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Review

Human-Centered and System-Level Control of Autonomous Vehicles: A Review of Safety, Intelligence, and Cooperation

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Abstract

Autonomous vehicles are evolving from isolated vehicle-control systems into interconnected mobility platforms that interact with surrounding traffic, intelligent infrastructure, and human users. While significant advances have been achieved in vehicle dynamics control, safety systems, connected mobility, and human–machine interaction, these research domains are often addressed independently. This fragmentation limits the development of autonomous mobility solutions capable of simultaneously achieving safety, efficiency, sustainability, and user acceptance. This paper presents a comprehensive review of autonomous vehicle control through a unified multi-level control framework comprising five interconnected layers: vehicle-level control, safety-critical control, cooperative control and traffic interaction, infrastructure-based control, and human-centered control. For each layer, state-of-the-art methodologies are examined, ranging from classical control techniques such as PID, LQR, Sliding Mode Control, and Model Predictive Control to emerging data-driven and reinforcement learning approaches. Beyond reviewing individual control strategies, the paper analyzes the interactions and trade-offs between vehicle performance, collision avoidance, traffic flow, infrastructure coordination, passenger comfort, and societal outcomes. Particular attention is given to connected and cooperative driving, fault-tolerant and safety-critical control, smart infrastructure integration, digital twins, and human factors including trust, comfort, and motion sickness. The review highlights current challenges, identifies emerging research directions, and discusses how future autonomous mobility systems will require coordinated decision-making across vehicle, infrastructure, and human domains. The proposed framework provides a structured foundation for the development of safe, resilient, efficient, and human-aware autonomous transportation systems.

Keywords: autonomous vehicles; cooperative control and traffic; infrastructure and smart mobility; human-centered control; active safety

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1. Introduction

Autonomous vehicle (AV) technology aims to enhance road safety, increase traffic efficiency, and improve passenger comfort. As automation levels rise, vehicle control is

no longer limited to the ego vehicle but also involves interaction with surrounding traffic, infrastructure, passengers, and other road users. This growing complexity places new demands on control decisions, which must now account for safety, coordination, and human experience. Understanding control approaches across levels of automation and system interaction is therefore essential for reliable and scalable autonomous mobility.

The Society of Automotive Engineers (SAE) defines six levels of driving automation, from Level 0 (no automation) to Level 5 (full autonomy), as shown in Figure 1 [1]. The levels differ mainly in how responsibility is shared between the driver and the automated system. At Levels 0–2, the human driver remains responsible for monitoring, driving, and decision-making, while the system provides assistance such as steering or acceleration control. At Level 3, the system performs the driving task within specific operational design domain (ODD) conditions while the driver remains ready to intervene. At Levels 4–5, the system assumes full control of the driving task within a defined (Level 4) or unrestricted (Level 5) environment. Alongside this shift in responsibility, control extends from manual operation to integrated and connected systems that include vehicle-to-vehicle and vehicle-to-infrastructure interaction. At every level, comfort, trust, and user acceptance remain central to road user safety and adoption [2,3].

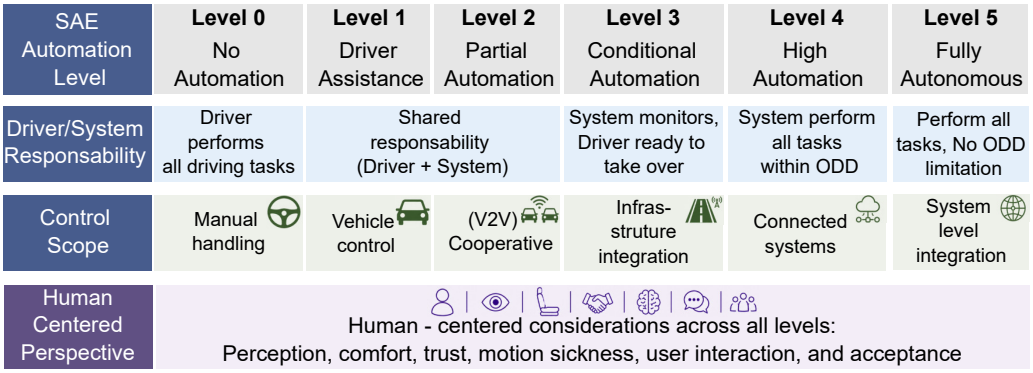


Figure 1. SAE J3016 automation levels extended with control and human-centered perspectives [1–3].

Safety is a second fundamental objective of AV control design. Figure 2 shows the operational timeline of active and passive safety systems as a function of the distance between the ego vehicle and the preceding object [4]. Active safety systems manipulate the lateral and longitudinal dynamics of the ego vehicle and continuously monitor the environment, through functions such as lane keeping assistance and adaptive cruise control. When a collision becomes possible and the vehicle reaches the warning zone, warning and mitigation strategies are deployed. If a hazardous event occurs, safety-critical functions attempt to avoid the collision, and once the "no-return" point is exceeded, the system shifts from accident prevention to damage mitigation. Passive safety systems, such as airbags and seatbelts, then reduce injury severity. This timeline underlines the need for timely and robust control strategies that can handle both preventive and reactive safety functions.

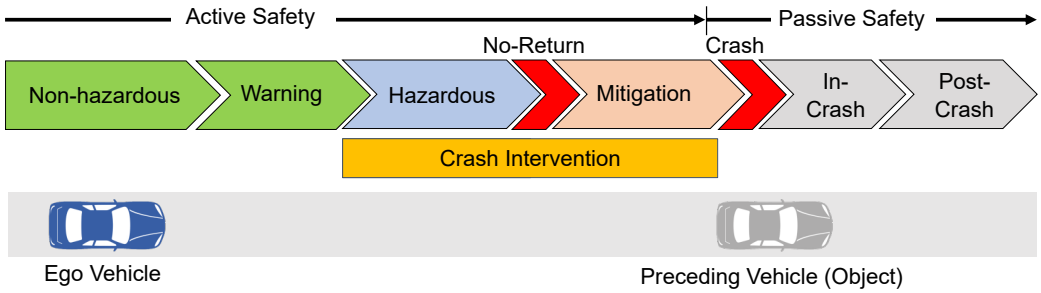


Figure 2. Operational timeline for active and passive safety systems depending on the proximity to other road users [4].

