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Concepts, key technologies, applications and development trends in autonomous transportation systems

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A R T I C L E I N F O

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A B S T R A C T

Autonomous Transportation Systems (ATS) represents a transformative advancement in modern transportation, surpassing traditional transportation systems (TTS), autonomous driving technologies (ADT), and intelligent transportation systems (ITS). Unlike vehicle-centric autonomy or information-driven support systems, ATS emphasises system-level autonomy, multi-vehicle collaboration, and dynamic optimisation across road, maritime, air and rail transport. This paper provides a comprehensive review of the current state and future trends of ATS. It first examines the theoretical foundations and the evolution of ATS concept, including system engineering methodologies, the closed-loop architecture of perception-awareness-decision-control-collaboration-improvement, and the integration of model-driven and data-driven approaches. It then defines the concept, components, and characteristics of ATS, systematically analysing autonomous vehicle, digital infrastructure, information platform, and traffic environment, as well as the core features required to achieve autonomy. Key technologies are reviewed, covering information perception, interoperability, collaborative computing, and digital twin. The standards and applications are discussed across different modes of transportation in facilitating industrial deployment. Finally, future research trends are outlined, with emphasis on theoretical integration, cross-modal collaboration, verifiable safety, and application scenarios. Overall, ATS is regarded as the ultimate form of ITS, offering significant potential in enhancing safety, efficiency, and sustainability, and promoting a paradigm shift towards the next generation of transportation systems.

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1. Introduction

Rapid advances in science and technology have activated new opportunities of transforming traditional transportation systems (TTS). The growing maturity of key technologies, including artificial intelligence, communication network, sensor fusion, and automatic control, has enabled systems not only to achieve enhanced perception, reasoning, and responsiveness (Alsamhi et al., 2024), but also to support dynamic collaboration and optimised decision-making among multiple vehicles (Hang et al., 2022; Zhang et al., 2025c). This technological progress provides the foundation for a paradigm shift from conventional, manually-operated systems to autonomous modes of operation. Consequently, achieving safe, efficient, and sustainable transport increasingly depends on the development of Autonomous Transportation Systems (ATS), and it represents a system-level transformation driven by advances in sensing, communication, control, transportation science, and computing (Jia et al., 2022). The advancement of ATS is therefore not merely an avenue of technological exploration, but also an inevitable path towards transforming and upgrading of global transportation systems.

ATS represents a new generation of transportation concepts, evolving from autonomous driving technologies (ADT) and intelligent transportation systems (ITS), and its core innovation lies in achieving system-level autonomy and multi-vehicle collaboration (You et al., 2024a). TTS primarily relies on manual driving, static regulations, and centralised scheduling to maintain operational order. Its management model is centred on the driver-vehicle-environment, in which human operators provide leadership, enforce standardised procedures, and coordinate division of tasks. In contrast, ADT constitutes one of the enabling technologies for intelligent or autonomous vehicles. They focus on autonomous environmental perception, path planning, and trajectory control at the level of individual vehicle (Sadid et al., 2023; Hinostroza et al., 2021; Zhao et al., 2024b), including car, ship, aircraft, and train.

ITS aims to improve operational efficiency and service quality through information-based methods (Ribouh et al., 2021), and is a foundational stage in the broader evolution toward ATS, representing an early era of integrating sensing, autonomy, and communication technologies into transportation systems. Characterised by information-driven, it emphasises information sharing and intelligent scheduling, yet largely remains a decision-support system rather than a fully autonomous one. The evolution from ITS to ATS represents a fundamental shift in system control authority and decision-making paradigms. This transition begins with information integration and decision support, progresses through vehicle-road-cloud collaboration to enable dynamic optimisation of traffic flows, and ultimately advances towards a fully autonomous scheduling ecosystem encompassing all system elements. Throughout this process, the system evolves from supporting human decisions to autonomously commanding intelligent transportation entities, with the overarching objective of achieving global optimisation in safety, efficiency, and sustainable mobility. ATS transcends these paradigms by adopting an integrated, closed-loop architecture of perception-awareness-decision-control-collaboration-improvement (Wan et al., 2024; W. Zhang et al., 2022b). ATS emphasises holistic system optimisation and supports self-adaptive, self-learning, and self-improvement capabilities. Thus, ATS is not merely an incremental extension of existing systems. It represents a fundamental reconfiguration of transportation architecture. It expands the scope of ADT from the level of individual vehicle to system-wide collaboration and may ultimately be regarded as the culminating stage of ITS evolution and the enhancement of autonomous capability.

Research on ATS remains in a rapid development stage (Mandel et al., 2022; Mumtaz et al., 2025). Driven by both demands and technologies, the USA and Europe have placed strong emphasis on supporting research in ATS (Jia et al., 2022). Meanwhile, China has also continuously promoted the development of ATS through sustained support for multiple National Key Technologies Research & Development Programes. However, current studies are characterised by fragmented domains, diverse methodologies, and heterogeneous application models, yet lack comprehensive reviews and theoretical synthesis. It is therefore necessary to provide a clear definition and set of characteristics for ATS, systematically analyse the current state of development, identify future demands and key technologies, and outline prospective applications and scenarios. Such an effort not only clarifies the research landscape and highlights emerging hotspots and critical issues, but also offers theoretical support for technological innovations, informs subsequent research, and provides strategic guidance for policy design and industrial deployment.

2. The theoretical, concept, and characteristics of ATS

2.1. Theoretical foundation

As a complex system, the construction and evolution of ATS rely heavily on robust theoretical foundations. The core theoretical framework underpinning its development can be distilled into three interrelated aspects as follows: 1) Systems engineering methodologies (Mandel et al., 2022), which provide a holistic approach to design, integration, and optimisation; 2) Closed-loop architecture of perception-awareness-decision-control-collaboration-improvement (Zhang et al., 2022b), which structures the operational logic of autonomous systems; and 3) Hybrid modelling mechanisms that integrate data-driven and model-driven approaches (Fan et al., 2025), ensuring both adaptability and interpretability in dynamic environments.

(1) System engineering methodology

System engineering provides with a comprehensive framework for the analysis, design, and integration of complex systems (Mandel et al., 2022). It emphasises starting from overarching objectives and systematically mapping system functions, physical components, and operational mechanisms to achieve coordinated subsystem interaction and optimal system-level performance. Applied to ATS, systems engineering is reflected in top-level architecture design, requirements modelling and functional decomposition, complete life-cycle management, multi-objective trade-offs, coordination mechanisms, and the treatment of complex coupling relationships. This methodology offers the theoretical and practical basis for standardised modelling, hierarchical collaboration, scalable integration, and verifiable evolution, thereby forming the foundation of system-level autonomy in ATS.

(2) Closed-loop architecture of perception-awareness-decision-control-collaboration-improvement

ATS demonstrates the capacity of generating and optimising its behaviour in complex, uncertain environments. This capability is underpinned by a closed-loop architecture of perception-awareness-decision-control-collaboration-improvement (as shown in Fig. 1), which constitutes the core logic of system operation. The process begins with integrating multi-source sensor data (Zhao et al., 2024a), such as LiDAR, computer vision, AIS, and ADS-B, to enable target detection, environment mapping, and state estimation (Liu et al., 2022; Xu et al., 2025c; Zhang et al., 2024; Yang et al., 2025b). The awareness stage involves a deeper understanding of the traffic scenario, including scene modelling, behaviour recognition, intention inference, and conflict prediction, thereby supporting real-time situational awareness (Zhao et al., 2024c). On this basis, the decision-making stage formulates behavioural strategies such as path planning, collision avoidance, energy-efficiency operations, and task scheduling (Reda et al., 2024). These strategies are subsequently translated into executable control instructions, which are realised through trajectory tracking, speed regulation, and attitude adjustment (Zou et al., 2018). In multi-vehicle scenarios, ATS supports information exchange, task allocation, negotiation, and collaborative behaviour among vehicles and infrastructure, thereby enabling coordinated operations. Finally, through continuous feedback from operational data and accumulated historical experience, the system refines its strategies, updates models, and evolves its capabilities, reflecting its self-learning and self-adaptive properties. This closed-loop paradigm draws upon theories from cybernetics, artificial intelligence, and multi-agent systems, and provides with a structured framework for the generation and evolution of ATS.

(3) Data-driven and model-driven integration method

ATS operates in highly dynamic, heterogeneous, and uncertain environments, which necessitate models that combine physical interpretability and engineering reliability with learning and generalisation capabilities. To meet these requirements, the integration of model-driven and data-driven approaches has emerged as a key direction of theoretical development (Fan et al., 2025).

Model-driven approaches emphasise reliance on physical mechanisms, control theory, and system-level modelling (Wang et al., 2022a). They are particularly suitable for tasks such as trajectory planning, stabilisation control, and scheduling optimisation. Representative methods include model predictive control (Wang et al., 2022b), hybrid logical dynamic system modelling (Platzer, 2025), and hierarchical state machines (Chen et al., 2018). In contrast, data-driven approaches depend on historical and real-time sensing data (Habib et al., 2021), employing machine learning, deep learning, and reinforcement learning to support pattern recognition, behaviour prediction, and strategy generation (Agrahari et al., 2024; Matsuo et al., 2022; Xu et al., 2025b). These methods are especially effective for situational awareness, intention inference, and strategy learning in complex scenarios.

