single-track railway scheduling with a novel gridworld model and scalable deep reinforcement learning. Transportation Research Part C, Emerging Technologies, 154: 104237

Yang S, Gao G L, Wang Z Y, Zeng S F, Ouyang Y, Zhang G L (2025b). Intelligent fault diagnosis system for running gear of high-

speed trains. Sensors, 25(17): 5269

Yang X, Lou M, Hu J, Ye H, Zhu Z, Shen H, Xiang Z, Zhang B (2024). A human-like collision avoidance method for USVs based on deep reinforcement learning and velocity obstacle. Expert Systems with Applications, 254: 124388

Yang Z P, Cheng Z K, Wu D (2025c). Deep learning driven prediction and comparative study of surrounding rock deformation in high speed railway tunnels. Scientific Reports, 15(1): 24104

Yao A, Li S, Feng K, Zhang T, Song X, Wang L, Wang R, He P, Zhou H, Li H, Ding S, Li D (2026). System-of-systems safety for low-altitude aviation transportation. Reliability Engineering & System Safety, 273: 112276

Yatziv Y, Haddad J (2025). Real-time train regulation with passenger flow control in urban rail systems. Transportation Research Part C, Emerging Technologies, 179: 105223

Ye W, Ren J J, Li C, Liu W G, Zhang Z Y, Lu C F (2024b). Intelligent detection of surface defects in high-speed railway ballastless track based on self-attention and transfer learning. Structural Control and Health Monitoring, 2024(1): 2967927

Ye W L, Ren J J, Lu C F, Zhang A A, Zhan Y, Liu J G (2024a). Intelligent detection of fastener defects in ballastless tracks based on deep learning. Automation in Construction, 159: 105280

Yin H D, Liu L N, Chang X M, Fu H, Wu J J (2025). Optimizing integrated train rescheduling strategies for diverse disruption scenarios using reinforcement learning. Computers & Industrial Engineering, 207: 111329

Yin M J, Li K, Cheng X Q (2020). A review on artificial intelligence in high-speed rail. Transportation Safety and Environment, 2(4): 247–259

Yin Z, Hardaway K, Feng Y, Kou Z, Cai H (2023). Understanding the demand predictability of bike share systems: A station-level analysis. Frontiers of Engineering Management, 10(4): 551–565

Ying C S, Chow A H, Yan Y M, Kuo Y H, Wang S Y (2024). Adaptive rescheduling of rail transit services with short-turnings under disruptions via a multi-agent deep reinforcement learning approach. Transportation Research Part B: Methodological, 188: 103067

Yoo S, Kim H, Kim W, Kim N, Lee J (2022). Controlling passenger flow to mitigate the effects of platform overcrowding on train dwell time. Journal of Intelligent Transport Systems, 26(3): 366–381

Yoon D D, Ayalew B, Nawaz Ali G M (2022). Performance of decentralized cooperative perception in V2V connected traffic. IEEE Transactions on Intelligent Transportation Systems, 23(7): 6850–6863

Yuan Y, Ding J, Feng J, Jin D, Li Y (2024). Unist: A prompt-empowered universal model for urban spatio-temporal prediction. In: Proceedings of the 30th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, August, Barcelona, Spain, ACM, 4095–4106

Adnan Yusuf S, Khan A, Souissi R (2024). Vehicle-to-everything (V2X) in the autonomous vehicles domain — A technical review of communication, sensor, and AI technologies for road user safety. Transportation Research Interdisciplinary Perspectives, 23: 100980

Zeng W, Quan Z, Zhao Z, Xie C, Lu X (2020). A deep learning approach for aircraft trajectory prediction in terminal airspace. IEEE Access: Practical Innovations, Open Solutions, 8: 151250–151266

Zhang C, Jin Z, Ng K K H, Tang T Q, Zhang F, Liu W (2025a). Predictive and prescriptive analytics for robust airport gate assignment planning in airside operations under uncertainty. Transportation Research Part E, Logistics and Transportation Review, 195: 103963

Zhang C F, Hu X L, He J, Hou N (2022a). Yolov4 high-speed train wheelset tread defect detection system based on multiscale feature fusion. Journal of Advanced Transportation, 2022(1): 1172654

Zhang D, Xiao F, Shen M, Zhong S (2021a). DNEAT: A novel dynamic node-edge attention network for origin-destination demand prediction. Transportation Research Part C, Emerging Technologies, 122: 102851