The automation levels and the safety timeline describe autonomy and vehicle behaviour in relation to traffic. The ego vehicle can also be analysed from a system architecture perspective, commonly segmented into perception (sensing), planning (computing), and actuation [5]. Perception interprets the surroundings of the ego vehicle through sensors, planning determines trajectories and decisions, and actuation produces the actuator commands needed to follow the planned trajectories. Ideal ego vehicle behaviour depends on all three segments functioning properly.

To address the gaps in the literature, this paper proposes a multi-level control framework for AVs that organizes control strategies into interconnected domains: vehicle-level control, safety-critical control, traffic-level coordination, infrastructure-based control, and human-centered control. The framework aims to give a unified perspective on AV control by highlighting the interactions and trade-offs across system levels. The main contributions of this work are as follows:

- A multi-level control framework for AVs that integrates vehicle dynamics, safety-critical control, traffic coordination, infrastructure interaction, and human-centered perspectives.
- A structured review of control approaches across automation and system levels, from classical control methods to learning-based techniques.
- A discussion of the interactions and trade-offs between safety, traffic efficiency, infrastructure coordination, and passenger comfort.
- An overview of emerging research directions, including connected mobility, digital twins, safe reinforcement learning, and human-aware vehicle control.

The paper is structured as follows. Section 2 introduces the proposed framework. Sections 2.1–2.6 review each control layer in turn, covering major methodologies, challenges, and recent developments. Section 3 covers digital twins, simulation, and experimental validation, and Section 4 integrates the layers into a system-level model. Cross-level trade-offs and future research directions are discussed in Sections 5 and 6, and conclusions are given in Section 7.

2. Multi-Level Control Framework for Autonomous Vehicles

Autonomous vehicles are developed to improve quality of life for society. They allow passengers to use travel time for other activities and, importantly, can reduce road accidents and deaths, which are currently caused mainly by human error [6]. The investments of companies and governments in vehicle automation pursue objectives that are also vehicle and system objectives: safety, efficiency, sustainability, user comfort, and equity, which ensures that mobility systems are fair, accessible, and beneficial to different groups in society. These control objectives and the proposed multi-level control framework are shown in Figure 3. Efficiency and sustainability cover vehicle-related aspects such as reduced fuel consumption, as well as technologies that reduce the carbon footprint of vehicle production

and supply chains [7]. They also cover the transportation system as a whole, including reduced travel time and congestion and the number of users transported per kilometer, and extend to the design of human-friendly cities that consider the effect of the system on people's daily lives, not only traffic and road optimization.

The framework is organized into five interconnected layers: vehicle-level control, safety-critical control, cooperative control and traffic interaction, infrastructure-based control, and human-centered control. Together they describe the evolution of AV control from individual vehicle dynamics to broader system-level and human-centered considerations.

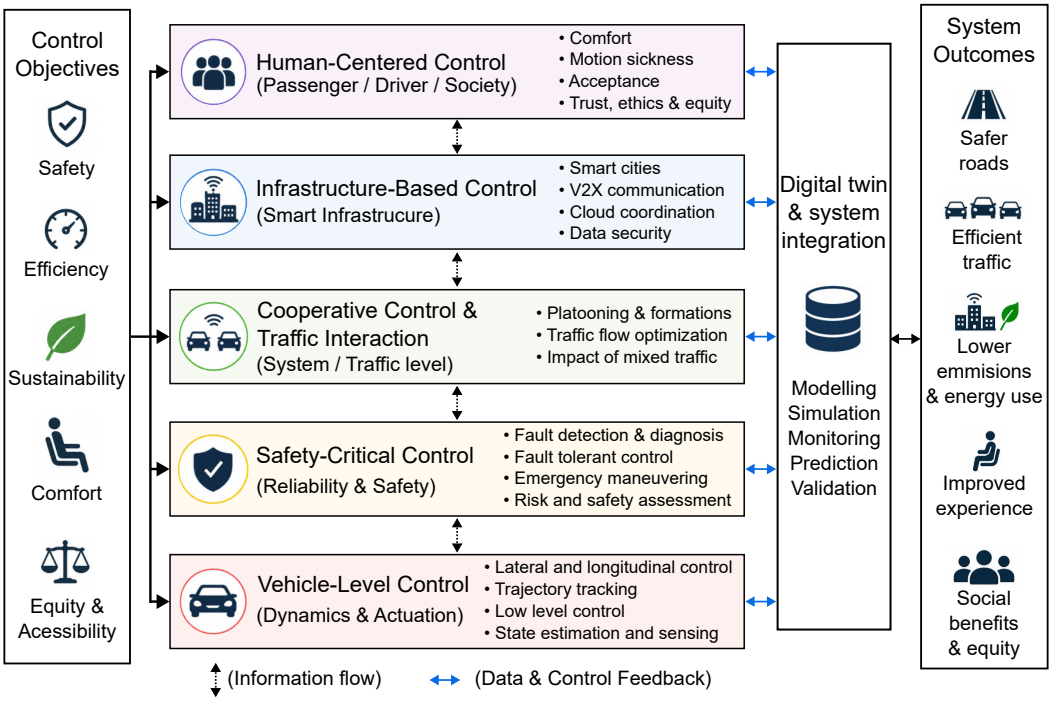


Figure 3. Multi-Level Control Framework for Autonomous Vehicles.

2.1. Vehicle-Level Control

The control of autonomous vehicles as a multi-disciplinary field is generally divided into three main components: environment perception, motion planning, and trajectory tracking control. Trajectory tracking control is the specific module responsible for executing planned actions by managing the vehicle's longitudinal (throttle/brake) and lateral (steering) dynamics while ensuring safety, comfort, and efficiency.