The integration of the two-type approaches has led to the emergence of new hybrid structures, such as physics-enhanced perception models (Hao et al., 2025), knowledge-guided learning models (Liu et al., 2024e), and rule-constrained data-driven models (Treesatayapun, 2025), which combine interpretability with adaptability. For instance, deep reinforcement learning augmented by prior physical models has shown promising results in ship collision avoidance decision-making (Wang et al., 2025c). Similarly, multi-task and transfer learning techniques have been demonstrated to enhance model generalisation (Chen et al., 2020). By leveraging such integration strategies, ATS can exercise decision-making in model-free or weakly modelled environments, achieve

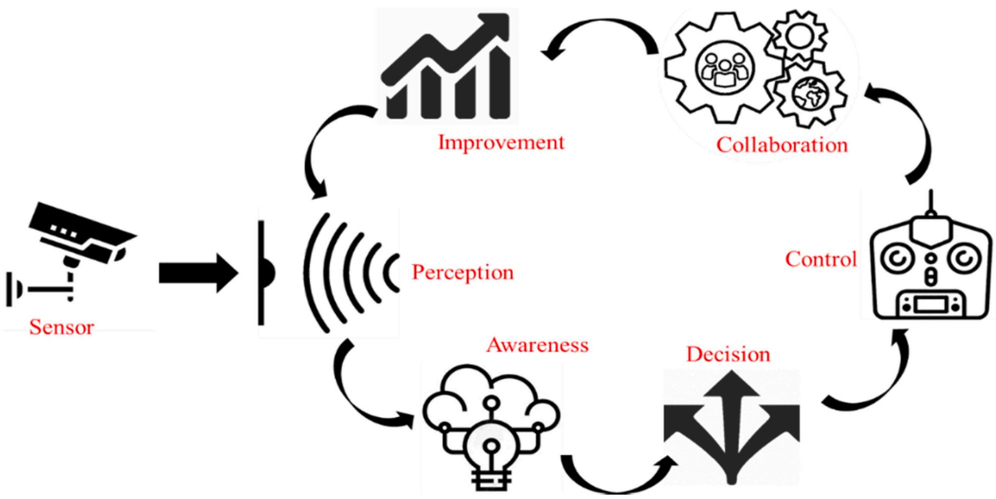

Fig. 1. Closed-loop architecture of perception-awareness-decision-control-collaboration-improvement.

optimal control in well-understood scenarios, and enable continuous learning and capability transfer. These hybrid approaches thus constitute a key theoretical foundation for the deployment of autonomous systems in complex real-world contexts.

2.2. Concept evolution

The introduction of ATS represents an inevitable stage in the intelligent evolution of transportation systems (You et al., 2024a). The concept did not emerge in isolation; rather, it developed along the technological trajectory of informatisation, intelligence, and autonomy, gradually taking shape by building upon the technological foundations of TTS, ITS and ATD. Its development can be generally divided into three stages: from single-vehicle intelligence, to interactive collaboration, and ultimately to system-level autonomy. This evolutionary path spans multiple transportation modes, including autonomous driving, intelligent shipping, air transportation, and automated train systems. A comparative summary of the core distinctions across these systems is provided in Table 1.

(1) From ITS to ATS

ITS was widely promoted worldwide in the early 21st century with the aim of improving traffic efficiency and operational safety (Yan et al., 2012). The basic concept of ITS is to employ information technologies, such as sensing, communication, control, and computing, under human supervision to provide decision-making and scheduling support (Almadani et al., 2025). Representative applications in road transportation include adaptive traffic light control (Noaeen et al., 2022), electronic toll collection (Shahrier et al., 2024). ATS, however, represents both an advancement and an expansion of ITS. Their objective extends beyond improving efficiency to enabling vehicles to operate autonomously in complex and dynamic environments without human intervention. Moreover, ATS is capable of cognitive interaction, behavioural collaboration, and system-wide optimisation in coordination with other participants, including drivers, vehicles, and infrastructure. ATS is also underpinned by a closed-loop architecture of perception-awareness-decision-control-collaboration-improvement, and can be regarded as truly complex autonomous systems with the capacity of intelligent decision-making, self-organising scheduling, and evolutionary system analysis.

(2) From intelligent vehicles to system autonomy

The development of ATS follows a gradual evolutionary trajectory, progressing from bottom-up innovations and localised functions to system-level autonomy. The pathways of autonomous cars and intelligent ships serve as representative examples of this evolution. The first stage is single-vehicle intelligence, exemplified by autonomous cars equipped with environmental perception and control capabilities. Such vehicles can perform functions such as lane keeping, automated lane changing, and path planning, thereby realising autonomy at the individual level (Yang et al., 2018). The second stage introduces vehicle-infrastructure collaboration, enabled by vehicle-to-everything (V2X) and related communication technologies. This allows vehicles and traffic infrastructure to exchange dynamic information, mitigate perception blind spots, and support applications such as traffic signal coordination and intersection priority management, ultimately enhancing overall traffic efficiency and safety (Abboud et al., 2025). The third stage involves system-level autonomy, achieved through edge-cloud collaborative architectures and multi-vehicle cluster scheduling mechanisms (Song et al., 2023b). These enable dynamic scheduling, global path optimisation, and coordinated task execution among multiple vehicles within urban networks, marking the transition from isolated intelligence to holistic autonomy at the transportation system level.

Similarly, the evolution of waterway transportation extends from intelligent ships to next-generation shipping systems (Li et al., 2025a). At the initial stage, intelligent ships possess the capability of navigation and collision avoidance, enabling safe operation in diverse environments, such as open seas (Zhang et al., 2015) and complex inland waterways (Wang et al., 2025b). The second stage is characterised by ship-shore collaboration, whereby shore-based control centres and ships engage in real-time information exchange

Table 1
Core distinctions of concepts related to ATS.

Concept		Control subject	Decision mechanism	System Resilience	Intelligent level	Operating mechanism	Related systems/ technologies
TTS		Human	Centralized	Passive	/	Rule-based operation	/
ITS		Human control with support	Centralized	Passive	Information-based intelligence	Static optimization and local scheduling	Traffic light control; Electronic toll collection (ETC)
ADT	Intelligent vehicle	Machine control	Distributed	Passive	Individual intelligence	Individual operation with self-control	Autonomous driving cars; Intelligent ships
	Intelligent vehicle with collaboration	Machine control with collaboration	Distributed with Collaboration	Local Active	Individual intelligence with collaboration (Group)	Multi-vehicle interaction with local scheduling	Vehicle-to-everything (V2X); Ship-Shore Collaboration
ATS		System control autonomously	System-level Collaboration	Active	System autonomous	System collaboration with optimal scheduling	ATS integrated platform

and cooperative operations (Xiu et al., 2025). These functions, including remote monitoring, route negotiation, and berthing guidance, significantly enhance the safety and efficiency of maritime transportation. The final stage involves the construction of an integrated autonomous operation system that combines ships, shore-based facilities, ports, and dynamic waterway conditions with weather forecasting, traffic state estimation, energy-efficiency optimisation, and intelligent scheduling. Such integration enables high-level autonomous shipping characterised by multi-ship collaboration, inter-route connectivity, and cross-waterway coordination.

2.3. Characteristics of ATS

ATS constitutes a comprehensive framework comprising multiple components, including autonomous vehicles, digital infrastructure, information platform, and traffic environment. The fundamental objective of ATS is to achieve autonomy, safety, efficiency, and sustainability within transportation systems. The component and characteristics of ATS is shown in Fig. 2. By leveraging advanced technologies, such as information perception (Cress et al., 2024), situational awareness (Wu et al., 2025), tracking (Shao et al., 2024), intention recognition (Qian et al., 2025; Rong et al., 2019), intelligent decision-making (Liu et al., 2025b), and autonomous control (Yang et al., 2025a; Meng et al., 2025), ATS enables transportation systems to operate in complex, dynamic, and multi-agent environment, while supporting multi-vehicle collaboration and system-level optimisation.

(1) Autonomous vehicle

As the core component of ATS, autonomous vehicles include various types, including autonomous cars, intelligent ships, unmanned aircrafts, and automated trains (Zhang et al., 2017). These vehicles typically adopt a closed-loop architecture comprising perception, awareness, decision-making, and control (Chen et al., 2025b; Perera et al., 2012). The perception module acquires data from both the environment and the vehicle itself (Wu et al., 2022), while the awareness module interprets this information to model scenarios, identify obstacles, and infer behavioural intentions (Wu et al., 2025). The decision-making module formulates operational strategies, such as path planning and collision avoidance through heading and speed adjustments (Liu et al., 2023). The control module then executes these strategies, ensuring accurate trajectory tracking and stable attitude control (You et al., 2024b). Within this closed-loop framework, vehicles are expected to operate independently of human intervention while also providing the capabilities necessary for both individual autonomy and coordinated multi-vehicle collaboration.

(2) Digital infrastructure

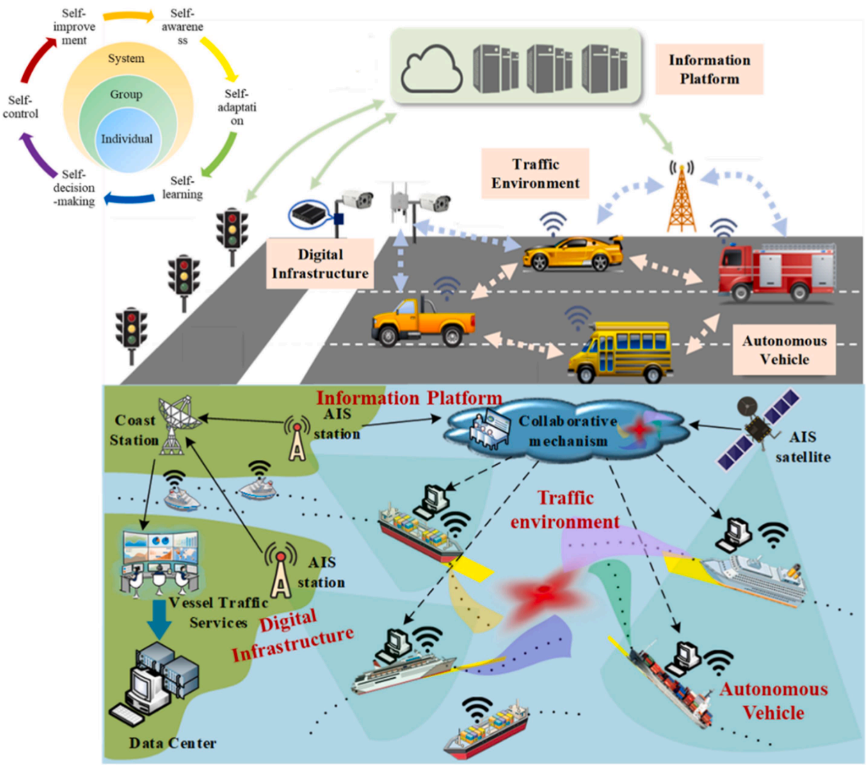

Fig. 2. The component and characteristics of ATS (Liu et al., 2025b).

Transportation infrastructure encompasses not only traditional physical facilities, such as roads, railways, waterways, and ports, but also digital infrastructure, such as intelligent installations with embedded computing and communication capabilities (He et al., 2022). Examples include roadside units (RSUs), automated port loading and unloading equipment, and railway signal control systems (Chen et al., 2025a; Sun et al., 2025; Wang et al., 2024). These infrastructures actively acquire external environmental information, such as traffic flow, weather conditions, and obstacles, while supporting low-latency, high-reliability communication technologies (Abboud et al., 2025; Wang et al., 2025a), including V2X and air-to-ground (A2G) links. Moreover, they participate in both local control and global scheduling, collectively forming a distributed collaborative network (Chen et al., 2023) that underpins the operation of ATS.

