

Shaping the future of transit: Innovations and prospects of intelligent connected bus systems

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ABSTRACT: As urbanization progresses, traffic congestion has become an increasingly severe issue confronting metropolitan areas worldwide. Intelligent connected bus systems (ICBS) emerge as a transformative solution to address this challenge. This review synthesizes ICBS as a layered closed-loop transit system that links infrastructure, intelligent buses, and operation platforms through continuous vehicle-road-cloud coordination. We first summarize its system architecture, including centralized operation platforms, smart intersections, smart bus stops, and intelligent connected buses, and explain how connectivity is translated into operational control. We then review two technical pillars under real-world deployment constraints: safety-oriented advanced driver assistance systems, covering cooperative perception, speed-signal coordination, and bus-oriented motion planning; and reliability-oriented intelligent scheduling, covering electrified fleet and charging management, automation-enabled dispatching, and fixed-flexible services. Finally, we discuss the transition toward precise public transit and highlight key challenges in system-level performance verification, robustness under uncertainty, infrastructure affordability and legacy integration, multi-purpose service integration and deployment, and bus-specific automated driving. Overall, ICBS should be understood as a service-oriented operational paradigm that enables more adaptive, reliable, and sustainable urban public transport.

KEYWORDS: intelligent connected bus systems (ICBS), vehicle-to-infrastructure, connected vehicle cloud platform, autonomous driving, intelligent dispatching

1 Introduction

Urban areas, though occupying merely 3% of the Earth's land surface, generate approximately 70% of the global Gross Domestic Product (GDP), consume over 60% of the world's energy, and account for 75% of carbon emissions (Haseeb et al., 2017; Kasman and Duman, 2015). Cities now accommodate more than 60% of the global population, making their development important for sustainability. Urbanization and economic growth also put greater pressure on urban road networks. When traffic demand approaches road capacity, congestion becomes a barrier to sustainable urban development (Çolak et al., 2016; Su and Yang, 2025).

Thus, selecting the appropriate urban transportation development model is not only a fundamental requirement for supporting sustainable urban development but also a critical decision in aligning with the trend of low-carbon city (Creutzig, 2016; Zhang et al., 2025; Othman et al., 2025). Intelligent connected bus systems (ICBS) can support this shift toward sustainable, low-carbon urban transport. Recent advancements in cutting-edge technologies such as big data, cloud computing, digital twins, and intelligent connected vehicles have paved new avenues for the development of innovative intelligent public transportation systems and the enhancement of service quality (Fei et al., 2024; Hancock et al., 2019; Zhang et al., 2024). However, on the one hand, existing public transit systems suffer from insufficient coverage in terminal road networks and imbalances in supply and demand across different time periods, resulting in limited ridership and demand coverage (Chen et al., 2020; Lin et al., 2025). On the other

hand, analysis results indicate that drivers are a critical factor in bus involved accidents (Feng et al., 2016). Consequently, the development of ICBS equipped with advanced driver assistance systems (ADAS) and intelligent scheduling capabilities is a necessity for enhancing traffic safety and alleviating urban congestion.

Research on intelligent public transportation systems can be dated back to the 1960s and 1970s, when rapid growth in private car ownership triggered severe congestion and motivated many countries to enhance transit service quality with emerging information technologies (Tanner, 1978). Early deployments and national programs emphasized foundational capabilities such as vehicle localization, passenger counting, real-time monitoring and dispatching support, bus priority and corridor control (Tsugawa, et al., 2001; Shaheen and Cohen, 2018; Zhang et al., 2024). With artificial intelligence and big data, bus schedule optimization can be coordinated with broader traffic management (Chavhan et al., 2020; Poinson et al., 2022). Coordinating services allows them to respond to real-time demand and can improve the passenger experience (Lyu et al., 2022; Zhang et al., 2025). More recently, the integration of connectivity and automation has further shifted the focus from information provision to closed-loop, system-level coordination across vehicles, infrastructure, and operation platforms (Bie et al., 2015; Wepulanon et al., 2020). This transition makes ICBS increasingly meaningful for addressing urban traffic issues, yet it also exposes practical bottlenecks that motivate the subsequent discussion in this survey, including safety under limited visibility and dense interactions, service reliability and headway regulation under

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stochastic disturbances, and deployment constraints stemming from legacy infrastructure and institutional coordination.

To unpack these bottlenecks, we structure this review around two technical pillars under real-world deployment constraints: safety-oriented ADAS and reliability-oriented intelligent scheduling. First, from the micro-level safety and efficiency perspective, bus operations have to be faced with dynamic interactions around stops and intersections, where occlusions, vulnerable road users, and dense mixed traffic make ego onboard perception and decision-making fragile (Kutela et al., 2023). Infrastructure-assisted sensing and cooperative decision support can cover blind spots and reduce conflict risks (Bai et al., 2024; Nie et al., 2024). Signal delays, demand fluctuations, and traffic interference can disrupt headways and cause bus bunching (Yang et al., 2024). ICBS uses real-time vehicle holding, fleet rescheduling, and corridor-level coordination to manage these disturbances. Transit priority and speed guidance coordinate control across consecutive stops and intersections (Li et al., 2026; Yuan et al., 2025). Existing infrastructure, equipment penetration rates, and cost effectiveness constrain sensing, control authority, and data sharing for safety and service reliability (Wu et al., 2018).

The remainder of this paper is organized as follows. Section 2 describes the ICBS architecture and core information interfaces. Sections 3 and 4 review ICBS-assisted ADAS in urban traffic and scheduling and fleet operations supported by connectivity and automation, respectively. Section 5 classifies the reviewed studies and discusses future research directions. Section 6 concludes the paper.

2 Intelligent connected bus systems: Concept and system architecture

This section introduces the overall concept of ICBS and presents a closed-loop system architecture that will be used in the subsequent sections on autonomous driving and intelligent dispatching. The fundamental principle of ICBS centers on enhancing both the intelligence and interconnectivity of public transportation networks through a collaborative vehicle-road-cloud ecosystem. Unlike traditional transit systems that operate as isolated units, ICBS couples buses, roadside intelligence, passenger terminals, and centralized operations through continuous data exchange and coordination. In this review, connectivity is treated as a prerequisite, and the emphasis is therefore placed on how system components form operationally meaningful feedback loops to support key transit objectives, including safety, punctuality, comfort, reliability, efficiency, and service accessibility. Fig. 1 provides a schematic overview of the main components and their interrelationships.

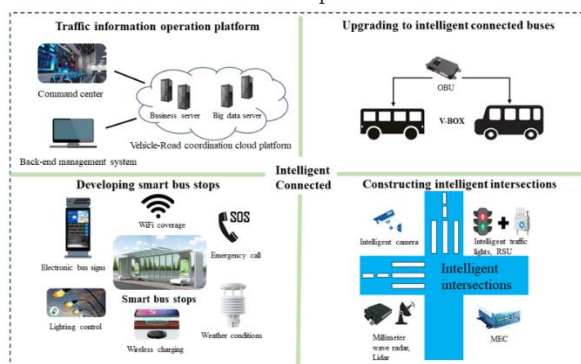


Fig. 1. Architecture of ICBS.

2.1. Core components

From an architectural perspective, ICBS refers to a bus-oriented intelligent transportation system that is commonly organized around four interacting components: a centralized operation and coordination platform, smart intersections as edge-intelligence nodes, smart bus stops as passenger-facing internet of things (IoT) terminals, and intelligent connected buses as mobile agents. This section defines each component by its system functions and interface boundaries.

The centralized operation and coordination platform manages ICBS operations, linking buses roadside nodes, and passenger terminals into a shared operating state (Dong et al., 2018). It consolidates multi-source data to support real-time situational monitoring, incident coordination, and network-level decision-making such as traffic management and strategic planning. The platform consists of a traffic command center, a back-end management system, and a vehicle-road coordination cloud platform (Hosu et al., 2015). The command center collects and processes city-wide data on bus status, traffic flow, and road conditions in real time. These data inform timely signal timing adjustments and bus route optimization to mitigate congestion and reduce delays. The back-end system uses historical and real-time data to forecast congestion and help plan operational responses in advance (Sun et al., 2021). The cloud platform connects the command center and management system with roadside infrastructure and buses. Through real-time data sharing, it supports interactions involving vehicles, roads, and pedestrians (Fu et al., 2023; Wang et al., 2023).