2.1.1. Longitudinal Control

Longitudinal control regulates motion along the vehicle's longitudinal axis, covering speed, acceleration, and safe inter-vehicle spacing [8,9], through automated management of the throttle and brake actuators. Its core functions are constant-velocity maintenance, spacing through constant time-headway policies that preserve string stability within a platoon [10], emergency collision avoidance by rapid braking [11], and ride comfort through minimal throttle–brake switching [12]. Powertrain dynamics are highly nonlinear and operating conditions vary [10], and three families of methods have been proposed in response. Classical PID control is simple to implement but needs frequent retuning across speed ranges. Neuro-fuzzy approaches such as Fuzzy Radial Basis Function Networks combine fuzzy reasoning with learning and avoid the need for a precise powertrain model. Model Predictive Control (MPC) coordinates longitudinal collision avoidance with lateral stability by predicting future states and optimising deceleration under hardware constraints. Many implementations use a hierarchical architecture with velocity, following, and emergency modes. The main design

challenges are low-speed powertrain nonlinearity, external disturbances (aerodynamic drag, tire traction, road grade), robustness to communication loss in platooning, and string stability, so that errors do not amplify upstream through a vehicle string.

2.1.2. PID and Fuzzy Logic Control

The PID algorithm remains widely used for lateral and longitudinal tracking because of its simplicity, although it can lack robustness to disturbances. Combining it with fuzzy theory improves robustness and handles processes that are hard to model. Both aim at smooth, accurate trajectory tracking with safety and comfort [13–15]. The standard PID law weights the current error, its accumulation, and its rate of change:

$$u(t) = K_p e(t) + K_i \int e(t)d(t) + K_d \frac{de(t)}{dt} \tag{1}$$

where K_p, K_i, and K_d are the proportional, integral, and derivative gains [16], valued for zero steady-state error and fast response [13]. Fractional-Order PID (FOPID) extends this law with a non-integer integral order (λ) and differential order (μ), broadening the achievable control points beyond the four fixed points of classical PID [17].

Fuzzy Logic Control (FLC), in contrast, emulates human reasoning to handle nonlinear and ill-defined dynamics without an explicit vehicle model [15,18,19]. It maps linguistic variables (e.g., "Lateral Error is Left") to reactive behaviours through expert-defined rule bases [20,21]. Whereas PID targets precision, FLC exploits tolerance for imprecision to favour robustness and smooth reactivity in partially known environments [22]. In speed advising, fuzzy logic computes a recommended speed V_R as a time-varying convex combination of the host and preceding vehicle speeds [23]:

$$V_R(t) = \alpha_R(T(t))V_N(t) + (1 - \alpha_R(T(t)))V_H(t) \tag{2}$$

Fuzzy strategies commonly use adaptive correction laws such as $\alpha(k) = \alpha(k-1) + K(y_{ref} - y(k))$ to compensate for unmodelled dynamics [24], and Takagi–Sugeno (T-S) models that represent nonlinear dynamics as a weighted sum of local linear subsystems [25]:

$$\dot{x} = \sum_{i=1}^{s} \mu_i(z)(A_i x + B_i u) \tag{3}$$

which enables Linear Matrix Inequality-based Lyapunov stability guarantees and Parallel Distributed Compensation, with the control action given by

$$u(x) = \frac{\sum_{l=1}^{M}(\Pi_{i=1}^{n}\mu F_i^l(x_i)\sum_{j=0}^{n}K_{lj}x_j}{\sum_{l=1}^{M}(\Pi_{i=1}^{n}\mu F_i^l(x_i))} \tag{4}$$

where μF_l^i denotes the membership degree of the state variables [26].

In practice, these controllers are usually combined. PID-based lateral control typically pairs an inner loop regulating yaw-rate error with an outer loop regulating lateral offset [27], with gains tuned by metaheuristics such as Particle Swarm Optimization and Genetic Algorithms, which outperform classical Ziegler–Nichols tuning on ISE/ITAE indices [20,28]. Multimodal designs use fuzzy logic as a high-level "copilot" that generates steering commands for a low-level PID loop [29], switch between straight, curve, and lane-change modes by adjusting membership functions [30], or use self-adaptive RBFNN-PID architectures that identify vehicle parameters online [22]. Fuzzy-observer-based models estimate unmeasurable states, such as sideslip angle, from camera data in GPS-denied environments, while adaptive schemes compensate for varying tire-road friction [31,32].

MPC is frequently used for longitudinal speed tracking, computing the desired acceleration from the reference–actual speed difference while enforcing hardware constraints,

although its computational burden can limit real-time performance relative to PID and fuzzy alternatives [33]. PID remains attractive for Adaptive Cruise Control (ACC) and Lane Keeping Control (LKC) because of its low complexity and robustness [34], while fuzzy control offers a model-free alternative for sensor-based obstacle avoidance, mapping crisp distance inputs into fuzzy sets via membership functions [35,36]. At high speed, PID speed control is often coupled with MPC-based lateral path tracking, and fuzzy-neural obstacle recognition can feed motion commands to an executing PID loop [37]. PID tuning, however, is highly sensitive to reference frequency and often needs extensive manual calibration, and tracking error accumulates in curves if changes in tire cornering slope are not captured [38]. Fuzzy control risks instability from poorly chosen membership functions and lacks the interpretability of model-based methods. Both must respect the tire friction limit, expressed through the friction circle [39,40]:

$$F_x^2 + F_y^2 \leq (\mu F_z)^2 \tag{5}$$

which is readily exceeded on low-friction surfaces such as snow ($\mu \approx 0.3$) or wet ground ($\mu \approx 0.6$) [41], so controllers must prioritise stability over precision as this limit is approached.