(3) Information platform

Information platform is the central nervous component of ATS, which is responsible for data aggregation, intelligent scheduling, collaborative optimisation, and system-wide coordination (Jiang et al., 2022; Yan et al., 2025b). It is typically composed of cloud-based data centres, edge computing nodes, and digital twin systems. Its primary role lies in the real-time processing of multi-source and heterogeneous data collected from vehicles and infrastructures. On this basis, it enables traffic state assessment, congestion prediction, and emergency response, while supporting task scheduling, path planning, energy management, and behaviour modelling. Furthermore, the platform synchronises and regulates the operational states of cross-regional and cross-modal systems, thereby ensuring coordinated and efficient system-wide operation.

(4) Traffic Environment

Traffic environment encompasses both natural conditions, such as sea states, weather, and spatial layout (Perera et al., 2015), as well as social factors (Nguyen-Phuoc et al., 2025), including other traffic participants, operational rules, and regulatory policies. To ensure reliable performance, ATS must dynamically perceive and model the environment while maintaining robust operation under conditions of uncertainty (Kadyrov et al., 2025; Gao et al., 2023). In complex traffic scenarios, environment modelling frequently relies on multi-source data fusion technologies (Trinh et al., 2024; Xu et al., 2024), including LiDAR, computer vision, Automatic Identification System (AIS), and Automatic Dependent Surveillance-Broadcast (ADS-B), complemented by high-precision digital maps.

(5) Overall characteristics of ATS

The overall characteristics of ATS arise from the deep coupling of its multiple components under a unified architecture and collaborative mechanisms. These characteristics emerge at the system-level autonomy through information sharing, collaborative decision-making, and continuous evolution among vehicles and other system components. The core characteristics of ATS are as follows: 1) Self-awareness, the ability to actively acquire both internal states and external environmental information; 2) Self-adaptation, the capacity to automatically adjust operational strategies in response to environmental changes; 3) Self-learning, the capability to continuously optimise behavioural models by leveraging historical data and operational experience; 4) Self-decision-making, the autonomy to generate behavioural strategies such as path planning, collaborative collision avoidance, and formation reconfiguration; 5) Self-control, the ability to ensure stable, precise, and controllable trajectory execution; 6) Self-improvement, the capacity to evolve through feedback during continuous operation, thereby enhancing overall efficiency and safety. In addition, ATS should integrate multi-source environmental data and employ multi-dimensional collaborative control mechanisms. Such capabilities enable coordinated tasks across diverse transportation modes, car platooning on highways (Jin et al., 2021), multi-ship collision avoidance at sea (Liu et al., 2025b), and coordinated flight in air traffic systems (Caranti et al., 2025), while maintaining stability in highly dynamic environments such as dense urban traffic (Zhang et al., 2025e) or complex waterways (Zhang et al., 2022a, Liu et al., 2024a).

3. Key technologies of ATS

In multimodal and multi-vehicle transportation systems, traditional architectures have shown clear limitations (Wang et al., 2022d; Zardini et al., 2023), including vulnerability to single-point failures and communication bottlenecks. As a result, ATS has gradually shifted toward distributed and collaborative frameworks, where perception, decision-making, and control are decentralised to vehicles and supported by edge computing, improving real-time performance and robustness (You et al., 2024a). The end-edge-cloud integration architecture further enables perception at the edge, decision-making at the end, and global scheduling at the cloud, enhancing both intelligence and stability (Gao et al., 2025).

These advances in distributed architecture and collaborative scheduling provide the foundation for ATS. On this basis, further progress depends on several key technologies: perception, interoperability, computation, digital twin (Jia et al., 2022), which in together support real-time awareness, coordinated decision-making, predictive system optimisation, ensured system security and promoted engineering practice.

3.1. *Information perception and situational awareness*

The operational safety and intelligence of ATS in dynamic environments rely heavily on accurate perception of external information, modelling of complex scenarios, intelligent prediction of behavioural intentions, and systematic risk assessment of potential conflicts (Demirci et al., 2025; Luo et al., 2025; Wu et al., 2013; Zhu et al., 2023). These demands place increasingly stringent requirements on the system's ability to perceive and interpret situational contexts. Through advanced information perception and situational awareness, ATS can "see" and "understand" complex traffic environments, enabling conflict detection and risk evaluation (Martelli et al., 2025; Shang et al., 2025). Therefore, perception and awareness form a core component underpinning both safety and robustness of ATS.

(1) Information perception

Information perception refers to the acquisition of both static and dynamic data from the traffic environment (Huang et al., 2025). With the advancement of multi-source sensing devices, perception systems have evolved to support multi-modal information collection, fusion, and real-time target recognition and tracking (Xiang et al., 2023).

ATS widely integrates heterogeneous sensing technologies to capture multi-dimensional data on the physical environment, traffic participants, and system operating states. However, due to differences across sensors in terms of information granularity, sampling frequency, and latency, effective multi-source fusion is required to produce accurate and reliable results. Typical approaches include Bayesian filtering, Kalman filtering, confidence-weighted fusion, and graph-optimisation-based methods (Dufera et al., 2025; Fang et al., 2021; Li et al., 2025b). In dynamic environments, it is essential to identify and track surrounding objects. This capability forms the foundation for situational awareness and further supports obstacle avoidance, path optimisation, and interactive decision-making. Recent advances in deep learning-based detection networks, have enabled robust multi-class target recognition. Similarly, multi-target tracking algorithms such as Simple Online and Realtime Tracking (SORT) and Deep SORT (Yang et al., 2024a) provide cross-frame tracking of dynamic objects, thereby enhancing the perception capacity.

(2) Situational awareness

Following information perception, ATS must comprehensively analyse the acquired data to infer environmental states, situation evolution trends, and associated risk levels, a capability referred to as situation awareness (Colombo et al., 2025; Liu et al., 2024c). Core components of situation awareness include scenario modelling, conflict detection, risk assessment, and behaviour and intention prediction.

Through techniques such as graph-structured modelling and semantic segmentation, environmental elements, spatial topology, and traffic rules can be transformed into structured inputs for scenario description. Based on variables such as target location, velocity, and heading, ATS can estimate the likelihood of potential collisions or conflicts and quantify risk levels to guide subsequent decision-making. Conflict detection approaches include geometric indicators, e.g., Time-To-Collision (TTC), Time to Closest Point of Approach (TCPA), and Distance at Closest Point of Approach (DCPA) (Saini et al., 2025; Zhang et al., 2025b), probabilistic risk prediction methods (e.g., Monte Carlo simulation) (Jiang et al., 2019; Perera et al., 2015), and risk-field modelling based on spatio-temporal relationships (Jeena et al., 2025; Rong et al., 2021). To improve robustness, uncertainty representations, such as confidence intervals, fuzzy sets, or adaptive risk thresholds, are often integrated into conflict detection and assessment frameworks (Perera et al., 2014). For dynamic traffic participants, predicting decision intentions and future behaviours is essential to enable proactive collision avoidance and route planning. Commonly used techniques include machine-learning models based on historical trajectory data, Transformer-based networks, multi-modal behaviour prediction frameworks, and game-theoretic modelling methods.

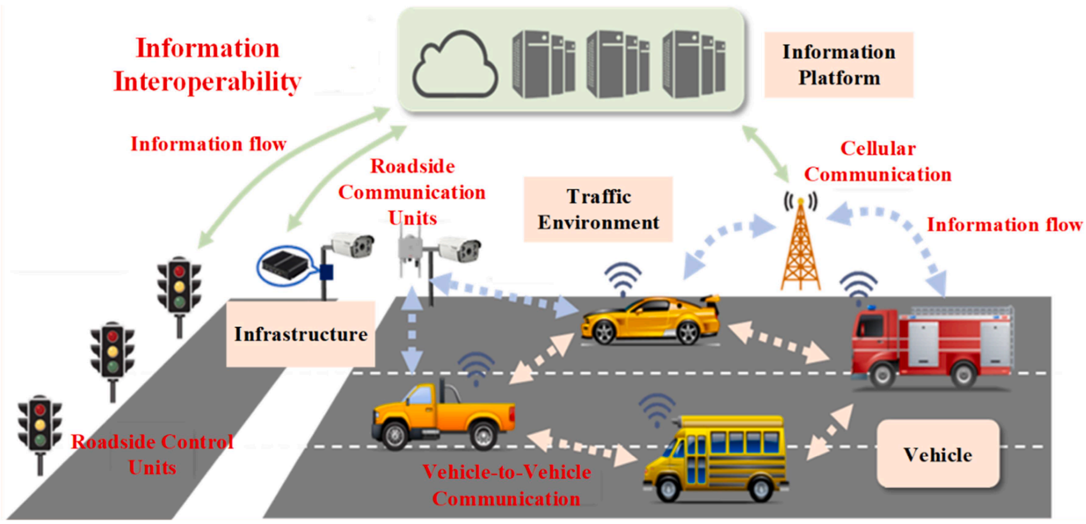

Fig. 3. Information interoperability of ATS.

These approaches have been widely applied in scenarios such as intersection negotiation for autonomous cars, intelligent ship trajectory prediction, and multi-unmanned aerial vehicles (Zhang et al., 2025a).

3.2. Interoperability of information, functional, element

Interoperability technologies that enable diverse traffic entities to collaborate and operate in synergy are central to the transition from human-dominated control to high-level autonomy in ATS (Jia et al., 2022). Their core function lies in facilitating information sharing, functional enhancement, and resource allocation among entities with varying degrees of autonomy (Tolk, 2013). The interoperability framework is typically organised into a three-level architecture with a logical progression, defined by the depth of information processing and the scope of system collaboration. These include information interoperability, functional interoperability, and element interoperability.

(1) Information interoperability: The ability to exchange and utilise information

Information interoperability refers to the capability to exchange and effectively use information, as shown in Fig. 3. Its primary objective is to eliminate barriers to information exchange among transportation entities and to enhance system compatibility across heterogeneous architectures. To achieve this, entities must both broadcast their own status information and receive essential information disseminated by others, while accounting for variations in granularity, frequency, and reliability across multi-source heterogeneous data. Unified interface protocols enable communication between different software and hardware platforms, while low-latency communication protocols ensure that data is transmitted securely and within the required timeframe. In this way, information interoperability improves both the safety and efficiency of ATS. Within this framework, information exchange underpins functions such as collaborative decision-making, thereby enhancing the system's overall intelligence.