Smart intersections play a pivotal roadside component in ICBS because many of the factors that degrade transit performance such as signal delay, mixed-traffic conflicts, occlusions, and interaction complexity concentrate at intersections (Dresner and Stone, 2006). Within ICBS, intersections combine multi-modal sensing, roadside units (RSUs) for communication, and multi-access edge computing (MEC) for low-latency analytics (Tewolde, 2012). Their system role can be understood as a pipeline: local sensing produces raw observations about traffic status, RSUs act as the hub for vehicle-to-infrastructure (V2I) communication by receiving bus signals and coordinating with intelligent traffic signal systems, and MEC enhances local processing and responsiveness to support routing and scheduling optimization that alleviates congestion and improves efficiency and comfort (Annu, 2023). In many urban contexts, this component is critical for improving bus punctuality and regularity under constrained right-of-way, since it allows temporal rather than spatial priority to be granted. Beyond these functional building blocks, representative studies further envision intersections as structured state-aware smart city nodes for high-bandwidth applications validated on large-scale testbeds (Raychaudhuri et al., 2020), and some studies further extend to centralized coordination for non-signalized intersections enabled by vehicle-to-everything (V2X) communication (Xu et al., 2020).

Smart bus stops extend traditional shelters by integrating sensing, information gathering, and passenger interaction through an IoT-enabled design (Kong et al., 2024). Sensors such as cameras allow these stops to monitor pedestrian and nearby traffic flow, providing the broader system with situational awareness of the stop area (Lu et al., 2024). As roadside nodes, smart bus stops complement smart

intersections by supplying passenger demand and local traffic data to support upstream operational decisions. They also provide information to passengers (Kamal et al., 2019).

Intelligent connected buses form the execution layer of the system. They carry out fleet-level decisions on the road and provide operational feedback on route choices, task time windows, and reference driving speeds. Onboard ADAS and V2X cooperative perception support safety-critical dynamic trajectory planning in mixed traffic. Planning under operational constraints can improve service safety and reliability (Wang et al., 2023). During the transition to L4, onboard personnel may monitor safety and intervene as deployment arrangements require. At L4, the automated driving system performs the driving task and handles fallback within its operational design domain without relying on human takeover. Driverless services can operate in limited settings, such as dedicated lanes or fixed routes, with remote supervision or automated monitoring.

2.2. Data and control flow

Data exchange and control actions connect the four ICBS components through two feedback loops. One links perception, planning, and actuation. The other connects real-time operations with strategic planning so that the system can adapt over time.

At the operational level, vehicle and roadside sensing collect real-time information on traffic conditions, bus trajectories, stop usage,

passenger arrivals and the status of intersections. These data are transmitted to the cloud-edge platform, where they are evaluated against service objectives such as safety, schedule adherence and headway regularity. The platform or a local edge node then aids the vehicle in some missions. Typical examples include speed profile guidance for approaching buses, docking and departure guidance at busy stops, and signal priority decisions at intersections. To avoid ambiguity, this paper distinguishes three spatial control scopes. Vehicle-level control concerns the perception, planning and actuation of an individual bus. Corridor-level coordination takes account of joint control across a sequence of stops and intersections serving one or more interacting bus routes. Network-level operation concerns fleet assignment, charging, and service-design decisions across multiple routes, depots, or service areas. These spatial scopes are distinct from strategic, tactical, and operational decision horizons

To clarify the scope of ICBS relative to related intelligent transit paradigms, Table 1 compares ICBS with intelligent transportation systems (ITS)-enabled transit, connected bus systems, and smart transit platforms in terms of their dominant system scope and operational logic. These categories are not mutually exclusive in practice; rather, the comparison identifies the extent to which vehicle, roadside, and cloud functions are explicitly integrated into a common closed-loop control architecture.

Table 1. Comparison of ICBS and related intelligent transit paradigms).

Dimension	ITS-enabled transit	Connected bus systems	Smart-transit platforms	ICBS
Components/scope	Vehicles + ITS infrastructure; information/traffic management	Buses + RSUs + V2X; safety/priority	Platform + fleet/passenger data; service management	Platform + smart roadside/stops + buses; integrated operation
Data flow	Monitoring and information dissemination	Real-time exchanges	V2X Vehicle- and passenger-side data aggregation for fleet/service decisions	Continuous multi-source bus-road-cloud exchange
Control authority	Operator/infrastructure-centered management	Vehicle/corridor level safety and priority	Platform-centered fleet and service management	Hierarchical vehicle-, corridor-, and network-level control
Vehicle-road-cloud coordination	Partial and application-specific	Explicit bus-road linkage	Central platform data integration, roadside sensing and actuation remain external	Explicit coordination spanning buses, roadside nodes, smart stops, and cloud-edge platforms
Closed-loop operation	Monitoring-oriented open-loop or periodic feedback-based management	Real-time feedback for specific safety or priority functions	Service and fleet feedback, usually without integrated roadside actuation	Perception-planning-actuation and operational-execution-strategic-planning loops

Accordingly, ICBS is distinguished not by the isolated adoption of ITS, V2X, or digital transit platforms, but by the coordinated integration of intelligent connected buses, smart roadside nodes, passenger-facing terminals, and cloud-edge platforms across vehicle-level, corridor-level, and network-level control.

3 Advanced driver assistance system of ICBS

This section discusses the core functionalities and applications of ICBS, aimed at enhancing efficiency, safety, and passenger experience of public transport services through ADAS technology.

3.1. Beyond visual range collision avoidance

Bus blind spots create serious collision risks by obscuring other vehicles, cyclists, and pedestrians from the field of view of the driver (Fig. 2). Therefore, implementing collision avoidance systems is crucial for enhancing public transportation safety and protecting both passengers and pedestrians. These systems can assist drivers in identifying and avoiding potential collision risks, thereby reducing traffic accidents and ensuring smooth and safe traffic flow (Gulur, 2015).

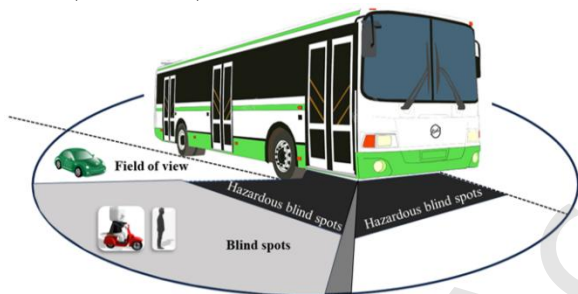


Fig. 2. Field of view and blind spots of the bus.

Existing research on blind-spot safety falls into three complementary strands. First, onboard perception methods employ fisheye cameras, convolutional neural networks (CNN) and Fast R-CNN-based detectors, or monocular depth-and-motion estimation to identify potential conflicts near the vehicle (Dooley et al., 2016; Muzammel et al., 2022; Ke et al., 2017). Second, monitoring and warning studies evaluate blind-spot interventions in naturalistic driving and develop collision-warning systems, including cooperative intersection warnings that relax line-of-sight constraints (Tomasch and Smit, 2023; Mertz et al., 2000; Miller and Huang, 2002). Third, planning and control studies show how vehicles can adjust trajectories or speeds in response to detected conflicts (Fernández et al., 2013; Milanés et al., 2012). These studies show the benefits of early warnings, but their approaches are not readily applicable to ICBS. Most evaluate sensing, warning, or control separately rather than assessing how these functions work together. They also use different vehicle types, sensor configurations, and test environments. Evaluation usually focuses on detection accuracy or conflict frequency. Less attention is given to bus-specific concerns, including interactions around stops, passenger comfort, schedule reliability, and service disruptions caused by false alarms. These limitations motivate the discussion of cooperative perception and vehicle-road coordination approaches below.