2.1.3. Sliding Mode Control

Sliding Mode Control (SMC) is a robust nonlinear methodology valued for its rapid response, simplicity, and low sensitivity to systematic uncertainties and external disturbances, despite the difficulty of constructing such controllers [4,42]. It steers the system state onto a purpose-designed sliding manifold and keeps it there [43], giving high-precision, disturbance-insensitive tracking once on the surface [44] through finite-time convergence of the sliding variable s to zero [45]. In lateral path following, the aim is to drive the lateral offset and heading error toward zero [46,47]; in longitudinal control, it is to track a reference velocity or acceleration while preserving platoon safety distances [48,49]. Design has two steps: defining a sliding manifold, commonly the linear surface $s = \dot{e} + ke$ for tracking error e [50,51], and selecting a control law that combines an equivalent term to maintain the surface with a switching term to reject uncertainty [52]:

$$u = u_{eq} + u_{sw} \tag{6}$$

Extensions that mitigate chattering include Integral Sliding Mode Control, which removes the reaching phase, Higher-Order approaches such as the Super-Twisting Algorithm, which yield continuous control signals [47], and hybrid Backstepping-SMC schemes that stabilise subsystems through independent Lyapunov functions [53]. Vehicle architectures often use a dual-loop structure, with an outer kinematic loop generating virtual velocity or position commands and an inner dynamic loop computing actuator inputs [54]; for Four-Wheel Independent Drive vehicles, SMC is combined with torque distribution to switch between cruise and collision-avoidance modes. Remaining limitations are chattering from finite-frequency switching and parasitic dynamics, actuator saturation [55], and uncertainty in tire-road friction, mass, and wind, which must be estimated to preserve precision.

2.1.4. Geometric and Optimal Path-Tracking Methods

Geometric controllers, most notably Pure Pursuit and the Stanley method, rely on the geometry of the vehicle and path rather than an explicit dynamic model [56,57]. They minimise the cross-track and heading errors between the vehicle and the desired path [58,59] while keeping steering inputs smooth, and are valued for simple, computationally efficient implementation and robustness to large initial errors [60]. Pure Pursuit models the vehicle as a 2-DOF bicycle and computes the curvature of a circular arc from the rear

axle to a lookahead point at distance l_d, mimicking a human driver's forward gaze [61,62], with steering angle

$$\delta(t) = \tan^{-1}\left(\frac{2Lsin(\alpha(T))}{l_d}\right) \tag{7}$$

where L is the wheelbase and α the angular offset to the lookahead point [63]. The method behaves as a proportional controller on cross-track error with gain $2/l_d^2$ [64]. The Stanley method instead places its control point at the front axle, combining heading error θ_e and cross-track error e [65]:

$$\delta = \theta_e(t) + \tan^{-1}\left(\frac{ke(t)}{v(t)}\right) \tag{8}$$

with gain k and longitudinal velocity $v(t)$. Adaptive extensions scale the lookahead distance with speed (e.g., $l_d = kv$) [66], adjust translational velocity in sharp turns via the Regulated Pure Pursuit algorithm, anticipate future states through a Predictive Stanley Controller [67], or optimise the lookahead distance with meta-heuristics such as the Salp Swarm Algorithm [68]. Both methods neglect vehicle dynamics and can become unstable above roughly 5 m/s (18 km/h). Pure Pursuit cuts corners when the lookahead is too long, while a well-tuned Stanley tracker avoids this but may overshoot and is sensitive to path discontinuities.

The Linear Quadratic Regulator (LQR) offers an optimal alternative, minimising a quadratic cost that penalises tracking error and control effort [69–71]:

$$J = \sum_{k=0}^{\infty}(X_k^T Q X_k + U_k R u_k) \tag{9}$$

It is implemented as a state-feedback law $u = -KX$ [72], and is often extended to Adaptive LQR/LQG architectures with a look-ahead-based Q-matrix, or to Iterative/Constrained iLQR for nonlinear constraint handling such as obstacle avoidance [71,73,74], typically within a cascade structure that separates position and dynamic control [75]. LQR is frequently coupled with MPC, the former handling lateral tracking and the latter longitudinal speed and acceleration [70], with LQG observers estimating states that are hard to measure directly amid sensor noise [76]. A related geometric approach, the Autodriver algorithm, synchronises the vehicle's instantaneous rotation centre with the road's curvature centre at every instant [77,78]. It uses a feedforward "ghost-car" reference with feedback (e.g., Sliding Mode) control to remove transient error [79], and has been extended with bicycle-roll models and clothoid road geometries. LQR-based systems remain sensitive to sensor noise, localisation error [80], and tire saturation on slippery roads. The Autodriver feedforward term relies on steady-state assumptions and can depart from the path during sudden manoeuvres or shifts in tire-road interaction [77], so errors from wind, road bank angle, and misalignment must be corrected by feedback. The curvature estimate also depends on the precision of the road function:

$$R_k = \frac{(1 + Y'^2)^{\frac{3}{2}}}{Y''} \tag{10}$$

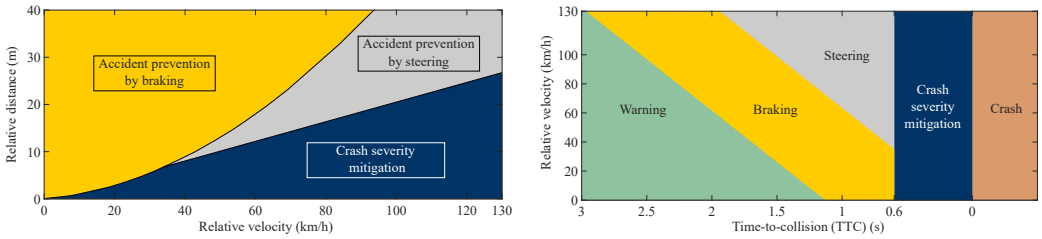
2.2. Safety-Critical Control

The safety-critical control layer keeps the vehicle stable and safe when conditions become demanding: during aggressive manoeuvres, in emergency situations, and when system faults or failures occur [4,81]. Two types of situation stand out. In the first, the vehicle operates near its physical handling limits, where nonlinear tire dynamics, actuator saturation, and rapid changes in motion strongly affect controllability and stability [4,82]. In the second, actuator, sensor, or communication faults and failures degrade the system; here a fault is an abnormal condition that changes system behaviour, whereas a failure is

the inability of a system to perform its designed function [83]. Safe operation therefore depends on two capabilities: maintaining stability during emergency manoeuvres, and coping with faults without losing that stability.