(2) Functional interoperability: The capacity to exchange and utilise functions

Functional interoperability denotes the ability of transportation entities to exchange and utilise functions, with the aim of enhancing their intelligence and supporting the self-organisation and autonomous operation of the overall system, as shown in Fig. 4. Given the heterogeneity of entities, achieving functional interoperability requires a semantic-consistency framework that ensures coherent representation of data and logic across domains and entity types. In addition, mechanisms for optimised allocation of sensing, communication, and control resources, coupled with swarm-intelligence-based game-theoretic decision-making, are essential. Within this framework, the exchange of functions enables entities with medium or low levels of intelligence to be elevated to higher levels, thereby fostering swarm intelligence across ATS.

(3) Element interoperability: The ability to exchange intelligence and enhance hybrid intelligence

Element interoperability represents the highest level of interoperability in ATS, referring to the capability of traffic entities to exchange intelligence and achieve hybrid intelligence enhancement, as shown in Fig. 5. At this stage, entities continuously learn and evolve autonomously through interactions such as data sharing, functional collaboration, and knowledge transfer with other entities, thereby improving their individual intelligence. Simultaneously, by coordinating element-level resources among entities with varying

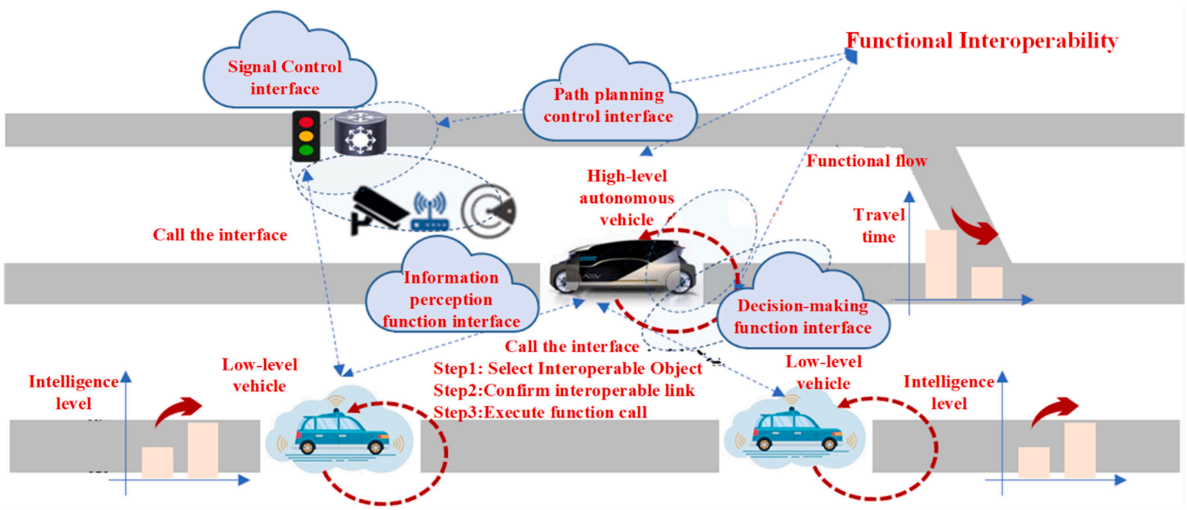

Fig. 4. Functional interoperability of ATS.

degrees of intelligence, an intelligent interaction framework can be established to realise collective hybrid intelligence enhancement across the ATS. At the functional interoperability level, traffic entities need to leverage the capabilities of other entities to enhance performance and are still at a relatively low level of intelligence. In contrast, traffic entities at the element interoperability level have achieved a true improvement and evolution of their own intelligence.

3.3. Collaborative computing technology

ATS is characterised by wide physical distribution and stringent real-time requirements. The perception and computing capacity of a single transportation entity are inherently limited, necessitating communication and collaboration among multiple entities to achieve human-like analysis and decision-making. This ensures overall system efficiency through collaborative computing technologies. Current research on ATS computing technologies is concentrated in three main areas: computing architectures and information models, multi-agent collaborative computing models, and security-oriented hierarchical assessment frameworks.

(1) Computing architecture and information model

Traditional architectures often suffer from limited interoperability, low efficiency in end-edge-cloud computing collaboration, and fragmented multi-modal information models. These limitations make their difficult to meet the stringent requirements of real-time computation and decision-making. As a result, research has shifted towards collaborative architectures and unified modelling approaches that emphasise vehicle-infrastructure cooperation and the integration of artificial intelligence with edge computing (Kumar et al., 2024). Information modelling plays a core role in this transition, encompassing the integration of Building Information Model (BIM), City Information Modelling (CIM), Geographic Information System (GIS), Internet of Things (IoT), and traffic simulation for both the full life-cycle management of transport facilities and the modelling of complex operational environments (Zhang et al., 2016; Belcher et al., 2023; Mirboland et al., 2021; Xu et al., 2021b). Increasingly, these models are being combined with artificial intelligence and data mining techniques to enhance adaptability and predictive capacity. Furthermore, standardised modelling methods such as Unified Modelling Language (UML) and Integrated Definition (IDEF) offer valuable tools for complex system representation, striking a balance between analytical rigour and practical flexibility (Shibayama, 2016; Zhou et al., 2004; Kermanshachi et al., 2019; Kim et al., 2003; Zhang et al., 2008).

(2) Multi-agent collaborative computing model

Collaborative computing is essential for achieving efficient decision-making in ATS. Current research primarily focuses on information timeliness and the integration of communication and computing. The Age of Information (AoI) has emerged as a key metric for assessing the effectiveness of information updates (Kosta et al., 2021); however, traditional linear models can hardly capture the dynamic value of information (Kam et al., 2013; Kam et al., 2016; Kosta et al., 2021). To address this, approaches based on mutual information and nonlinear fitting have been introduced. Meanwhile, joint optimisation of communication and computation has been investigated using methods such as non-convex optimisation and reinforcement learning, enabling adaptive resource allocation for reasoning and training (Jiang et al., 2023; Liang et al., 2024; Pervez et al., 2024; Tang et al., 2025). These advances have improved efficiency in areas such as user selection, spectrum allocation, in-flight computing, and model compression (Chen et al., 2021b; Sun et al., 2022). Nevertheless, most existing approaches continue to treat communication and computation in isolation, overlooking the coupled effects that directly influence control performance and system reliability. The multi-agent collaborative computing framework is shown in Fig. 6.

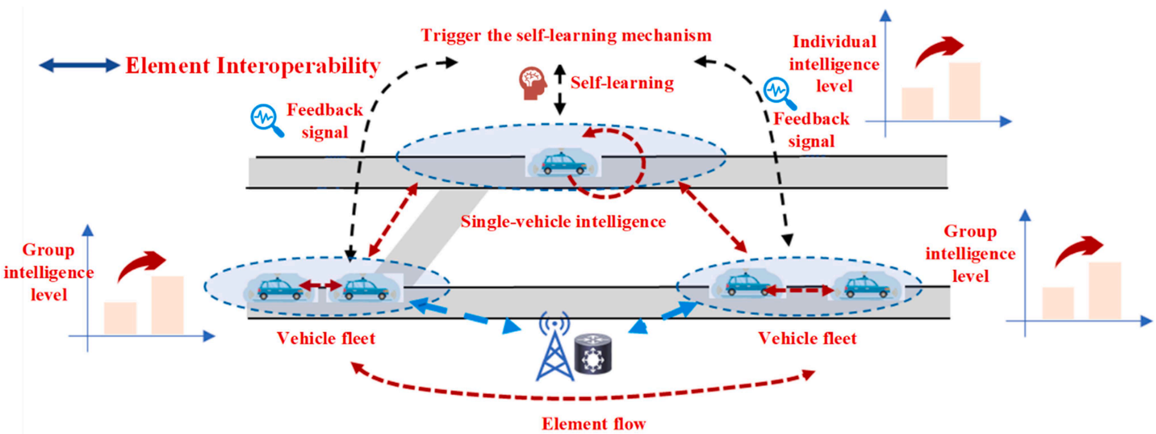

Fig. 5. Element interoperability of ATS.

(3) Security hierarchical assessment model

Security is fundamental to the reliable operation of ATS. Poisoning attacks compromise learning by contaminating training data, while adversarial attacks deceive perception and decision-making models through carefully crafted perturbations. Existing studies have highlighted vulnerabilities in both the training and inference stages, but they are largely limited to static images or conventional models and fail to capture the complexity of dynamic transportation environments (Chen et al., 2021a; Xu et al., 2021a). Therefore, it is necessary to establish a hierarchical security assessment framework tailored to dynamic and multi-modal scenarios. Such a framework should integrate distributed and trustworthy training mechanisms with lightweight, real-time detection and adaptive defence methods. This will enable ATS to progress beyond passive defence towards active immunity, thereby enhancing resilience against increasingly sophisticated security threats.

3.4. Digital twin architecture and state evolution

Digital twin technology for ATS provides the core foundation for achieving autonomous decision-making, comprising three key stages: meta-model construction, cross-domain interoperability, and state evolution (Kusic et al., 2023). Meta-model construction establishes the underlying architecture of the system, offering the structural basis for the digital twin entity. Cross-domain interoperability ensures real-time data synchronisation and bidirectional interaction between the physical and digital spaces, enabling dynamic mapping and collaborative control. State evolution serves as the intelligent core, undertaking simulation, autonomous learning, and decision optimisation, thereby advancing the system towards higher-level awareness and prediction capabilities.

(1) Meta-model construction

Meta-model construction employs a multi-dimensional and multi-level approach to digitally model the ATS, as shown in Fig. 7. The physical system is divided into system, equipment, and component levels to support cross-scale analysis and integration. Across model dimensions, it encompasses geometry, physics, rules, and behaviour, enabling detailed modelling (Tao et al., 2018; Zhang et al., 2023). Finally, UML is adopted to clearly define the meta-attributes and their relationships within the meta-model.