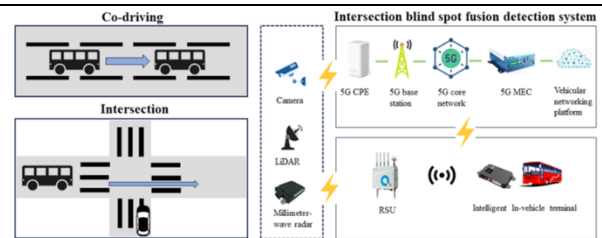


Fig. 3. Intelligent networked bus collision avoidance system powered by 5G.

Accordingly, beyond-visual-range collision avoidance in ICBS can be understood as a cooperative perception-and-warning problem under the premise of V2X connectivity, where buses, RSUs, and MECs exchange relevant information to compensate for occlusions and limited onboard sensing (Cammin et al., 2023). As illustrated in Fig. 3, a 5G-enabled architecture can combine camera, LiDAR, and millimeter-wave radar observations with RSU, MEC and in-vehicle terminals to fuse blind-spot information in co-driving and intersection scenarios and deliver cooperative collision warnings. Advanced vehicle-road coordination at intersections can capture high-precision, real-time information, detect hazards such as pedestrian jaywalking, rule violations, and blind-spot conflicts, and broadcast alerts to nearby vehicles; such functions rely on the integration of multi-modal sensing devices with MEC-supported processing for prompt risk identification (Hasarinda et al., 2023). Fig. 4 further illustrates real-time vehicle-road coordination, in which roadside and onboard sensing, RSU/MEC processing, and intelligent traffic signals jointly support context-responsive speed and movement adjustments for buses. Zhang et al. (2025) further explored optical communication strategies for information transmission to support cooperative driving. Moreover, RSUs and in-vehicle terminals can deliver instant safety information and alerts, reinforcing cooperative driving capabilities; related algorithms include V2V-based collision warning assistance (Cai et al., 2025; Zhang et al., 2022) and next-intersection collision risk prediction with vulnerable road user identification via thermal imaging (Kunashko et al., 2021).

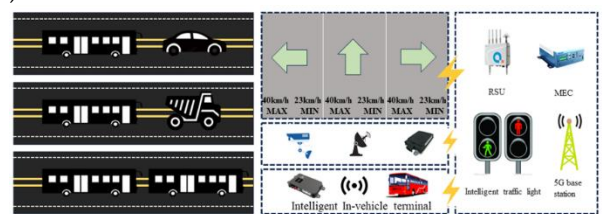


Fig. 4. Real-time intelligent connected bus and road coordination system.

Beyond warning delivery, recent studies emphasize that achieving robust beyond-visual-range safety requires explicit reasoning about occlusion-induced uncertainty and constructing conservative yet informative safety estimations for hidden road users (Wei et al., 2025; Zhou and Yuan, 2020). For example, a

POMDP-based behavior planner extends the phantom object concept to include pedestrians and infers their appearance probability and future motion using map and topology information, improving occlusion scenario coverage while avoiding unnecessary braking and deadlocks in heavily occluded urban situations (Zhang et al., 2021). Complementarily, V2X-enabled shared situational awareness frameworks integrate set-membership estimation to provide safety guarantees under occlusions by bounding vulnerable road users within constraint sets (e.g., zonotopes) based on shared perception data between vehicles and roadside units (Narri et al., 2025). Since cooperative perception and risk inference also rely on consistent spatiotemporal alignment across agents, cooperative localization using onboard vision and V2X communication has been proposed to achieve robust pose estimation in Global Navigation Satellite System (GNSS) challenged urban environments, thereby strengthening the reliability of downstream collision-risk assessment and warning delivery (Wong et al., 2025). Consequently, comprehensive blind spot detection at intersections supports an ICBS service, where LiDAR and high-definition cameras provide full-scene perception of pedestrians, motor vehicles, and non-motorized vehicles and support behavior prediction to reduce bus-involved crash risk at intersections.

Overall, current studies indicate that beyond-visual-range collision avoidance in ICBS is evolving from isolated onboard blind-spot detection toward cooperative perception and uncertainty-aware risk assessment supported by vehicle-road-cloud coordination. Existing methods have significantly improved the detection and warning of hidden conflicts involving pedestrians, cyclists, and nearby vehicles, especially in occluded and interaction-intensive urban scenarios. However, many of these approaches still rely on strong assumptions regarding sensing quality, communication reliability, and deployment conditions, and their large-scale applicability in real mixed-traffic bus operations remain insufficiently validated.

3.2. Coordinated speed optimization and signal control for corridor efficiency

Coordinated speed optimization and signal control (visualized in Fig. 5) aim to improve corridor-level bus operation efficiency by jointly shaping bus speed profiles and intersection control actions, thereby reducing stop-and-go behaviors, lowering energy consumption and emissions, and improving passenger comfort and satisfaction (Lai et al., 2012; Vlassenroot et al., 2011).

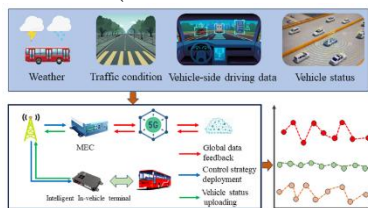


Fig. 5. Coordinated speed guidance.

V2I communications support priority passage control and dynamic routing based on traffic flow predictions to improve ICBS efficiency and safety (Conrad et al., 1998). Transit signal priority (TSP) gives buses priority at intersections. Wang and Li (2015) adjusted signal timings and phase sequences while limiting

disruption to general traffic. Ekeila et al. (2009) developed dynamic priority-selection rules to reduce bus delays. Wang et al. (2025) jointly optimized signal priority and bus trajectories. Their approach can maintain schedule reliability on multi-line corridors with conflicting control decisions and balance bus punctuality against delays to other traffic.

Green wave speed guidance uses real-time signal timings from RSUs at upcoming intersections to adjust bus approach speeds for green phases. This can reduce unnecessary deceleration and idling and support steady movement (Chen and Chang, 2017). Combined with TSP, speed guidance can smooth trajectories, improve ride comfort, reduce local congestion, and increase intersection throughput (Zhang et al., 2024).

Related studies address speed planning and its coordination with other control measures. Zhou et al. (2020) developed a dynamic speed control strategy for autonomous buses using a velocity planning model based on triangular curves to minimize intersection stops. Hao et al. (2020) developed a dynamic planning model that jointly optimizes bus speeds along road segments and signal timings at intersections to improve schedule adherence. Luo et al. (2019) proposed an IoT-enabled public transit framework combining bus holding and speed adjustments to improve scheduling and traffic resource utilization. For high-frequency routes, Bie et al. (2020) formulated a headway control model that jointly optimizes speed guidance and intersection signal timing to reduce bunching. For overlapping routes, Yang et al. (2024) coordinated arterial signals, multi-line timetables, and real-time speed guidance. This coordination reduced bus delays and travel time while limiting disruption to general traffic. To account for stochastic queues and signal uncertainty, Xue et al. (2026) used chance-constrained rolling-horizon trajectory planning with probabilistic bounds. Their method produced smoother trajectories and improved timetable compliance.

3.3. Motion planning with bus-specific constraints

Bus dynamics and operational requirements demand more road space and driving precision than passenger cars. Bus motion planning therefore considers ride comfort, standing passenger safety, and stop-docking accuracy.

Villagra et al. (2012) combined continuous-curvature paths and polynomial speed profiles in a global planning framework to reduce travel time while keeping lateral and longitudinal acceleration within specified limits. In physical experiments, Krašna et al. (2021) found that higher jerk triggered earlier muscle activation and stepping responses. Sustained excitation led to greater passenger displacement, while forward acceleration posed a greater fall risk than braking. Depending on the combination of jerk and acceleration, passengers recovered their balance through fixed-support, single-step, or multi-step strategies. Karekla et al. (2021) examined acceleration thresholds for passenger stability. Their results suggest that acceleration below 1.0 m/s^2 can help passengers remain stable and reduce fall risk under the conditions studied. For autonomous emergency braking (AEB), Matthaei et al. (2021) also linked jerk to standing passenger instability. They combined AEB policies with braking profiles that account for passenger safety, using smoother deceleration when risk permits and hard braking for imminent emergencies. The aim is to reduce

non-collision injuries while preserving stopping performance.