2.2.1. Emergency Manoeuvres and Handling Limit

The emergency scenario depicted in Figure 2 develops according to the relative distance and velocity between the ego vehicle and the object ahead. A collision can be avoided by emergency braking, by evasive steering, or by a combination of both [4,84]. Figure 4a shows which action applies for a given relative velocity and distance, and Figure 4b gives the equivalent view in terms of time-to-collision [4,85]. Once braking alone is no longer sufficient, steering has to be added to the braking action [86,87]. When neither action can prevent the crash, the objective changes to crash-severity mitigation, that is, minimising injury to all road users involved.



(**a**) (**b**)

Figure 4. (**a**) Crash avoidance regions based on relative distance and velocity through braking and steering maneuvers, including the unavoidable collision region [4,84]. (**b**) Illustration of time-to-collision (TTC) as a function of relative velocity and distance between vehicles [4,85].

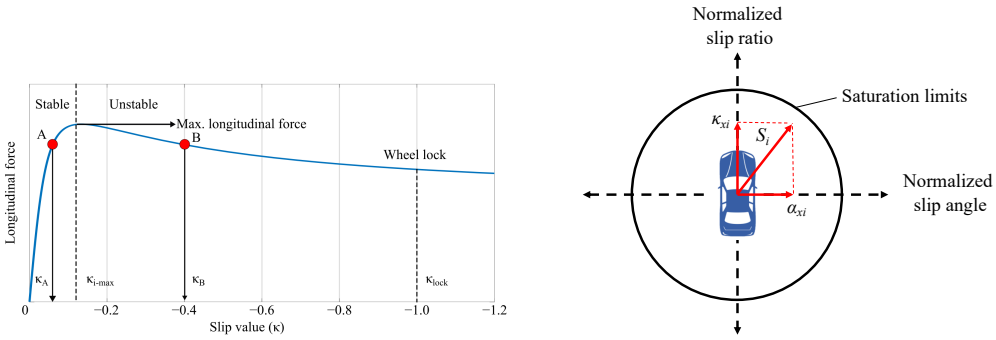
An emergency manoeuvre pushes the vehicle to its handling limit, which is set by how much longitudinal and lateral force the tire can generate as a function of slip. Figure 5a shows the nonlinear relationship between longitudinal tire force and slip ratio κ. Force rises through the stable region (point A, κ_A) up to the friction limit (κ_{i-max}); beyond it, the tire enters an unstable region in which the force decreases and the wheel may lock (point B) [4]. Lateral tire dynamics behave in a similar way.

From a control point of view, the characteristic in Figure 5a shows how much longitudinal force is still available during an emergency manoeuvre. In the stable region, the controller can use a share of the available tire-road friction up to the maximum-force point. Beyond that point it has to work in the unstable region, with lower forces and increasing slip. Safety-critical controllers should therefore hold the tire close to the usable friction limit and avoid sustained operation towards wheel lock, especially under hard braking [4].

In practice, longitudinal and lateral loading occur together during emergency manoeuvres, so proximity to tire saturation has to be monitored continuously. Figure 5b presents a normalized tire utilization indicator built from the normalized longitudinal slip ratio κ_{xi} and the lateral slip angle α_{yi} [87]:

$$S_i = \sqrt{\kappa_{xi}^2 + \alpha_{yi}^2}, \tag{11}$$

Figure 5b shows that longitudinal and lateral tire forces cannot be treated independently during combined braking and steering. As the longitudinal force grows, less lateral force can be generated; likewise, when aggressive steering is needed, the lateral force limits what is left for braking. As S_i approaches the saturation boundary, the remaining control authority shrinks and separate lateral and longitudinal control actions begin to compete for the same finite friction. This motivates integrated control and control-allocation strategies that distribute steering, braking, and drive actions according to the remaining tire-force capacity [4,87].



(**a**) (**b**)

Figure 5. (**a**) Longitudinal tire force versus longitudinal slip ratio κ [4]. (**b**) Tire monitoring circle via the normalized slip ratio and normalized slip angle [4].

Emergency controllers have only a short time window in which to react, and they must remain stable and robust to disturbances and uncertainties [4]. This separates them from comfort-oriented controllers, for which avoiding a crash is not the dominant objective. The controllers investigated for this purpose include PID, MPC, SMC, Pure Pursuit, fuzzy control, and machine learning-based approaches [4]. MPC is among the most widely applied, because it handles prediction horizons, actuator and tire constraints, and multiple objectives explicitly; integrated nonlinear MPC formulations have been proposed that combine steering and braking while accounting for tire saturation and torque allocation [86,88]. More recent work extends MPC to over-actuated platforms with four-wheel steering, torque vectoring, and independent wheel actuation. By exploiting the actuator redundancy, these controllers regulate yaw rate, sideslip angle, and tire-force distribution together near the handling limit [4,89–91], which improves manoeuvrability, stability, and fault tolerance in aggressive evasive manoeuvres [89,92]. The concept of Regions of Feasible Handling adds that the achievable vehicle behaviour depends strongly on which actuators are available, so reference targets for yaw rate, sideslip, and lateral acceleration must remain physically achievable for the available actuator set [90].