Zhang H, Lin Z, Zhou J, Sun J, Zhou T, Cao C (2025b). A comprehensive review of traffic flow prediction: from traditional models to deep learning architectures. Digital Transportation and Safety, 4(4): 281–297

Zhang H X, Lu G Y, Zhang Y Q, D'Ariano A, Wu Y X (2025c). Railcar itinerary optimization in railway marshalling yards: A graph neural network based deep reinforcement learning method. Transportation Research Part C, Emerging Technologies, 171: 104970

Zhang J, Xie C, Cai H, Shen W, Yang R (2024a). Knowledge distillation-based spatio-temporal MLP model for real-time traffic flow prediction. IEEE Transactions on Intelligent Transportation Systems, 25(11): 18122–18135

Zhang J, Zhang J (2023). Artificial intelligence applied on traffic planning and management for rail transport: A review and perspective. Discrete Dynamics in Nature and Society, 2023(1): 1832501

Zhang N, Zhang M, Low K H (2021b). 3D path planning and real-time collision resolution of multirotor drone operations in complex urban low-altitude airspace. Transportation Research Part C, Emerging Technologies, 129: 103123

Zhang P, Yang X, Wu J, Sun H, Wei Y, Gao Z (2023). Coupling analysis of passenger and train flows for a large-scale urban rail transit system. Frontiers of Engineering Management, 10(2): 250–261

Zhang R, Wang B, Zhang J, Bian Z, Feng C, Ozbay K (2025d). When language and vision meet road safety: Leveraging multimodal large language models for video-based traffic accident analysis. Accident Analysis and Prevention, 219: 108077

Zhang S, Han L (2026). Low-altitude infrastructure and economic growth: Evidence from general aviation airports. Transport Policy, 175: 103880

Zhang S, Zhou L, Chen X, Zhang L, Li L, Li M (2020). Network-wide traffic speed forecasting: 3D convolutional neural network with ensemble empirical mode decomposition. Computer-Aided Civil and Infrastructure Engineering, 35(10): 1132–1147

Zhang T (2024). Network level spatial temporal traffic forecasting with hierarchical-attention-LSTM. Digital Transportation and Safety, 3(4): 233–245

Zhang X, Fu X, Xiao Z, Xu H, Qin Z (2022b). Vessel trajectory prediction in maritime transportation: Current approaches and beyond. IEEE Transactions on Intelligent Transportation Systems, 23(11): 19980–19998

Zhang X, Wan G, Zhang H (2025e). Transfer learning for cross-city traffic prediction to solve data scarcity. Transportation Research Record: Journal of the Transportation Research Board, 2679(3): 697–706

Zhang X, Zhong S, Mahadevan S (2022c). Airport surface movement prediction and safety assessment with spatial–temporal graph convolutional neural network. Transportation Research Part C, Emerging Technologies, 144: 103873

Zhang Y, Cheng T (2020). Graph deep learning model for network-based predictive hotspot mapping of sparse spatio-temporal events. Computers, Environment and Urban Systems, 79: 101403

Zhang Y, Peng S, Zhou Y (2025f). Spatial–temporal graph transformer network for traffic network flow prediction using parallel training based on cloud computing. Applied Soft Computing, 180: 113422

Zhang Y, Yang C, Zhang C, Tang K, Zhou W, Wang J (2024b). A multi-agent reinforcement learning approach for ART adaptive control in automated container terminals. Computers & Industrial Engineering, 193: 110264

Zhang Z P, Zaman A, Xu J X, Liu X (2022d). Artificial intelligence-aided railroad trespassing detection and data analytics: Methodology and a case study. Accident Analysis and Prevention, 168: 106594

Zhang Z Y, Miao R S, Wang C, Qin Y (2025g). Bogie doctor: Automated fault diagnosis in high-speed trains via deep learning-based maintenance log analysis. Engineering Applications of Artificial Intelligence, 162: 112683

Zhao J, Zhao W, Deng B, Wang Z, Zhang F, Zheng W, Cao W, Nan J, Lian Y, Burke A F (2024). Autonomous driving system: A comprehensive survey. Expert Systems with Applications, 242: 122836

Zhao L, Roh M I (2019). COLREGs-compliant multiship collision avoidance based on deep reinforcement learning. Ocean Engineering, 191: 106436