Once comfort and safety constraints have addressed the issue of riding experience, another physical limitation needs to be considered: the impact of bus body size and chassis structure on motion planning. To this end, Oliveira et al. (2021) formulated an optimization objective incorporating front and rear-axle offsets to achieve precise lane centering. Moreover, to alleviate the risk that the front wheels may steer and collide with the curb when entering the bus stop, this work designed a steering-angle-based linearized collision detection mechanism, enabling precise rear wheel control to maintain a distance of 20 cm from the curb during stops.

The aforementioned studies all focus on motion planning in environments without other traffic participants. In other words, they do not address decision-making related aspects. For certain specific bus operational scenarios, such as in-transit docking for autonomous modular buses, Han et al. (2024) devised a quadratic programming (QP) framework built upon a hierarchical planning architecture. This framework enables real-time decision-making on docking time, target docking speed, and corresponding speed profile planning. Compared with the classic cooperative adaptive cruise control (CACC) model, their approach reduces docking time by 45.8%. Based on the joint optimization of signal timing and bus speed profiles, Wang et al. (2025) improved the throughput of bus platoons at signalized intersections by intervening in human-driven vehicles.

Collectively, recent works suggest that motion planning for ICBS is evolving from geometry-centered trajectory planning toward bus-specific planning that explicitly accounts for ride comfort, standing-passenger safety, and docking precision. Existing methods have shown clear progress in incorporating longitudinal and lateral comfort constraints, braking smoothness, and large-vehicle kinematics into planning formulations, thereby making ICBS operation more consistent with practical service requirements. However, most approaches address only deterministic planning problems in structured, weakly interactive environments and are difficult to extend to dynamic interactive scenarios containing heterogeneous traffic participants, which are central to L4 ICBS operation.

3.4. Trajectory planning in dynamic interactive scenarios

In this survey, the dynamic interactive scenarios refer to an urban mixed-traffic environment in which multiple interaction possibilities may unfold. In this setting, the complexity of planning and decision-making arises from several factors, including the heterogeneity of traffic participants, the intrinsic uncertainty of their behaviors, and their reactive responses to the ego vehicle behavior. Fig. 6 illustrates an example of dynamic interactive scenarios around the bus stop area. As Bus A pulls into the stop, the cyclist in the bicycle lane may either yield or accelerate and rush, and the latter aggressive maneuver is highly influenced by the docking behavior of Bus A.

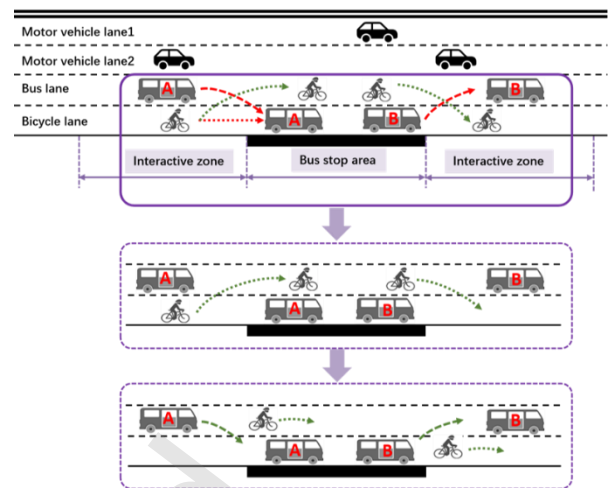


Fig. 6. Interactive scenario example around bus stop area.

For the passing problem in an unsignalized intersection, Shu et al. (2024) proposed a game-theoretic planning framework that incorporates an attention-based risk filter for identifying critical interactive agents, thereby achieving the safe traversal of a campus shuttle bus. Similarly, some studies have sought to develop a single rule-based (Fan et al., 2018) or data-driven (Le Mero et al., 2022; Vitelli et al., 2022) optimal policy capable of generating a safe and efficient trajectory for the ego vehicle across a diverse range of scenarios. However, the inherent nature of autonomous driving necessitates the existence of multiple feasible policies even with identical scenario contexts, which makes the single-policy planning difficult to handle the uncertainty and stochastic events in dynamic interactive scenarios.

Recently, multi-policy planning has garnered increasing attention in autonomous driving. The core idea is to generate multiple feasible trajectories and then select the most appropriate one based on specific criteria (Galceran et al., 2017). To get the candidate trajectories, Dauner et al. (2023) proposed a single policy augmentation strategy, which incorporates lateral offsets and sets different scales of target speed limits. This method is easy to implement and computationally efficient, but remains based on the same driving behavior, resulting in limited trajectory diversity. Li et al. (2024) utilized an offline trajectory vocabulary that was collected by rule-based or pre-trained planners, thus achieving highly diverse candidates. However, the vocabulary is fixed, and most of it is not applicable to the current scenario, leading to a waste of computational resources in trajectory selection. To enhance the adaptability of candidate trajectories to the environmental context, Huang et al. (2024) generated multiple kinematic feasible trajectories by sampling different target waypoints and speeds on different centerlines, but in some scenarios their sampler fails to find a trajectory close to the expert demonstration. Considering the computational efficiency advantage of neural networks in online inference, Cheng et al. (2024) employed a transformer-based decoder for online inference to obtain candidate trajectories, achieving a balance between trajectory diversity and computational efficiency. However, the derived trajectories lack the guarantee of satisfying vehicle kinematics constraints, necessitating the use of a separate trajectory post-processing module.

Given multiple candidate trajectories, another challenge is how to evaluate their performance and select the best one for the current scenario. Especially in safety-critical scenarios, the interaction between the ego vehicle and other agents plays an important role in trajectory scoring. The interaction modeling can be divided into two groups: single-stage (Hagedorn et al., 2025) and multi-stage approaches (Huang et al., 2024). Single-stage interaction modeling methods either prioritize the surrounding agents and make ego decisions based on predicted future agent trajectories (Ding et al., 2022) or use a transformer-based decoder to jointly infer the future trajectory of the ego vehicle and other agents (Sun et al., 2024). In prediction-based planning, performance is heavily dependent on the prediction quality. On the other hand, the latter style implicitly assumes that agents cooperate with the ego vehicle to minimize the loss function, which is a strong assumption that often diverges from real-world driving. In multi-stage approaches, the bi-directional interaction between the ego vehicle and surrounding agents is simulated, meaning their future trajectories are mutually influential, and the interaction results are often presented in the form of a scenario tree, which improves interpretability (Zhang et al., 2020). However, the number of nodes in the tree also increases exponentially with the growth of the number of trajectory modalities and expansion stages (Chen et al., 2023).

In multi-policy planning, a crucial issue is how to evaluate the performance of different policies, that is, how to construct a proper scoring utility function for the current scenario. Generally, the utility function comprises multiple terms and corresponding weights to get a final score. Bansal et al. (2019) laid a solid foundation by manually designing a cost function that considers multiple factors, including collision, road departure, heading, speed limit, and geometric constraints. This approach shows advantages in terms of interpretability but lacks generalization

ability in different scenarios due to fixed combinations. To alleviate this limitation, there have been solutions that either learn the weight (Sadat and Ren, 2019) or the components (Li et al., 2024) of the cost function. Xiong et al. (2025) further extended to learning temporal logic neural networks as explainable scoring rules. However, all methods mentioned above only capture one scoring tendency over various kinds of scenarios. In reality, different scenarios are supposed to be evaluated adopting different emphasis. For example, safety-critical scenarios should prioritize metrics like time-to-collision, while normal ones prefer comfort and driving progress. To address this issue, Sun et al. (2025) introduced a mixture of experts (MoE) model to construct a dynamic multi-tendency evaluation system. However, this method requires a large model (more than 800M parameters) and suffers from interpretability.