SMC has also been applied extensively to evasive steering under handling-limit and tire-saturation constraints [93]. For over-actuated vehicles, extensions combine second-order SMC, fuzzy-based slip regulation, torque vectoring, and path preview, allowing simultaneous emergency braking and steering while preserving stability [4]. Other work looks beyond the ego vehicle: risk-based emergency steering frameworks with uncertainty-aware pedestrian prediction and MPC-based trajectory planning target pedestrian protection [94], while cooperative emergency braking and adaptive time-gap strategies for connected automated vehicles improve stability and reduce collision risk in mixed traffic [95]. Overall, the literature has moved from isolated steering or braking interventions towards integrated, predictive, over-actuated architectures, with MPC providing strong constraint handling and SMC providing robustness and fast response [4,91,93]. Open challenges include nonlinear tire dynamics, actuator saturation, road-friction uncertainty, computational complexity, and perception uncertainty, all of which make it difficult to preserve stability in real time when longitudinal and lateral action are needed simultaneously under rapidly changing conditions.

2.2.2. Faults, Reliability, and Fault-Tolerant Control

As automation increases, vehicles depend on a growing number of embedded sensing, computing, communication, and actuation systems, which makes reliability and fault tolerance basic safety requirements. Faults can arise from actuator degradation, sensor malfunction, communication delay, hardware or software failure, or adverse environmental conditions, and even a minor fault can seriously compromise stability, tracking, and

collision avoidance in a safety-critical situation [4,83]. Perception sensors (cameras, radars, LiDARs) and state-estimation sensors (GNSS, IMUs, wheel encoders, steering angle sensors) are prone to signal loss, drift, bias, calibration degradation, interference, and environmental disturbance [96,97]. Because perception errors propagate into planning and control, modern systems increasingly rely on sensor fusion, redundancy, cross-validation, and self-diagnosis to remain robust [96,97]. Steering, braking, and drive actuators can likewise suffer bias, loss of effectiveness, stuck conditions, asymmetric actuation, delayed response, or complete failure [4]. Steering bias faults lead to trajectory deviation and yaw instability [98], and brake or drive faults produce asymmetric tire forces and unwanted yaw moments, which are especially critical in over-actuated vehicles [4,99].

Fault Detection and Isolation (FDI) determines whether a fault has occurred, using model-based observers, residual generation, Kalman filtering, and analytical redundancy [83]. Observer-based methods offer low-complexity, uncertainty-robust fault estimation [98], whereas data-driven neural-network and anomaly-detection approaches can detect faults earlier but depend on the quality and generalisation of the training data [97]. A study combining Failure Mode and Effects Analysis, Design of Experiments, and ANOVA found that steering faults become particularly critical when they coincide with low road friction and high velocity (up to 130 km/h) [100].

Fault-Tolerant Controllers (FTC) are either passive, accommodating a predefined range of uncertainty, or active, detecting faults explicitly and reconfiguring the controller accordingly [83]. Over-actuated platforms are well suited to this task because of their actuator redundancy [4,99]. An MPC-based FTC has achieved path tracking, velocity control, and compensation of actuator degradation within one optimisation framework, keeping the velocity error below 3 km/h and the path-tracking error below 0.5 m under multiple faults [99]. An active nonlinear MPC has compensated steering faults and cornering-model mismatch at velocities up to 20 km/h [101]. Reinforcement-learning-based FTC has been explored at velocities up to 130 km/h, where steering and torque-distribution policies adapt online to improve crash avoidance under degraded conditions [4]. For brake faults, fault-tolerant anti-lock braking with redundant electronic control units and dual-winding motors has preserved braking functionality [102], which shows how important redundancy management and fail-operational design are.

Several challenges remain for FTC deployment. Performance depends strongly on the accuracy of vehicle models or training datasets, which limits generalisation under varying friction, tire wear, and unseen faults. Real-time computational limits restrict how complex the optimisation or deep-learning components can be. And sensor redundancy alone cannot guarantee fault-free operation, since correlated faults or environmental disturbances can affect several sensing modalities at once. Future architectures are therefore likely to combine observer-based diagnosis, redundancy management, adaptive control allocation, predictive control, and learning-based adaptation.

2.2.3. Learning-Based Approaches for Safety-Critical Control

Machine learning is being adopted at a growing rate in vehicular systems, as the steady rise in related patents across autonomous driving, control, perception, and predictive maintenance shows [103]. Deep learning architectures such as CNNs and RNNs are well established in perception tasks including object detection, lane recognition, and sensor fusion [104], and have also been applied to fault diagnosis [105]. In vehicle control, Bayesian optimisation combined with a velocity-prediction MPC has been used to tune controller parameters automatically near the handling limit [106]. Reinforcement learning (RL) and inverse reinforcement learning more broadly offer adaptable, environment-interactive policy learning that suits the uncertainty and nonlinearity of safety-critical driving. A

recent review of advanced FTC techniques for electric and autonomous vehicles, covering neural networks, fuzzy logic, adaptive control, reinforcement learning, and hybrid data-driven approaches, concluded that learning-based methods can improve fault detection accuracy, isolation, and controller adaptability compared with conventional model-based techniques, particularly under highly nonlinear and uncertain conditions [107].

RL is attractive for safety-critical vehicle control because it can learn nonlinear dependencies among vehicle states, actuator states, and control actions through interaction with the environment. This is especially valuable for over-actuated vehicles, where redundant steering, braking, and drive actuators offer several ways to keep the vehicle stable after a component fault. Actor–critic methods such as Deep Deterministic Policy Gradient (DDPG), Twin Delayed Deep Deterministic Policy Gradient (TD3), Soft Actor–Critic (SAC), and Proximal Policy Optimization (PPO) have gained attention for continuous control problems in which steering angles, braking forces, and wheel torques are adjusted continuously. Training can also include variations in road friction, vehicle parameters, disturbances, sensor noise, and actuator degradation, so the learned policy can adapt to operating conditions that are hard to capture in a single fixed controller formulation [4,81].