Zhao Z, Wang K, Chen X M, Chang X, Li G, Wu J, Zhen L (2026). Planning, operations, and management for urban air mobility: A comprehensive review and future research directions. Engineering Management, 1–35

Zhao Z, You J, Gan G, Li X, Ding J (2022). Civil airline fare prediction with a multi-attribute dual-stage attention mechanism. Applied Intelligence, 52(5): 5047–5062

Zhen L, He X, Zhuge D, Wang S (2024). Primal decomposition for berth planning under uncertainty. Transportation Research Part B: Methodological, 183: 102929

Zheng D Y, Li L M, Zheng S B, Chai X D, Zhao S G, Tong Q Q, Wang J, Guo L Z (2021). A defect detection method for rail surface and fasteners based on deep convolutional neural network. Computational Intelligence and Neuroscience, 2021(1): 2565500

Zheng Y, Luo J, Hu M (2026). Spatial-temporal incident-aware dynamic graph convolution networks for traffic flow prediction. Expert Systems with Applications, 305: 130689

Zhong Q, Yu Y, Huang Y, Zhang T (2025). Prediction and optimization of civil aviation flight delays based on machine learning algorithms. International Journal of Computational Intelligence Systems, 18(1): 189

Zhou J, Wu Y, Cao Z, Song W, Zhang J, Chen Z (2023a). Learning large neighborhood search for vehicle routing in airport ground handling. IEEE Transactions on Knowledge and Data Engineering, 35(9): 9769–9782

Zhou P, Kortoçi P, Yau Y P, Finley B, Wang X, Braud T, Lee L H, Tarkoma S, Kangasharju J, Hui P (2022). AICP: Augmented informative cooperative perception. IEEE Transactions on Intelligent Transportation Systems, 23(11): 22505–22518

Zhou R, Yu Y, Wang Z, Ke L, Zhao J (2025). How does shared mobility impact metro-based urban commercial travel accessibility and Equity? Transportation Research Part D, Transport and Environment, 138: 104523

Zhou W, Pham D T, Alam S (2023b). AirFusion: A machine learning framework for balancing air traffic demand and airspace capacity through dynamic airspace sectorization. In: Proceedings of IEEE 26th International Conference on Intelligent Transportation Systems (ITSC), September, Naples, Italy, 5324–5331

Zhou Y, Turkmen S, Pazouki K, Norman R (2026). Route and speed optimisation of a general cargo ship using extreme gradient boosting and enhanced Deep Q-Network approaches. Transportation Research Part E, Logistics and Transportation Review, 206: 104555

Zhu A F, Xie J X, Wang B, Guo H, Guo Z L, Wang J, Xu L, Zhu S, Yang Z P (2024a). Lightweight defect detection algorithm of tunnel lining based on knowledge distillation. Scientific Reports, 14(1): 27178

Zhu J, Xie N, Cai Z, Tang W, Chen X (2023a). A comprehensive review of shared mobility for sustainable transportation systems. International Journal of Sustainable Transportation, 17(5): 527–551

Zhu L, Zhang Q, Jian X, Yang Y, Li L (2026). Spatio-temporal traffic accidents detection via graph based generative adversarial network. Engineering Applications of Artificial Intelligence, 165: 113488

Zhu R (2020). Traffic condition prediction of urban roads based on neural network. In: Proceedings of the 2020 6th International Conference on Computing and Artificial Intelligence, Tianjin, China, ACM, 30–36

Zhu X, Jian L, Chen X, Zhao Q (2024b). Reinforcement learning for multi-flight dynamic pricing. Computers & Industrial Engineering, 193: 110302

Zhu Z, Chen X, Zhang X, Zhang L (2019). Probabilistic data fusion for short-term traffic prediction with semiparametric density ratio model. IEEE Transactions on Intelligent Transportation Systems, 20(7): 2459–2469

Zhu Z, Xu M, Ke J, Yang H, Chen X M (2023b). A Bayesian clustering ensemble Gaussian process model for network-wide traffic flow clustering and prediction. Transportation Research Part C, Emerging Technologies, 148: 104032

Zhuge D, Wang S, Zhen L (2024). Shipping emission control area optimization considering carbon emission reduction. Operations Research, 72(4): 1333–1351

Zong X, Yan H, Qi Y (2026). Recent advances in multi-source data fusion for traffic flow prediction: A review. Archives of Computational Methods in Engineering, 33(1): 1181–1203