Based on the investigation above, trajectory planning in dynamic interactive scenarios is moving from single-policy planning toward interaction-aware and multi-policy planning under uncertainty. Existing methods have improved the diversity of candidate trajectories and the ability to reason about complex interactions with surrounding agents, which is particularly important in mixed-traffic bus operations near stops, intersections, and other conflict-prone areas. Nevertheless, many of these approaches still face major challenges related to prediction quality, computational burden, limited interpretability, and insufficient adaptation to bus-specific operational requirements. Table 2 provides a compact taxonomy of the ADAS-related technologies reviewed in this section. It compares their tasks, input data, method types, bus-specific conditions, and remaining limitations.

Table 2. Taxonomy of ADAS-related technologies for ICBS: tasks, data, methods, bus-specific conditions, and limitations.

Theme / representative study	Task	Input data	Method	Bus-specific condition	Limitation
Beyond-visual-range collision avoidance (Dooley et al., 2016; Muzammel et al., 2022; Cammin et al., 2023; Narri et al., 2025)	Detect and assess hidden conflicts involving vulnerable road users or nearby vehicles	Onboard camera/LiDAR, roadside perception, V2X messages, maps	Deep neural detection, cooperative perception, risk prediction, partially observable or set-membership estimation	Large blind zones, bus stop entry	Sensing coverage, localization alignment, and large-scale validation
Speed-signal coordination for corridor efficiency (Wang and Li, 2015; Bie et al., 2020; Wang et al., 2025; Xue et al., 2026)	Optimize speed profiles and signal timing	Bus trajectories and arrival estimations, signal phase and timing, traffic and schedule states	Adaptive signal priority control, rolling-horizon and chance-constrained control	Dwell time, headway, passenger comfort, multi-line corridors	Trade-off with general traffic, uncertainty in queues, and dependency on reliable V2I coverage
Motion planning with vehicle and operational constraints (Villagra et al.,	Generate dynamically feasible trajectories, braking profiles,	Vehicle and route states, geometric constraints, obstacle states,	QP, model predictive control (MPC), hierarchical planning	Large vehicle geometry and swept path, standing-	Weak treatment of dynamic interactions and uncertainty

2012; Matthaei et al., 2021; Oliveira et al., 2021; Han et al., 2024)	and docking actions	dynamic constraints		passenger safety, stop docking	
Trajectory planning in dynamic interactive scenarios (Cheng et al., 2024; Huang et al., 2024a,b; Shu et al., 2024; Sun et al., 2025)	Generate multiple trajectories and select the best candidate in mixed traffic	Agent history states, maps, obstacles, speed limits, reference routes	Multi-policy sampling, transformer-based encoder and decoder, game theory	Bus stop approach and departure, interaction with cyclists and pedestrians	Computational efficiency, interpretability, bus-specific validation

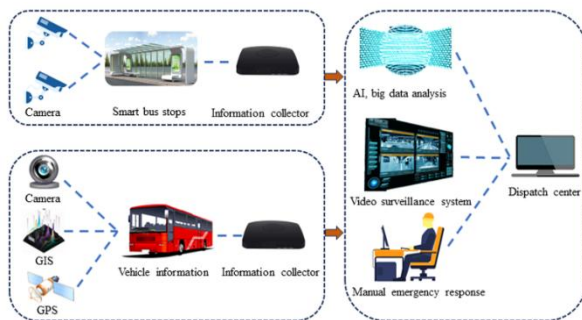


Fig. 7. Real-time vehicle command and dispatching.

4 Intelligent dispatching and fleet management in ICBS

This section investigates intelligent dispatching and fleet management as the control layer that turns cooperative situational awareness from ICBS into operational actions. Fig. 7 illustrates the information-to-execution chain underlying this control layer: data from smart bus stops and buses are collected through cameras, GPS, GIS and onboard terminals, processed through AI-enabled analytics and video surveillance, and then delivered to the dispatch center to support operational decisions and manual emergency response. Traditional bus scheduling often suffers from poor punctuality, inefficient resource utilization (e.g. high rates of deadheading), and excessive passenger waiting times, largely due to limited real-time adaptive analysis capabilities (Ceder, 2004; Sano and Suga, 2007). Building upon ICBS infrastructure, bus dispatching can be framed as a multi-timescale decision-making problem that links strategic-level infrastructure location planning (Wu et al., 2021) with operational-level headway and re-routing control with objectives spanning service reliability, resource utilization, and safety. Accordingly, this is organized around three representative groups of problems: (1) electrified fleet scheduling and charging management, (2) dispatching and scheduling under automation and connectivity, and (3) demand-responsive and customized bus services.

4.1. Electrified fleet scheduling and charging management

The electrification of bus fleets reshapes dispatching from a timetable-centric problem into a joint service-energy feasibility problem. Vehicle schedules have to remain compatible with state-of-charge (SoC) evolution, charging infrastructure availability, and battery health. Therefore, researchers have moved from sequential

scheduling and charging to integrated formulations that jointly optimize timetables, charging decisions, and infrastructure procurement (Zhang et al., 2023; Zhao et al., 2025; Zhong et al., 2024).

A dominant group of approaches focuses on integrated scheduling and charging under uncertainty and operational constraints. Bie et al. (2021) used field data to model random variations in travel time and energy consumption. They introduced charging during idle time to reduce the uncertainty accumulated over successive trips. For en-route charging under uncertain energy consumption, Zeng et al. (2024) extended a deterministic mixed-integer linear programming (MILP) model with a robust counterpart that accounts for time-varying energy consumption deviations and electricity prices. Other studies used the structure of the scheduling problem to improve computational efficiency. Zhang et al. (2021) developed a set-partitioning model that includes battery degradation and nonlinear charging profiles, and solved it with a custom branch-and-price algorithm. A later mixed-integer nonlinear programming (MINLP) model included time-of-use electricity pricing, partial charging, and limited charger availability, with reported cost savings of up to 22% (Zhang et al., 2024).

Lacombe et al. (2023) developed a MILP controller to coordinate charging schedules with real-time operating speeds. Over a rolling horizon, the controller predicts conflicts over charger capacity and adjusts schedules to avoid charging queues that cannot be accommodated. For regional networks, Lacombe et al. (2024) combined charging scheduling and real-time control in a hierarchical framework. They obtained feasible solutions on the Chicago city dataset using Lagrangian relaxation decomposition and heuristic local search. With the wider use of rapid charging, opportunity charging must work within short charging windows and remain reliable when delays spread quickly (Abdelwahed et al., 2020). To minimize delays in opportunity charging schedules, McCabe et al. (2025) formulated a MILP model and developed two solution methods: an exact algorithm based on Benders decomposition and a polynomial-time heuristic. These methods aim to solve the scheduling problem within practical time limits. For systems with multiple lines and depots, Zhang et al. (2024) used a two-stage framework to coordinate vehicle routing and charging. To handle larger systems, the framework combines a time-space network model with label-setting dynamic programming (DP) for trip generation.

replacement, depending on passenger acceptance. Zhang et al. (2023) optimized ICBS dedicated lane networks with limited access for intelligent connected passenger vehicles. Flexible access could improve lane utilization and attract passengers, according to their results.

Service design needs to account for operational constraints and journey quality. Sadrani et al. (2022) optimized service frequency and vehicle capacity with congestion externalities and travel time uncertainty. Their work supports accounting for changing demand and capacity constraints in service design. Passenger preferences also matter for scheduling objectives. On an autonomous electric transit service in Oslo, passengers reported a high perceived level of safety but preferred higher operating speeds and fewer sudden braking events (Mouratidis et al., 2021). More broadly, a synthesis of public transit planning in the era of automation argues that next generation data-driven approaches need to translate emerging technologies into service improvements and ridership gains (Ma et al., 2021).