Lyapunov-based approaches address the limitation that comes with this adaptability by supporting stable learning and policy convergence. In [4], a Lyapunov-based reward-reshaping strategy supported stable convergence of the RL policy, while the underlying SMC retained the vehicle-level stability properties of the controller. The distinction matters, because a stable learning process does not necessarily imply a physically stable vehicle. These limitations motivate hybrid architectures in which RL provides adaptive fault compensation and actuator reconfiguration, while model-based controllers remain responsible for stability and physical constraints [4,81,107,108].

2.2.4. Comparative Assessment of Safety-Critical Control Approaches

Table 1 summarizes the main characteristics, limitations, and validation levels of the approaches discussed in Sections 2.2.1–2.2.3. No single methodology provides strong robustness, constraint handling, adaptability, low computational complexity, and formal safety guarantees at the same time. MPC offers predictive constraint handling, and SMC offers robustness against disturbances and model uncertainties. FTC improves adaptability, but depends on reliable fault detection and control allocation. Learning-based methods adapt well under nonlinear dynamics and degraded conditions, but formal safety guarantees remain a significant challenge.

Table 1. Comparison of safety-critical control approaches for autonomous vehicles.

Approach	Application	Main Strengths	Main Limitations	Validation and Representative Work
MPC/NMPC	Emergency steering and braking, handling-limit control, and FTC	Explicit constraint handling; predictive and multi-objective control	High computational demand and dependence on model accuracy	Simulation and vehicle/prototype studies [86,88,89,99,101]
Sliding Mode Control (SMC)	Evasive manoeuvres and stability control near tire saturation	Strong robustness to disturbances and model uncertainties; fast response	Chattering and less explicit handling of physical constraints	Simulation and model-based validation [87,92,93]
Fault Detection and Isolation (FDI)	Detection and isolation of sensor and actuator faults	Model-based methods are interpretable; data-driven methods can capture nonlinear fault patterns	Model-based methods depend on model accuracy; learning-based methods depend on training data and generalisation	Model-, observer-, and data-driven studies [83,97,98,105]

Table 1. *Cont.*

Approach	Application	Main Strengths	Main Limitations	Validation and Representative Work
Fault-Tolerant and Over-Actuated Control	Maintaining stability and control following actuator or sensor degradation	Uses actuator redundancy and control reconfiguration to preserve vehicle functionality	Depends on reliable fault diagnosis; increased allocation and system complexity	Simulation, prototype, and scaled-vehicle studies [89,90,92,99,101,102]
Reinforcement Learning/Deep RL	Adaptive FTC, torque distribution, and emergency manoeuvring under degraded conditions	High adaptability to nonlinear dynamics and changing actuator availability	Limited formal safety guarantees, generalisation, explainability, and certification	Simulation and scaled-vehicle experimental validation [81,108]
Hybrid Model-Based + Learning	Adaptive safety-critical control combining learning with conventional controllers	Combines learning-based adaptability with model-based robustness and constraints	Higher architectural complexity and limited mature experimental validation	Mainly simulation and data-driven studies [106,107]

2.3. Open Issues and Future Directions in Safety-Critical Autonomous Vehicle Control

Several open issues remain. Tire-road friction and vehicle states are still difficult to estimate reliably near the handling limits. Real-time implementation, robust fault detection, and control reconfiguration for concurrent faults need further work, particularly for over-actuated vehicles. For learning-based controllers, generalisation to unseen scenarios, limited fault data, and the lack of formal safety guarantees remain the main obstacles. In addition, many proposed approaches have been validated only in simulation or on scaled platforms, so experimental validation under realistic safety-critical conditions is still needed [4,81,107]. Looking ahead, fault diagnosis, control allocation, and learning-based techniques are likely to become more tightly integrated. Over-actuated architectures will remain attractive for their manoeuvrability, stability, and fault-tolerance benefits, despite their added complexity. Learning-based methods are expected to complement rather than replace conventional controllers, and hybrid architectures combining MPC, SMC, FTC, and RL promise improved adaptability while preserving stability guarantees. Safety-critical control should also be seen as one part of a wider multi-layer system that depends increasingly on cooperation with surrounding vehicles, intelligent infrastructure, and human-centered interaction.

2.4. Cooperative Control and Traffic Interaction

Cooperative control extends autonomous driving beyond the isolated ego vehicle to interactions among several vehicles in the traffic stream. Vehicle-level control deals with the stability, trajectory tracking, and actuation of a single vehicle; cooperative control asks how one vehicle's motion decisions affect surrounding vehicles, traffic flow, congestion, and safety. It is particularly relevant for connected and autonomous vehicles (CAVs), which exchange speed, acceleration, manoeuvre, and local traffic information via V2V communication and can therefore coordinate more effectively than purely sensor-based autonomy [109,110]. Local decisions such as car-following, lane changing, merging, braking, and gap selection have system-level consequences. An overly conservative or sudden braking action may avoid a local conflict but generate stop-and-go waves, reduce capacity, or increase rear-end risk, whereas cooperative information sharing can reduce unnecessary acceleration and braking and make surrounding traffic more predictable [111,112]. Cooperative control therefore aims to support safe ego-vehicle motion alongside stable, efficient, and predictable collective traffic behaviour.

Figure 6 gives an overview of how information exchange, cooperative decision-making, behavioural and motion planning, vehicle-level execution, traffic interaction, and system-level evaluation connect. Panel A covers local sensing and V2V information, cooperative decision-making, behavioural planning, motion planning, manoeuvre-level evaluation, and vehicle-level execution. Panel B shows how the executed manoeuvre interacts with the operating context and communication uncertainty to produce mixed-traffic responses and system-level outcomes. Solid arrows mark the primary information–decision–action pathway, and the dashed feedback path represents adaptation of decision, planning, and control policies based on observed safety, stability, efficiency, emissions, comfort, and fairness outcomes.