(2) Cross-domain interoperability

In Fig. 8, cross-domain interoperability is categorised into three levels: within the physical spaces, between the physical and digital spaces, and within the digital spaces. Each level facilitates information exchange, collaborative operation, and resource sharing to deliver safe, efficient, and seamless transportation services. Interoperability within the physical spaces emphasises data interaction between environmental sensing devices and on-board sensors within the perception unit of transportation equipment. Its core lies in constructing a local closed-loop framework centred on sensor fusion at the vehicle side, supported by intelligent processing through edge computing devices and collaborative communication (Hidayat et al., 2022). Interoperability between the physical and digital spaces aims to connect perception, modelling, and communication channels between physical-world entities and their digital twin models, thereby establishing a bidirectional, interactive, and dynamically evolving closed-loop framework. Interoperability within the

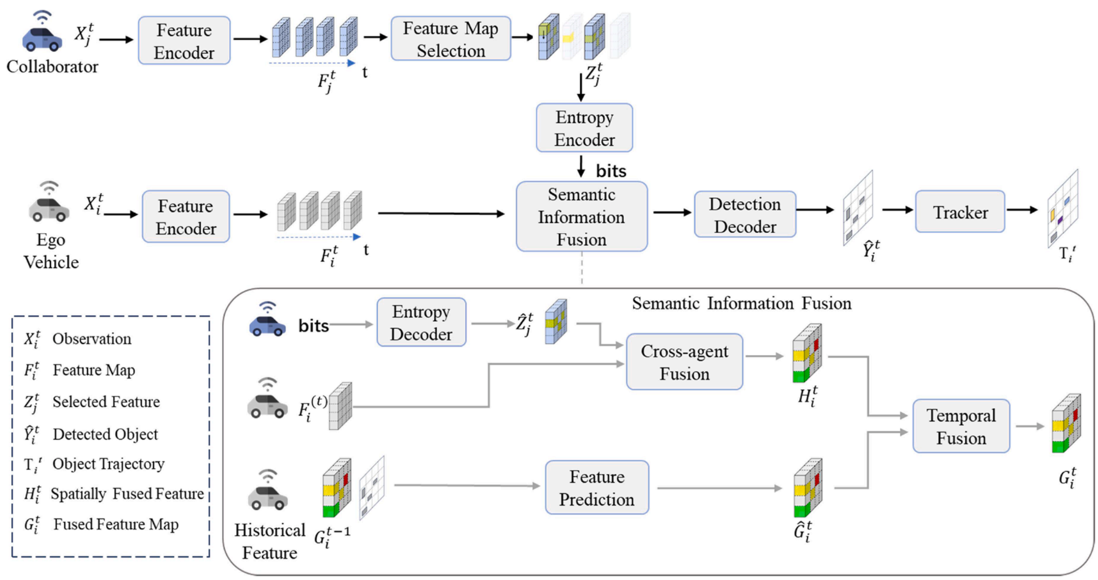

Fig. 6. Multi-agent collaborative computing framework (Shao et al., 2025).

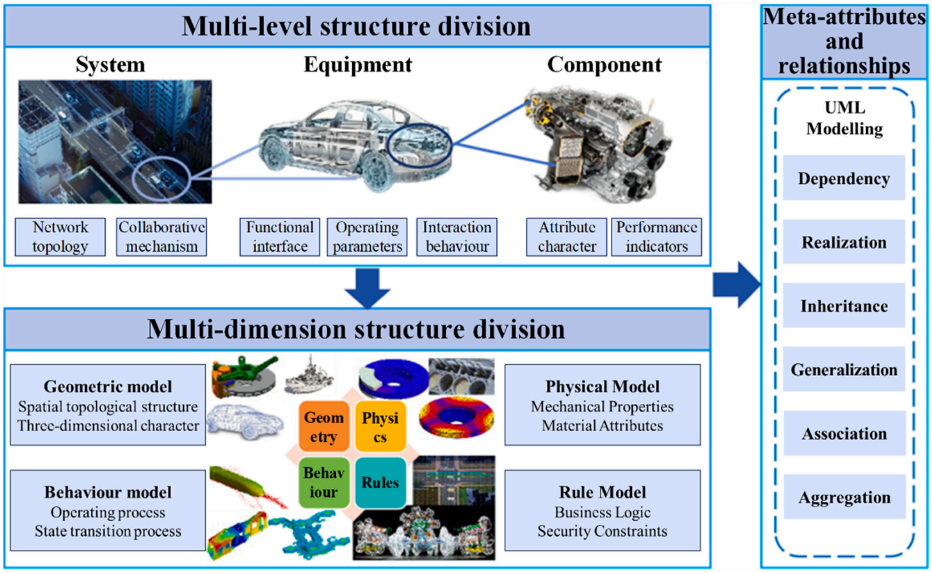

Fig. 7. Diagram of meta-model construction.

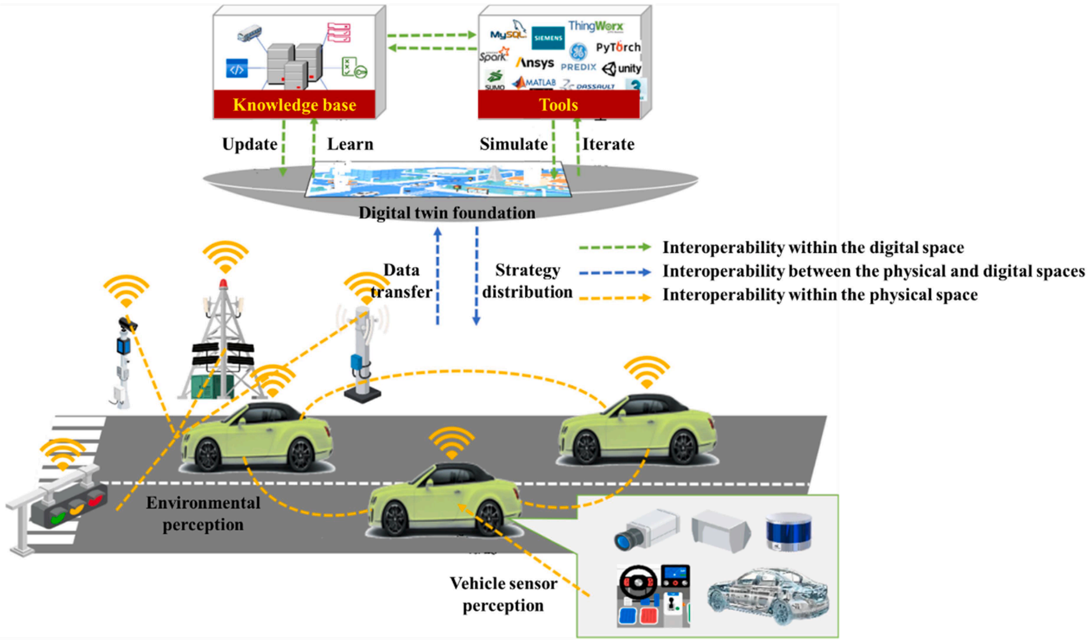

Fig. 8. Cross-domain interoperability technology.

digital spaces refers primarily to data sharing and simulation coordination mechanisms among different platforms, subsystems, or algorithmic modules. Unlike the previous two levels, it does not directly involve physical entities but focuses on achieving functional complementarity, model linkage, and data consistency across simulation environments.

(3) State evolution

State evolution refers to a closed-loop framework that integrates multi-scale data fusion, knowledge-model integration, state simulation, and level simulation, as shown in Fig. 9. By constructing a prediction-evolution link through the integration of artificial intelligence and mechanism-based models, it enables intelligent simulation of traffic system state changes, hazard identification, and emergency control (Rathore et al., 2021; Wu et al., 2017). In combination with digital meta-models and cross-domain interoperability, prediction results can be leveraged to drive multi-level simulation environments, thereby enabling dynamic reproduction and verification across the system-equipment-component (Yan et al., 2025a).

4. Standards and applications of ATS

4.1. Standard and regulatory frameworks

Standard and regulatory frameworks provide the fundamental assurance for the engineering implementation, industrialisation, and cross-system interoperability (Dinckol et al., 2023). Given that ATS integrates complex software and hardware architectures, the absence of unified standards would significantly hinder collaborative operation across autonomous vehicles and constrain the development of the wider industrial ecosystem.

(1) International standard formulation

At present, a preliminary framework of standards has gradually emerged across road, maritime, and air and rail transport domains.

- Road vehicles: The Society of Automotive Engineers (SAE) has proposed the widely-adopted classification standard named SAE J3016, which defines six levels of driving automation (Yu et al., 2023). The International Organization for Standardization (ISO) introduced ISO 26,262 and 21,448, international functional safety standards for road vehicles, designed to prevent risks associated with functional failures (Sari et al., 2025). In addition, organisations such as the Institute of Electrical and Electronics Engineers (IEEE) and the European Telecommunications Standards Institute (ETSI) have developed V2X communication protocols, laying the foundation for vehicle-infrastructure collaboration.
- Maritime transport: The International Maritime Organization (IMO) has advanced a regulatory framework for Maritime Autonomous Surface Ships (MASS), defining four levels of autonomy (Liu et al., 2024d; Xu et al., 2025a): L1) automated processes and decision support, L2) remote control with crew onboard, L3) remote control without crew, and L4) fully autonomous operation. Standardisation is expanding beyond terminology and classification to encompass safety verification, liability attribution, and operational regulations.
- Airspace: The International Civil Aviation Organization (ICAO), the Radio Technical Commission for Aeronautics (RTCA), and the European Union Aviation Safety Agency (EASA) has developed protocols for unmanned aircraft systems covering communication, safety access, identity verification, and operational rules. Standards such as ISO 21,384–3 (ISO, 2023), addressing the operational procedures for unmanned aircraft systems in different modes and airspace conditions, are being adopted.
- Rail transport: The International Electrotechnical Commission (IEC) and ISO have issued a series of standards for railway control and communication, including IEC 62,290 for urban guided transport management and command/control systems (Baranov et al., 2022). In Europe, the European Train Control System (ETCS) and the European Rail Traffic Management System (ERTMS) have