At the operational layer, greater controllability makes more aggressive real-time dispatching and headway reliability control more achievable. Booking-based or demand-responsive autonomous transit provides a new direction for autonomous public transit services. Cao et al. (2025) proposed a real-time multi-objective framework that reacts to new bookings and jointly reduces passenger waiting time, timetable deviation, and fleet size. Their case study shows meaningful reductions in waiting time and fleet size with the assumption of ideal demand prediction. Considering the uncertainty of vehicle trip travel time and energy consumption, Zhang et al. (2025) designed a departure-time shifting strategy to simultaneously optimize ICBS scheduling decision components like trip chains, charging decisions, and timetables. These works treat automation as an enabling prerequisite for executing scheduling adjustments that are hard to enforce consistently with human drivers. Headway instability remains another key issue for dense operations. Yang et al. (2024) investigated bus bunching solutions in terms of intervention targets including operations, traffic control, driving rules and passenger behaviors, and further suggests automation in ICBS can create new avenues for addressing bunching structurally. Building on the recent shift toward learning-based control, Xu et al. (2025) conducted a systematic evaluation of reinforcement learning (RL) configurations for bus bunching mitigation using real-world bus data. Their results demonstrate the practical utility of simpler state representations, discrete holding actions, and generalizable learning-based policies.

Early deployments of ICBS also introduce emerging challenges like safety driver resource constraints and mixed traffic environments. In many systems, the human mission shifts from continuous driving to supervision and emergency takeover. Wang et al. (2024) formalized the safety driver scheduling problem and developed exact and heuristic methods using historical operation data. This connects dispatching to institutional constraints such as labor rules and takeover procedures. Commercialization-oriented reviews of the intelligent and connected vehicle industry similarly emphasize coordination barriers and readiness factors beyond algorithms (Zhao et al., 2024). This indicates that ICBS schedules

and safety-driver resources must be co-designed during transitional phases. The system-level benefits of automation and connectivity are strongly influenced by mixed traffic interactions and penetration levels. Li et al. (2024) modeled ICBS-oriented traffic state prediction in partially connected environments under varied penetration levels with and without dedicated bus lanes. Their results highlight the effect of penetration rate, dwell time, and stop locations on corridor dynamics. This aligns with scenario evidence that lane support can be decisive for performance (Oikonomou et al., 2020). Mixed traffic constraints also interact with ICBS service equity and coverage. If the service is deployed only where ICBS is easiest to implement, then areas with great travel demand may be deprived of the benefits ICBS could otherwise provide.

Overall, these studies suggest that with increasing automation and connectivity level of ICBS, intelligent scheduling should be treated as a coupled problem across deployment, real-time control, supervisory labor, service equity, and mixed traffic constraints.

4.3. On-demand and flexible bus services

In ICBS, demand-responsive and flexible bus services are increasingly viewed as a complementary layer to conventional fixed-route operations, particularly when travel demand fluctuates greatly in time and space. The connectivity of ICBS improves observability of demand and traffic states, while centralized platforms and MECs enable faster replanning, consistent passenger information gathering, and tighter coordination with fixed-route services. The key question is therefore which degree of flexibility is operationally sustainable under capacity, equity, and reliability constraints (Vansteenwegen et al., 2022; Zhou et al., 2025).

Offline planning uses historical origin-destination distributions, travel demand patterns, and taxi trajectories to set stop sequences and route packages for service windows. Multi-trip vehicle chaining can improve fleet utilization (Delgado, 2022). Chen et al. (2021) modeled custom bus routing as a multi-trip pickup-and-delivery problem with time windows and quantified travel time penalties. Their results showed lower fleet requirements with little additional passenger delay through vehicle chaining.

Huang et al. (2020) addressed demand-route feedback with two stages: strategic route generation and operational vehicle allocation. Demand estimates update iteratively with service levels and price elasticity. This decomposition improves computational feasibility and identifies where route flexibility is appropriate, but remains sensitive to behavioral parameters and misses demand changes within service windows.

Beyond classic VRP constraints, Huang et al. (2025) considered operational consistency. Partial similarity between morning and evening shuttle routes reduced empty trips and staff training requirements, with small increases in passenger travel time. Ma et al. (2023) used taxi trajectories to generate custom routes for high-demand corridors without existing service. Taxi users may not represent bus passengers, and the routes may violate bus road-geometry constraints. ICBS therefore needs data filtering and network feasibility checks.

Offline planning may assume stationary demand distributions and fixed decision thresholds. Online routing and ride sharing respond to new requests under changing or unpredictable demand

(Kim et al., 2019). Fielbaum et al. (2022) addressed the mismatch between vehicle locations and new demand through anticipatory routing. Their mechanisms use forecasts to encourage repositioning toward high-demand areas or sample synthetic future requests for dispatch decisions.

To expand service capacity through en-route transfers, Fu and Chow (2022) modeled pickup-and-delivery with synchronized vehicle encounters and strict time windows. Their heuristics achieved small optimality gaps in the evaluated instances. Deployment requires passenger willingness to transfer and precise coordination of vehicle encounters. Electric services also need to account for charging. Wang et al. (2024) developed a zone-based, on-demand minibus system for dynamic dispatch within zones. The system jointly optimizes zone partitioning, charging infrastructure location, and fleet size.

To improve service coverage without undermining corridor reliability, hybrid systems that combine offline fixed routes and online adaptations have garnered more attention. Hybrid fixed-flex schemes build on the offline service backbone by enabling bounded real-time adjustments under explicit structural constraints such as the online response service area and capacity (Fielbaum et al., 2024; Ng and Mahmassani, 2023). The effectiveness of such designs depends jointly on corridor-level supply conditions, service-level operation constraints, and network-level co-evolution between fixed lines and flexible services.

At the corridor level, this requires aligning operational optimization (e.g. departure frequency) with road space allocation since responsive services can interact nonlinearly with congestion and even yield counterintuitive outcomes under hypercongestion (Zhang et al., 2018). This motivates joint consideration of flexible operations and bus priority space allocation rather than treating them as separate components. At the service level, transit designs often maintain a stable backbone, such as trunk routes (Ng and Mahmassani, 2023) or terminal sequences (Wang et al., 2024), while permitting controlled deviations driven by immediate demand and slack resources. This structure enables real-time adaptation while keeping the system explainable and schedulable. At the network level, ICBS enables data-driven co-evolution of fixed and flexible layers. More specifically, trajectories from on-demand operations can be used to identify persistent high-frequency segments that should be converted into fixed routes, while residual demand remains flexible, supporting an iterative explore-consolidate design paradigm (Fielbaum and Alonso-Mora, 2024). Integration can also be achieved by running small on-demand vehicles in parallel with fixed bus lines and co-designing pricing and frequency decisions. In this case, although benefits become more pronounced when automation reduces operating cost, feasibility depends on vehicle availability and right-of-way constraints (Fielbaum et al., 2024a). In hybrid systems, on-demand services are not limited to last-mile feeders and may also operate in semi-direct or direct patterns according to urban form and demand density (Fielbaum et al., 2024b).

Overall, existing works indicate that on-demand and flexible bus services in ICBS are moving from fixed customized route design toward hybrid, adaptive, and network-level service coordination. Real-time data and centralized dispatching can expand service

coverage and reduce deadheading. Deployment, however, must account for interacting constraints on demand prediction, transfer synchronization, and charging availability, while balancing operational flexibility with service reliability.

The electrification, automation, and flexible service strategies reviewed in Sections 4.1-4.3 draw on the same limited time, energy, road space, and infrastructure resources. Traffic and demand disruptions can affect several operations at once. A local traffic queue or a sudden increase in passenger numbers can change bus headways, cumulative energy consumption, and queues at charging points. Vehicle holding, speed guidance, and traffic light priority can help restore timetable regularity, but these measures may conflict with charging windows, accelerate battery degradation, reduce passenger comfort, or increase overall traffic delays (Bie et al., 2021; Lacombe et al., 2023; Wang et al., 2025).

With flexible routing, service coverage can increase and deadheading can decrease, but trip times, transfer connections, and charging opportunities may become less predictable. These operational ripple effects make systematic coordination with the fixed-route backbone indispensable (Fielbaum et al., 2022; Fielbaum and Alonso-Mora, 2024). Automation and connectivity enable rolling-horizon adjustments but do not remove uncertainty in demand, travel time, charger availability, or grid capacity, nor the constraints imposed by mixed traffic and human supervision. Table 3 synthesizes the resulting coupled decisions, practical trade-offs, and deployment gaps.

Table 3. Taxonomy of ICBS operational research: coupled decisions, methods, practical trade-offs, and deployment gaps.

Operational stream / representative study	Coupled decision	Method	Practical trade-offs	Deployment gap
Electrified fleet scheduling and charging management (Liu et al., 2021; Zhang L. et al., 2024; McCabe et al., 2025; Zeng et al., 2022, 2023)	Timetables, trip chains, charging time/location/capacity	Mixed-integer and time-space optimization	Punctuality and frequency vs. charging time and battery degradation, depot assets vs. grid capacity	Uncertainty from travel time, demand, energy consumption, grid conditions, and charger availability
Automation- and connectivity-enabled scheduling (Cao et al., 2025; Yang C. et al., 2024; Xu et al., 2025; Li X. et al., 2024)	Headway, holding, signal priority, reference speed, safety-driver allocation	Multi-objective optimization, RL, heuristic design	Transit signal priority vs. general traffic delay, aggressive intervention vs. comfort and energy consumption, automation consistency vs. supervisory labor and mixed traffic risk	Penetration and connectivity, human takeover, robustness, service equity
Demand-responsive and flexible services (Chen et al., 2021; Fielbaum et al., 2022; Fielbaum and Alonso-Mora, 2024; Fu and Chow, 2022; Wang T. et al., 2024)	Design of routes and stops, vehicle assignment, transfers, charging scheduling	Pickup-and-delivery and dial-a-ride models, two-stage optimization, anticipatory routing	Flexible routing vs. timetable regularity and transfer coordination, deadheading vs. passenger waiting time/detours, service range vs. charging limits	Demand uncertainty, cross-zone coordination, infrastructure, public acceptance
Cross-layer operational coordination (synthesis of Sections 4.1-4.3)	Joint scheduling, charging, priority, routing and infrastructure planning	Hierarchical decomposition, rolling-horizon control	Local cost gains vs. network reliability and equity; infrastructure investment vs. service flexibility	System evaluation, data interoperability, legacy-system integration

5 Development trends and challenges of intelligent connected public transit

5.1. Synthesis and taxonomy of ICBS

The preceding sections indicate that ICBS should be understood not as a collection of independent technologies, but as a multi-layered, closed-loop decision system that continuously transforms data into coordinated control actions across vehicles, infrastructure, and operation platforms. Through vehicle–infrastructure–cloud integration, ICBS links perception, decision-making, and execution over multiple spatial and temporal scales, enabling public transport systems to respond more effectively to dynamic traffic conditions and heterogeneous passenger demand. From this perspective, literature can be interpreted through a hierarchical decision structure in which system functionality emerges from the interaction of several tightly coupled layers. At the foundation, cooperative perception, passenger sensing, and traffic state estimation expand system observability beyond onboard sensors, providing shared situational awareness under uncertainty. At the vehicle level, onboard planners translate system objectives into executable trajectories and behavioral control. These planners need to address passenger comfort, docking accuracy, and interactions with other road users in

mixed traffic. In complex urban environments, vehicle control is moving from deterministic single-policy planning toward multi-policy decision-making with explicit consideration of these interactions.

At the corridor level, V2I communication connects buses, traffic signals, and roadside systems. Joint speed guidance and signal priority can reduce stop-and-go driving and improve corridor service regularity. At the network level, real-time data supports joint optimization of scheduling, dispatching, charging, and headway control. Fleet management can then use closed-loop operations instead of relying on static timetables. Service design also extends from fixed routes to demand-responsive and hybrid fixed–flexible layouts to match demand changes across time and space.

These control scopes depend on coordination among perception, control, infrastructure, and fleet operations. Connectivity provides the communication links needed for this coordination. Yet most studies still examine operational layers separately and give limited attention to feedback between layers and network-level trade-offs. Addressing these gaps is important when extending local demonstrations to network-wide transit operations. Table 4 synthesizes this cross-layer perspective by mapping the reviewed literature across decision layers and control scopes, together with the associated key decisions, objectives, key enablers, methodologies, and development trends.

Table 4. Taxonomy of ICBS by decision layer, control scope, key decisions, objectives, key enablers, methodologies, and development trends.

Decision layer	Control scope	Key decisions	Objective	Key enabler	Methodology	Trend
Sensing and estimation	System observability	Traffic state, passenger demand, vehicle state (e.g., SoC), object detection	State accuracy, uncertainty reduction	V2X communication, IoT sensing, cloud-edge platforms	Data fusion, machine learning, cooperative perception, state estimation	From isolated onboard sensing to cooperative, shared situational awareness
Vehicle dynamics and control	Single-vehicle behavior	Trajectory, speed, braking, docking, interaction decisions	Safety, comfort, feasibility under constraints	Onboard ADAS, cooperative perception, vehicle-road coordination	Optimal control (QP, MPC), POMDP, imitation learning, multi-policy planning	From deterministic trajectory planning to interaction-aware, uncertainty-aware decision-making
Infrastructure and corridor coordination	Multi-vehicle local coordination	Signal timing, priority, speed guidance	Corridor efficiency, punctuality, safety	RSU, MEC, V2I communication	MILP, DP, rolling-horizon optimization, MPC	From isolated signal control or speed advice to joint signal–trajectory co-optimization
Network operations and fleet management	System-level resource allocation	Timetables, vehicle assignment, charging schedules,	Reliability, cost efficiency, energy feasibility	Centralized platforms, automation, real-time system monitoring	MILP/MINLP, decomposition methods, reinforcement learning,	From sequential planning to integrated service–energy–

Service design and demand interaction	Network-wide service structure	headway control			stochastic optimization	operations optimization
		Route design, service frequency, ride-pooling, zone partitioning	Accessibility, coverage, demand responsiveness, equity	Demand data, centralized coordination, automation	Pickup-and-delivery models, two-stage optimization, online routing, hybrid control	From static fixed routes to adaptive, demand-responsive and hybrid fixed-flex systems

5.2. Emerging trends

Building on the synthesis above, the future development of ICBS is increasingly shaped by the mismatch between conventional uniform bus operations and highly heterogeneous urban mobility demand. In practice, demand varies substantially across peak and off-peak periods, major corridors and peripheral areas, as well as stable commuting trips and more dispersed local travel needs. This suggests that the evolution of ICBS is not simply a matter of adding more sensing, communication or automation functionalities, but of reorganizing transit services so that vehicle scale, service structure, and control logic can better respond to spatiotemporally uneven demand.

1) Transition toward right-sized and miniaturized transit fleets

An important trend in ICBS is the transition from uniform large-vehicle operation toward right-sized and multi-scale fleets. Large buses remain suitable for high-demand trunk rapid transit corridors, but they are often less effective in low-demand districts, narrow terminal road networks, and last-mile services. Transit operators can complement conventional high-capacity services with minibuses and automated shuttles to match vehicle capacity to fluctuating passenger demand (Sadarani et al., 2022; Oikonomou et al., 2020). This fleet downsizing adapts the broader transit system to uneven demand, sparse terminal coverage, and narrow street geometries, moving beyond simple vehicle replacement.

2) Increasing operational complexity under fleet miniaturization

Smaller vehicles, however, do not simplify transit operation. Maintaining equivalent service capacity and network coverage requires higher departure frequencies, larger active fleets, and tighter schedule coordination across routes, stops, and service windows. Complexity simply shifts from vehicle capacity to fleet orchestration under volatile demand and traffic disruptions, headway regulation, stop allocation, charging schedules, and trunk-feeder coordination become tightly interdependent (Vansteenwegen et al., 2022; Fielbaum et al., 2022; Xu et al., 2025). Accordingly, ICBS is moving away from static timetable-centered operation toward finer-grained and higher-frequency service management, in which decisions must be updated more frequently and executed more consistently.