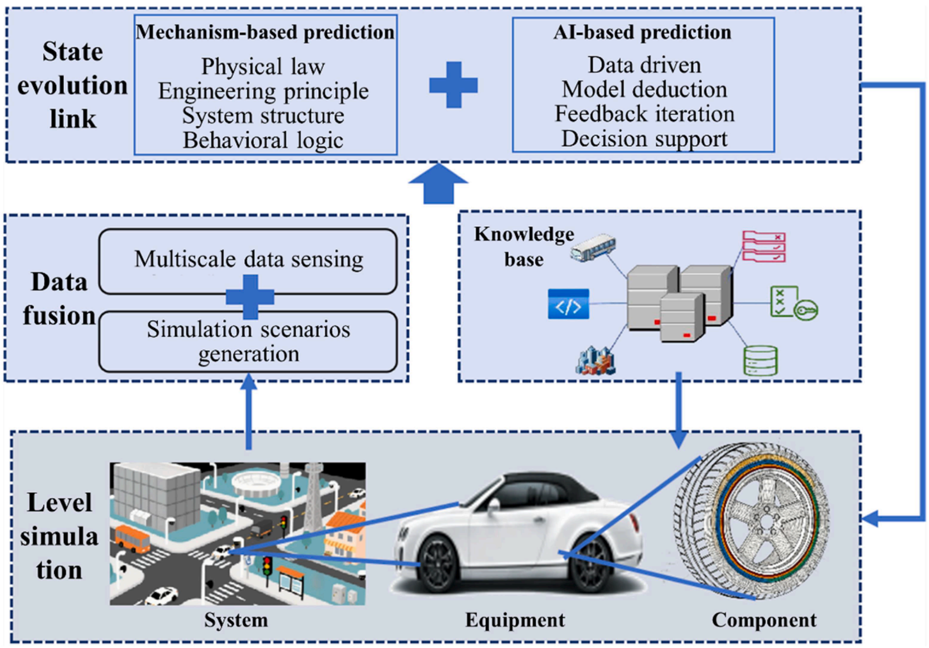

Fig. 9. Diagram of state evolution technology.

established unified signalling, control, and communication protocols to ensure interoperability across countries. For driverless metro systems, the International Association of Public Transport (UITP) has released guidelines on grades of automation (GoA1–GoA4) (Niu et al., 2021), where GoA4 corresponds to fully unattended train operation (UTO). These standards provide a clear reference for the classification, safety, and verification of intelligent rail transit systems.

Across these domains, a common trajectory is evident: the move toward task classification, functional modularisation, safety verification, and regulatory traceability. Unified terminology, functional specifications, and safety frameworks are becoming key pillars for cross-domain, collaborative development.

(2) Testing and certification systems

As levels of autonomy continue to advance, traditional paradigms of real-vehicle or physical prototype testing become insufficient to meet the safety requirements of large-scale, multi-scenario deployment (Xin et al., 2025). Accordingly, multi-tiered testing systems are being established, combining simulation platforms, closed test fields, and open operational trials, alongside the standardisation of test methods, performance indicators, and certification processes (Ji et al., 2025; Wang et al., 2022c).

- Road vehicles: Representative initiatives include PEGASUS in Germany (Shi et al., 2025), and China's intelligent connected vehicle testing (Zhang et al., 2025d). These projects assess performance across multiple dimensions, including sensor accuracy, perception fusion, path-planning robustness, behavioural rationality, and resilience under extreme scenarios.
- Maritime transport: Testing remains at an early stage. Current efforts focus on module-level verification, such as sea trials for autonomous navigation, collision avoidance, and remote operation. Guidelines like the IMO MASS Code and the technical specifications of the China Classification Society (CCS) provide reference processes (Liu et al., 2024b), but unified international evaluation standards are still lacking.
- Air traffic: Platforms are being developed for unmanned aircraft cluster coordination, autonomous obstacle avoidance, and low-altitude traffic management (De Luca et al., 2025). However, due to stringent safety requirements and fragmented regulatory boundaries, most testing remains at the project or regional level. Systematic integration and international harmonisation are still required for global deployment (Pongsakornsathien et al., 2025).
- Rail transport: Intelligent rail systems, particularly driverless metro networks, have developed relatively mature testing and certification frameworks. Testing focuses on communication-based train control (CBTC) systems, platform screen door coordination, and emergency handling under fully unattended train operation (GoA4) (Wang et al., 2018).

Collectively, these efforts highlight a shift from traditional prototype-based verification toward standardised, systematic, and internationally harmonised testing regimes, which not only ensure technological reliability and safety but also provide with the institutional foundation for regulatory acceptance and public trust in ATS.

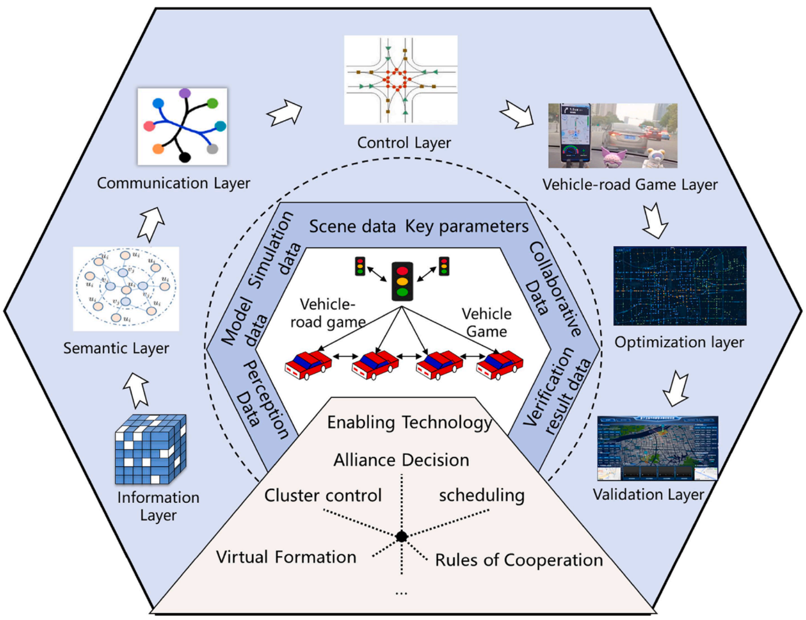

Fig. 10. Schematic diagram of a crowd-intelligence decision-making control system based on interoperability.

4.2. Application cases

(1) A crowd-intelligence decision-making control system based on interoperability

The interoperable swarm intelligence decision-making and control system is a technological achievement (Fig. 10) (BUAA, 2025). With the rapid development of next-generation information technology, the transition from driver assistance to autonomous intelligence is inevitable for vehicles, including cars, ships, aircraft, and trains. The mixed traffic of autonomous vehicles with multiple levels of intelligence will inevitably become a necessity in future traffic systems. Traditional traffic control paradigms are unable to adapt to the open and collaborative environment of heterogeneous vehicles, and system performance has reached a bottleneck. To this end, the concept of swarm intelligence control was proposed, which enables interoperable negotiation between different levels of traffic agents to achieve efficient and balanced control of traffic systems in future mixed traffic environments.

Based on the concept of swarm intelligence control, driven by interoperable perception, communication, and control technologies, cooperative rules for traffic agents were established with different levels of autonomy and a coalition consensus decision-making model was constructed, enabling the automatic generation and continuous iterative updating of optimal control strategies in dynamic traffic scenarios. To meet the task requirements of traffic agents with varying levels of autonomy, the team achieved breakthroughs in coalition-based hierarchical empowerment control technology and developed an interoperable swarm intelligence decision-making control system, enhancing the control system's intelligence and control capabilities.

The performance of the interoperable swarm intelligence decision-making control system was validated through practical demonstrations (Fig. 11). The system supports various traffic control types, including road signal negotiation control and vehicle-road game control, as well as 12 typical interoperable application scenarios, including vehicle-road game priority and vehicle-platooning control. The system achieved a system decision time $\leq$10 min and a control system response time $\leq$500 milliseconds, increasing the average road vehicle speed by 5.2 % and significantly improving traffic efficiency.

(2) Autonomous ship navigation brain system based on artificial intelligence

The autonomous ship navigation brain system is a scientific and technological achievement developed (Wang et al., 2023). It is believed that the core of autonomous ship technology lies in intelligent navigation. By exploring the substitution of the "machine brain" for the "human brain" based on artificial intelligence and enabling machines to learn from the navigation experience of crew members, the functions of perception, awareness, and decision-making for autonomous ship navigation can be realised (Yan et al., 2022). The architecture of the autonomous ship navigation brain system is illustrated in Fig. 12.

The demonstration ship (Yujiaotou 001, as shown in Fig. 13) equipped with an autonomous ship navigation brain system has achieved a "shore-based control as the primary approach, supplemented by ship-side monitoring" operation mode (Yan et al., 2024), by integrating the three parts of the holographic perception system (Fig. 13(a)), the on-board autonomous navigation system (Fig. 13(b)), and the remote control platform at the shore (Fig. 13(c)).

The demonstration ship successfully implemented multiple core functions, including autonomous navigation, remote control, fully

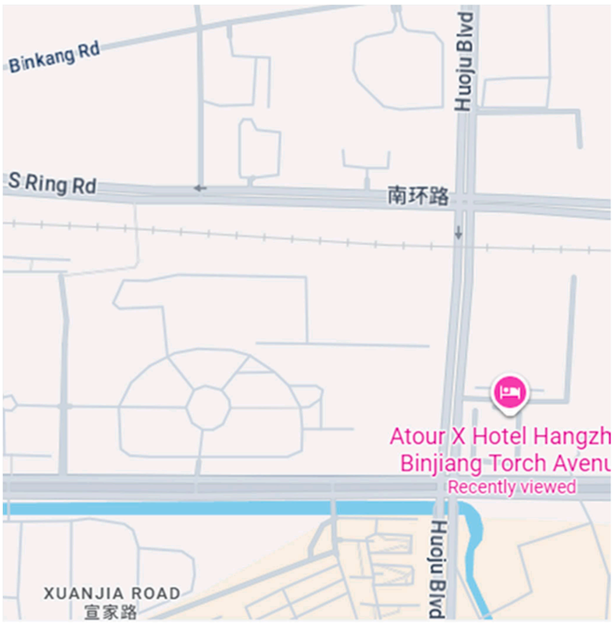

Fig. 11. System Verification Scenario.

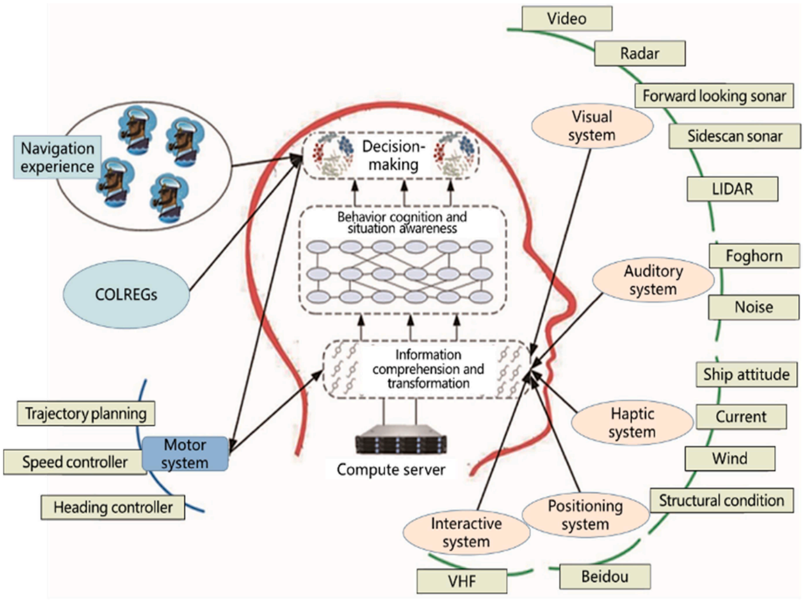

Fig. 12. Architecture of autonomous ship navigation brain system (Yan et al., 2022).

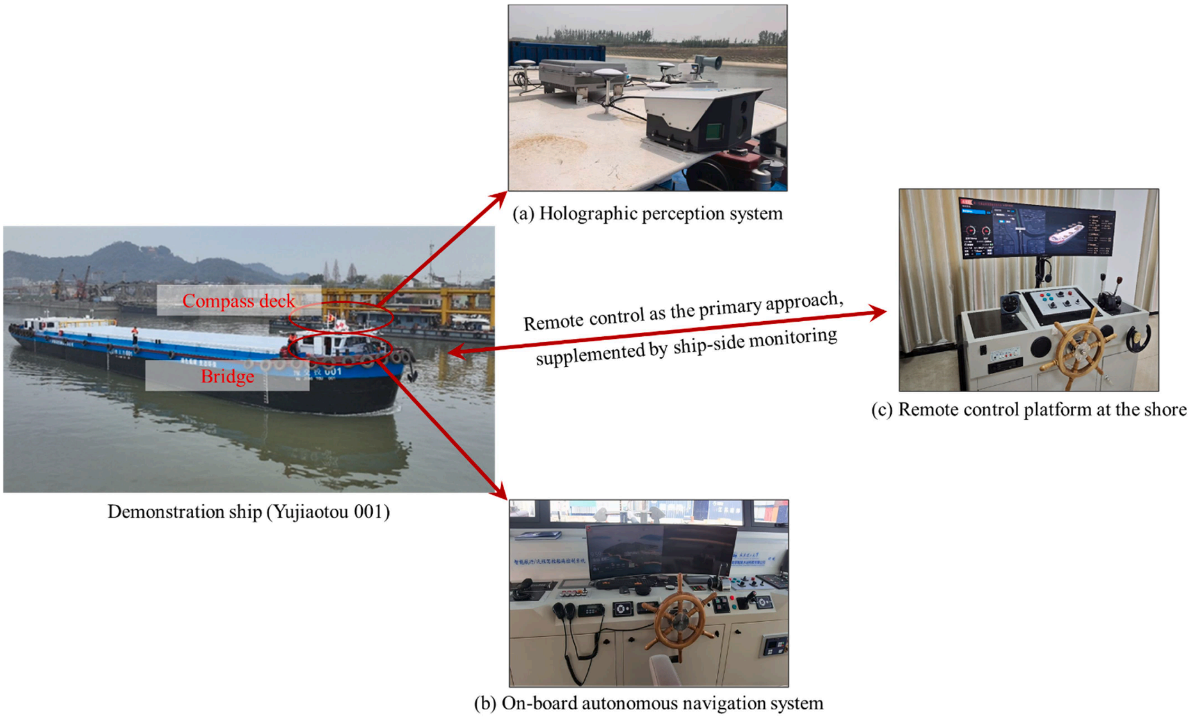

Fig. 13. Demonstration ship (Yujiaotou 001).

autonomous operation under human supervision, and collision avoidance. During navigation across the Qiantang River and the Yangtze River, the ship focuses on testing high-level navigation support functions, and all design requirements are fully achieved. The number of manual interventions and takeovers per 10 km is reduced to 0.371. In the 28 km Class IV inland waterway from Pingdingshan Port to Junli Lock (which includes five low bridges), the ship successfully completed the world's first autonomous long-distance navigation test in a complex and narrow inland river channel, achieving stable autonomous navigation. Over the entire 1328 km voyage, the control accuracy remains within 5 m, successfully avoiding various obstacles, and maintaining a turning speed above 10 km/h even in sharp bends. Performance evaluation shows that, after the new generation shipping system is officially deployed, it can reduce crew's working burden by 50 %, increase single-ship loading capacity by 20 %, and shorten voyage time by 50 %, which significantly enhance transportation efficiency.

(3) Autonomous train Operation-Oriented automatic train operation architecture

The architecture for autonomous train operation provides a representative framework for realising fully intelligent railway systems (Jia et al., 2022). The essence of autonomous operation lies in constructing a "Train brain" that is capable of replacing and surpassing the functions of human drivers and dispatchers. By shifting from manual decision-making to machine intelligence, the system enables trains to achieve autonomous perception, intelligent planning, coordinated decision-making, and precise control under complex railway conditions. The operation mechanism of "Train brain" is illustrated in Fig. 14.

Driven by advances in artificial intelligence and digital twin technologies, the proposed architecture establishes a tri-layer collaborative framework encompassing the physical, virtual, and interaction spaces (Wei et al., 2024). Integrating theories from cognitive science and systems engineering, the system forms a closed-loop operational mechanism characterized by perception, cognition, decision-making, control, execution, memory, and learning. The architecture is illustrated in Fig. 15

The entire process operates as a continuously evolving intelligent loop. Specifically, the interaction space enables a comprehensive perception of the physical environment, which is accurately mapped into the virtual space. Within this virtual domain, the system conducts situational understanding and predictive simulation to generate coordinated decisions. After validation, these decisions are executed by the train in the physical world. Simultaneously, all operational data are archived and used to refine the digital models through simulation-based learning. This iterative optimisation fosters self-evolution of the system, thereby ensuring autonomous, intelligent, and safe operation of trains in dynamic and complex environments (Song et al., 2023a).

5. Outlook for ATS

5.1. Research gaps assessment

To advance the development of ATS towards maturity, several research gaps must be addressed. The following outlines the core challenges that require further research.

Current theoretical foundations are inadequate to support the complexity and extensibility of ATS. A limitation is the lack of a system-of-systems theory capable of modelling interoperability, dynamic optimization, and emergent resilience across heterogeneous transport subsystems. Furthermore, despite the adoption of hybrid modelling, a coherent framework for formal verification, safety certification, and explainability, remains developing, hindering progress towards a reliable and adaptable system architecture.

Moreover, there are still many limitations in key technologies. In perception, the shift from passive perception to dynamic perception networks requires advances in cross-modal data fusion and uncertainty representation. For interoperability, standardised, intelligent and secure functions will move cross-domain collaboration from isolated breakthroughs to integrated system-level solutions. The computing technologies still lacks efficient solutions for integrated system architecture, multi-entity decision-making under latency and energy constraints, and security with defence, which are essential for reliable large-scale deployment. Meanwhile, the digital twin technology still faces technical challenges in High-fidelity meta-model construction, real-time cross-domain interoperability, and closed-loop state reasoning.

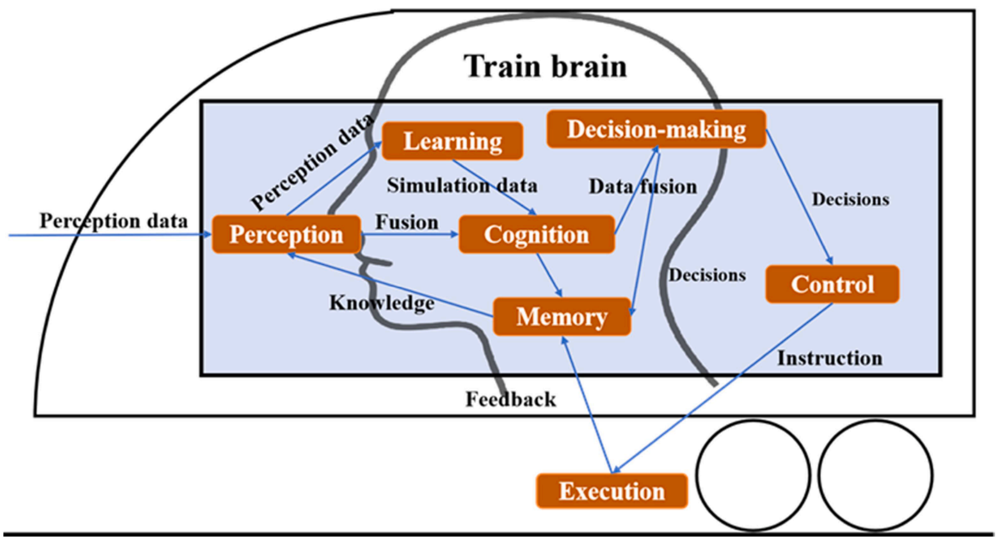

Fig. 14. The operation mechanism of the Train brain.

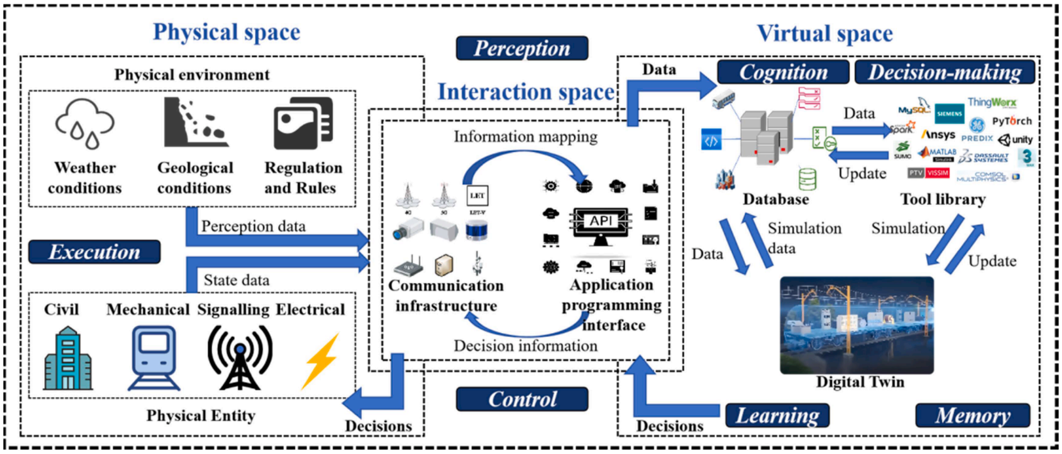

Fig. 15. Autonomous transportation system digital twin system.