3) Higher-level automation and closed-loop coordination as

an operational necessity

Under such conditions, higher-level automated driving capabilities and closed-loop coordinated dispatching become not merely desirable, but increasingly necessary. When service frequency rises and operational control becomes more fine-grained, conventional human-centered operation faces several practical constraints, including growing driver labor costs, driver scheduling pressure, inconsistent execution of real-time control strategies, and limited responsiveness to stochastic disruptions (Wang et al., 2024). Advanced automation can improve the consistency of speed guidance, docking, holding, and cooperative maneuvers (Zhou et al., 2020; Han et al., 2024; Cao et al., 2025), while closed-loop vehicle-road-cloud coordination enables continuous feedback among roadside perception, fleet status, passenger demand, and operational decisions (Wang et al., 2025; Yang et al., 2024). In other words, fleet miniaturization and service refinement make high-level automation and coordinated control a natural and, in many cases, unavoidable direction for ICBS development.

4) Toward precise public transit with fewer unnecessary stops and transfers

Based on these developments, the long-term trend of ICBS is toward precise public transit. Precise public transit does not simply refer to a more digitalized form of public transport; rather, it denotes a service mode in which vehicle size, service frequency, stopping patterns, routing decisions, and transfer organization are continuously aligned with real-time demand and traffic conditions. Through closed-loop coordination across infrastructure, vehicles, and operation platforms, ICBS can reduce unnecessary stops, avoid redundant detours, improve the synchronization of feeder and trunk services, and minimize avoidable transfers while improving the reliability of necessary ones (Fielbaum and Alonso-Mora, 2024; Fu and Chow, 2022; Zhou and Wang, 2025). The objective is to use automation to match transit services to actual travel demand and improve system efficiency and responsiveness.

5) Toward multi-purpose ICBS: urban logistics and infrastructure awareness

Buses can carry parcels on fixed routes using spare capacity during off-peak hours or on selected corridors. Bus stops, terminals, depots, parcel lockers, and microcenters can serve as parcel transfer points for electric cargo bikes, drones, and other last-mile modes (Machado et al., 2023; Osorio and Ouyang, 2025; He et al., 2025). Smart bus stops and depots

also support passenger boarding, freight delivery, recharging, and intermodal coordination. Connected buses can act as mobile probes, using sensors to monitor road surfaces, traffic assets, and corridor conditions for municipal infrastructure maintenance (Crainic and Montreuil, 2016). Operators can restrict freight services to off-peak hours, use dedicated loading bays, and adjust freight capacity to real-time passenger occupancy.

5.3. Challenges and research gaps

The trends discussed above face implementation challenges in five related areas: system-level benchmarking, robustness to uncertainty, infrastructure compatibility and affordability, integration and deployment of passenger-freight services, and bus-oriented automated driving capabilities. Studies report progress in collision avoidance, signal coordination, fare optimization, and dynamic transportation management. However, much of the evidence comes from small-scale testbeds or numerical simulations under idealized assumptions. These conditions limit what the findings can establish about performance in operational public transportation networks.

1) Benchmarking of system-level transit outcomes

Current assessments emphasize collision avoidance, path flow, fare collection costs, and intersection delays. Evidence on ridership increases, overall travel costs, network reliability, and long-term service competitiveness remains limited. Transportation agencies use these broader outcomes in their decisions, so evaluations of technical improvements should include them. Hierarchical simulation platforms for public transportation can connect vehicle-level automation with agency-level planning and assess ICBS operations through network accessibility, schedule adherence, and operational sustainability.

2) Robustness under demand uncertainty and different deployment conditions

Urban bus operations face uncertain demand, variable travel times, mixed traffic, and uneven infrastructure. Assumptions of perfect forecasts, continuous V2X connectivity, and high-quality sensors may limit applicability as ICBS expands beyond fixed corridors to flexible and hybrid services over larger, more varied areas. Robust and adaptive methods need to maintain service despite communication interruptions, mixed traffic interference, and uneven infrastructure readiness.

3) Infrastructure cost and legacy system integration for flexible services

Fixed-route corridors allow concentrated investment in RSUs, MECs, and sensors. Flexible, on-demand, and zone-based coverage can increase capital, communication, and coordination costs. New infrastructure must also integrate with existing signal controllers, dispatch platforms, and stop facilities.

4) Deployment of integrated passenger-freight services

Coordinating passenger transport, freight logistics, and mobile infrastructure monitoring requires extending conventional ICBS dispatch frameworks with multi-objective optimization. When spare bus capacity is used for

parcels, operations need to account for uncertain passenger loads while maintaining headway regularity and ride comfort and keeping dwell times within service requirements. Dynamic routing and scheduling models therefore need to extend pickup-and-delivery and on-demand transport formulations to handle passengers, parcel deliveries, returns, and urgent medical supplies.

Transfers between transport modes also impose timing constraints. Buses operating on fixed schedules have limited time to wait for delayed drones or ground couriers. Transfer nodes therefore need safety margins and dispatch protocols that account for these delays. Finally, strategic facility siting must co-optimize the locations of stops, terminals, depots, lockers, and consolidation micro-hubs against capital activation costs and catchment accessibility, while jointly managing opportunity charging and battery degradation across multimodal fleets.

5) Bus-oriented autonomous driving

Compared with passenger cars, buses face distinct operational and safety challenges. These include differences in vehicle body size and geometry that affect sensor placement and perception coverage, the requirement to protect standing passengers under acceleration and braking, entry and exit maneuvers at stops, dense interaction with pedestrians and cyclists at near-stop areas, lane-changing decision-making related to dedicated bus lanes, and intent recognition during boarding, alighting, and door operation. Thus, directly transferring passenger-car autonomous driving algorithms to buses is insufficient. Future ICBS research should specialize bus-oriented perception, planning, and human-interaction algorithms grounded in transit operating scenarios.

6 Conclusions

This paper shows that ICBS should be understood as a layered closed-loop transit system spanning infrastructure, onboard vehicle intelligence, and operation service management. Rather than treating connectivity as an end in itself, the survey demonstrates how vehicle-road-cloud coordination converts sensing, communication, and computation into operational control for safety, punctuality, regularity, comfort, efficiency, and accessibility. Across the literature, ICBS is developing along two closely related directions: bus-oriented automated driving supported by cooperative perception, signal-speed coordination, and interaction-aware planning; and reliability-oriented operational control integrating dispatching, charging, and flexible services. Together, these advances indicate that the value of ICBS lies in enabling public transit systems to respond more consistently and intelligently to real-time traffic, vehicle, and passenger states.

Looking ahead, the long-term direction of ICBS is toward precise public transit, in which vehicle size, service frequency, stopping patterns, routing decisions, and transfer organization are better matched to spatiotemporally heterogeneous demand. The shift toward right-sized and miniaturized fleets, higher-frequency operations, and hybrid fixed-flexible services also makes closed-loop coordination and higher-level automation increasingly necessary.

However, future progress depends on addressing deployment-oriented challenges, including verification of system-level transit benefits, robustness under uncertainty and heterogeneous deployment conditions, infrastructure affordability and compatibility with legacy systems, multi-purpose service integration and deployment, and bus-specific automated driving capabilities. In this sense, ICBS should be understood not simply as a bus automation technology, but as a service-oriented operational paradigm for building more adaptive, reliable, and sustainable urban public transport.

Author contributions

Shijie Cong: Writing – original draft, Writing – review & editing, Methodology, Investigation. **Wei Zhang:** Writing – original draft, Writing – review & editing, Investigation, Supervision, Project administration, Conceptualization. **Kai Wang:** Writing – review & editing, Investigation, Supervision. **Balázs Kulcsár:** Writing – review & editing, Validation, Supervision, Methodology. **Marianna Jacyna:** Writing – review & editing, Validation.

Replication and data sharing

The data and materials used to support the findings of this study are available from the corresponding author upon reasonable request.

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Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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