5.2. Development trends of the theoretical

The theoretical foundations of ATS, rooted in systems engineering methodologies, closed-loop architecture, and the integration of model-driven and data-driven approaches, are evolving in line with the growing complexity of autonomous and multimodal transport. Future development trends can be summarised in three complementary directions:

- From systems engineering to system-of-systems integration: While systems engineering has provided the methodological basis for top-level design, requirement decomposition, and hierarchical coordination, future research will move toward system-of-systems theory. This emphasises interoperability among heterogeneous transport subsystems, multi-objective optimisation across modes, and resilience against uncertainties at the system level.
- From closed-loop architecture to adaptive and human-like awareness: The perception-awareness-decision-control-collaboration-improvement architecture will evolve to incorporate adaptive mechanisms that mirror human reasoning. This includes cognitive modelling of behaviour, intention-aware decision-making, and real-time learning capabilities that allow ATS to function robustly in highly dynamic, uncertain, and mixed-traffic environments (Durlik et al., 2025; Zhang et al., 2025f).
- From hybrid modelling to trustworthy, verifiable learning frameworks: The integration of data-driven and model-driven methods will expand into physics-informed learning and rule-constrained AI, ensuring both adaptability and interpretability (Liu et al., 2025a). Moreover, more emphasis will be placed on formal verification, safety certification, and explainability, creating theoretical guarantees for the trustworthy and transparent deployment of ATS.

5.3. Development trends of key technologies

In the future, the development of key technologies for ATS will move towards deeper integration, distributed intelligence, and strengthened system resilience.

Ubiquitous perception and environment mapping technologies will increasingly focus on extending the scope of perception and enhancing cross-modal modelling capabilities. The trend is shifting from passive perception based on fixed sensors to dynamic perception networks that are deployable, collaborative, and shareable. This includes data collaboration across multiple platforms, ground, air, and sea, as well as semantic mapping of dynamic scenarios and joint representation of multi-source uncertainties. Beyond identifying explicit targets, these technologies will also enable the detection of potential risk factors and the anticipation of scenario evolution trends.

The research on interoperability technologies will evolve in three key directions towards standardised, intelligent and secure functions. First, emphasis will be placed on semantic unification and standardisation, building consistent cross-domain frameworks and standards to enable efficient information, functions, and element exchange. Second, interoperability will advance dynamically from information exchange to function sharing and ultimately to element-level intelligence enhancement, driving entities to shift from passive data carriers to autonomous intelligent agents and supporting system-wide collaboration. Third, increasing attention will be given to security and trustworthiness, with scalable protection and trusted interaction mechanisms established to ensure robustness in complex traffic environments. Overall, the future of ATS interoperability lies in moving from isolated breakthroughs to integrated system-level solutions, forming a cornerstone for cross-domain collaboration and system autonomy.

The computing technologies are expected to advance along three main directions. First, system architectures will evolve from separated designs to integrated cloud-edge-end frameworks, enabling the fusion of BIM/CIM with dynamic sensing data and the development of unified semantic models and interoperability standards to support digital twin transportation. Second, collaborative computing will progress from isolated transmission and computation to coupled optimisation, supported by scenario-adaptive timeliness models and methods such as federated learning, airborne computing, and model compression, thereby improving multi-entity decision-making under latency and energy constraints. Finally, security will shift from static defence to dynamic immunity, with an emphasis on lightweight real-time detection, adaptive defence for time-series and multi-modal data, and distributed trustworthy training mechanisms based on federated learning and blockchain. Collectively, these trends will provide a solid foundation for the reliable, intelligent, and secure operation of ATS in increasingly complex transportation environments.

The digital twin constitutes the core foundation of ATS through three key processes: meta-model construction, cross-domain interoperability, and state reasoning, which will drive ATS towards the intelligent paradigm of full-scale autonomy, collaborative symbiosis, and trustworthy sustainability. This transformation shifts the transportation system from a passive management object into an organic, adaptive entity capable of dynamically responding to complex environments, making unsupervised decisions, and enabling cross-domain collaboration. It lays the groundwork for a multimodal, collaborative, green, efficient, and reliable three-dimensional transportation network.

5.4. Development trends of standards and applications

Research on standard and regulatory frameworks is moving towards greater integration and international harmonisation. Across road, maritime, air, and rail transport, standards are converging to common principles of task classification, functional modularisation, safety verification, and regulatory traceability, providing a shared foundation for multimodal interoperability. Meanwhile, testing and certification are evolving from traditional prototype trials to multi-tiered systems that combine simulation, closed testbeds, and open operational environments, with a growing emphasis on standardised methods, resilience evaluation, and extreme-scenario validation. The trend is shifting from fragmented, mode-specific approaches to unified, systematic, and internationally recognised frameworks, which will be essential for ensuring safety, fostering public trust, and supporting the sustainable evolution of ATS.

Meanwhile, future applications of ATS are expected to transition from isolated use cases to a new stage characterised by multimodal integration, cross-regional collaboration, and increasingly complex task requirements. Two major directions can be identified as follows:

(1) Enhancement of autonomous operation in highly complex traffic scenarios

In urban transportation, autonomous cars must cope with dense pedestrian flows, irregular behaviours, and inconsistent traffic signals. This demands advanced semantic recognition, human-machine cooperation mechanisms, and game-theoretic decision-making (Rahman et al., 2023). In the maritime, autonomous ships will need to conduct collision avoidance, route re-planning, and collaborative berthing with tugboats under conditions of heavy traffic, narrow waterways, or rapidly changing weather (Xin et al., 2025). In low-altitude airspace, emerging applications such as urban air mobility (UAM) and disaster rescue require autonomous aircraft to support multi-layer scheduling, three-dimensional obstacle avoidance, and integrated air-ground communication, meeting stringent safety and real-time performance requirements (Yang et al., 2024b).

(2) Emergence of cross-modal collaborative autonomous systems

The future of ATS will be defined by land-sea-air integrated operations, where cars, ships, and aircraft operate in coordinated networks. In port logistics, seamless task coordination will be realised among autonomous trucks, unmanned ships, and intelligent storage yards (Zhang et al., 2018). In urban or coastal scenarios, cooperative scheduling between aerial drones, ground-based unmanned vehicles, and intelligent patrol boats will become commonplace (Chai et al., 2024; Zhao et al., 2025). These systems demand a high degree of consistency in task planning, communication protocols, operational standards, and command logic, alongside capabilities for cross-modal data fusion, cross-domain path optimisation, and coordinated behaviour control.

Overall, ATS are evolving beyond the intelligence of individual vehicles toward the system-level autonomy of heterogeneous collaboration, cross-platform integration, and semantics-driven task execution. This represents not only an extension of autonomous functions but also a reconfiguration of the transportation ecosystem into a unified, resilient, and adaptive system.

6. Conclusion

ATS, as a pivotal direction in the evolution of transportation, is rapidly advancing from theoretical exploration to practical deployment (You et al., 2024a). It represents a transformative paradigm in transportation, marking the transition from human-centred operation to system-level autonomy. As a complex system integrating autonomous vehicles, digital infrastructure, information platform, and traffic environment, ATS aims to realise autonomy, safety, efficiency, and sustainability across all modes of transport. It extends the technology from individual vehicle to coordinated, multi-agent transportation systems and ultimately becomes the advanced evolutionary form of ITS.

This review systematically examines the current state and future trends of ATS. The theoretical foundations are summarised from the system engineering methodology, the closed-loop architecture, and the hybrid modelling mechanism. It clarified the concept, composition, and characteristics of ATS, and comparatively analysed its relationships and evolutionary pathways with TTS, ADT, and ITS. Moreover, the key technologies, including information perception, interoperability, collaborative computing, and digital twin, are comprehensively reviewed, accompanied by standard and regulatory frameworks and practical application cases. Looking ahead, ATS will continue to evolve through advances in multimodal perception, game-theoretic and learning-based decision-making, distributed collaborative control, and verifiable safety assurance. Cross-modal and cross-scenario integration, spanning urban traffic networks, maritime logistics, and low-altitude airspace, will foster a more closely interconnected transportation ecosystem. Supported by policy guidance, standardisation efforts, and industrial collaboration, ATS are expected to represent the ultimate evolution of ITS, driving a paradigm shift in global transportation toward autonomy, resilience, and sustainability (Jia et al., 2022).

CRediT authorship contribution statement

Jiongjiong Liu: Writing – original draft, Visualization, Methodology, Data curation, Conceptualization. **Haiyang Yu:** Writing – original draft, Visualization, Methodology, Formal analysis. **Ailing Huang:** Visualization, Investigation, Data curation. **Xiaoping Ma:** Writing – original draft, Visualization, Software, Funding acquisition, Conceptualization. **Bing Wu:** Writing – original draft, Visualization, Software, Conceptualization. **Jian Sun:** Validation, Methodology, Conceptualization. **Limin Jia:** Visualization, Supervision, Conceptualization. **Yong Chen:** Visualization, Investigation, Conceptualization. **Yunpeng Wang:** Writing – original draft, Supervision, Methodology. **Jin Wang:** Writing – original draft, Visualization, Supervision, Resources, Formal analysis, Conceptualization. **Xinping Yan:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Formal analysis, Conceptualization. **C. Guedes Soares:** Writing – review & editing, Writing – original draft, Supervision, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: The author Yong Chen is currently employed by Commercial Aircraft Corporation of China Ltd. The authors Xinping Yan and C. Guedes Soares are Editors-in-Chief, the authors, Yunpeng Wang, Jin Wang and Limin Jia, are Associate editors, the author Yong Chen is an Editorial Board Member, the author Bing Wu is an assistant Editor, the author Jiongjiong Liu is a Managing editor for *Autonomous Transportation Research*, and all of them were not involved in the editorial review or the decision to publish this article. All other authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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