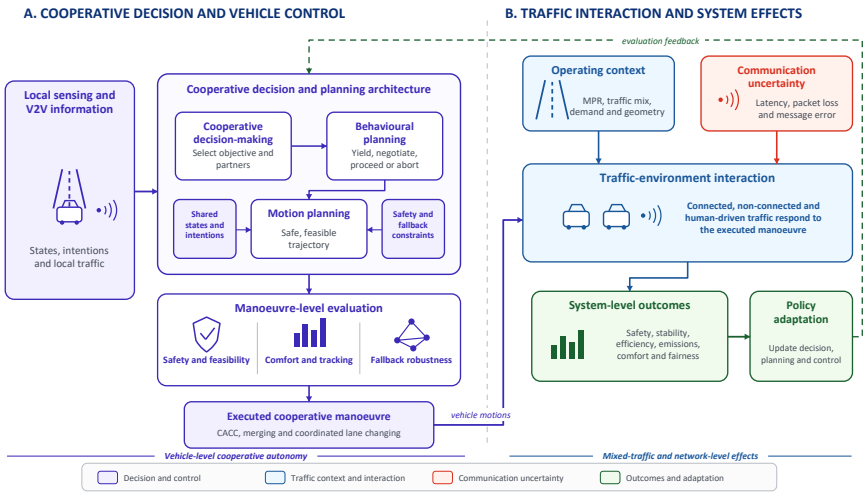


Figure 6. Integrated cooperative-control and traffic-interaction framework.

2.4.1. Vehicle-to-Vehicle Communication and Distributed Decision-Making

V2V communication lets connected vehicles exchange position, velocity, acceleration, desired trajectory, and manoeuvre intentions instead of relying only on onboard sensing, which improves both local decision-making and traffic-stream coordination [109,110]. Decision-making at this layer is typically distributed: each vehicle combines its local information with communicated data, which meets the short time windows of real-time manoeuvres and scales to traffic with heterogeneous automation and communication capabilities [113]. It must also remain robust to delays, packet loss, inconsistent protocols, and inaccurate state information, and it cannot assume that all nearby vehicles are connected or automated. This matters most during the transition period, when connected, non-connected, and human-driven vehicles coexist [110,114].

The decision-making layer sits between communication and vehicle control. Received states and intentions are first converted into behavioural decisions, for example to yield, form or leave a platoon, request a gap, proceed, or postpone cooperation, before a motion planner generates a feasible trajectory. Cooperative decision-making selects the participants and the interaction objective, behavioural planning selects a socially interpretable manoeuvre, and motion planning turns it into a collision-free, dynamically feasible trajectory. Keeping these roles distinct makes it easier to see whether a failure originates in information exchange, interaction strategy, trajectory generation, or vehicle control, as illustrated in Panel A of Figure 6.

2.4.2. Platooning and Cooperative Adaptive Cruise Control

Platooning and cooperative adaptive cruise control (CACC) are among the most representative cooperative applications. By exchanging acceleration, braking, and desired-

velocity information, vehicles can coordinate their longitudinal motion and hold shorter, more stable headways than human drivers typically achieve [111]. The main objective is to keep spacing safe while ensuring string stability, so that disturbances in speed or spacing do not amplify upstream through the platoon, as they often do with the delayed, heterogeneous reactions of human drivers [111,112]. Field experiments have shown that even a small share of automated vehicles can damp stop-and-go waves and improve flow stability [112], and later feedback-control studies showed that automated vehicles can act as mobile control agents that stabilize nonlinear mixed traffic [115]. Cooperative benefits can therefore appear before full market penetration is reached. Their size still depends strongly on penetration rate, communication reliability, traffic demand, and road geometry, and the larger system-level effects, such as increased capacity and reduced congestion, generally emerge as penetration rate increases [110,116].

These studies provide complementary but not directly interchangeable evidence. The field experiment in [112] shows that an automated vehicle can damp disturbances in real traffic, but its ring-road setting and narrow objective limit generalization to open networks, lane changes, and unreliable communication. The feedback-control approach in [115] offers a clearer analytical mechanism, although its performance depends on the assumed sensing, actuation, and behavioural models. Broader assessments such as [110,116] show how benefits vary with penetration rate and traffic conditions, but aggregated or simulation-based findings cannot establish that a specific controller stays safe in rare or highly uncertain interactions. Collectively, they support the traffic-stabilizing potential of CACC while leaving generalisability, communication robustness, and real-world deployment open [110,116].

2.4.3. Cooperative Merging and Lane-Change Coordination

Cooperative merging and lane-change coordination matter most at freeway on-ramps, lane drops, weaving sections, and congested multilane roads, where uncoordinated or overly conservative local decisions cause unnecessary braking, unstable flow, and higher conflict risk. Connected and automated vehicles can instead communicate their intended trajectories, lane changes, and gap-acceptance decisions. Mainline and merging vehicles can then adjust their speeds in advance, and vehicles in the target lane can anticipate the manoeuvre, as demonstrated in recent studies of freeway on-ramp merging and multi-lane mixed traffic [117,118]. Mixed traffic makes this harder, because human drivers may respond unpredictably, fail to create the expected gaps, or exploit the conservative behaviour of automated vehicles. Cooperative merging controllers must therefore operate safely and predictably under uncertainty, including when surrounding vehicles are human-driven or non-connected [110,114].

Unlike longitudinal platooning, merging and lane changing require joint coordination of longitudinal and lateral motion. The approaches in [117,118] go beyond car-following by creating gaps in anticipation and adjusting trajectories jointly before a conflict becomes critical. This capability, however, depends on intention prediction, gap acceptance, trajectory compatibility, and the willingness of surrounding drivers to cooperate. Performance shown in a structured on-ramp or modelled multi-lane scenario may therefore not transfer to dense weaving sections, opportunistic human driving, partial connectivity, or failed negotiations without explicit fallback behaviour [110,114]. In addition, executing a cooperative manoeuvre changes the surrounding traffic: human-driven, connected, and automated vehicles may respond differently, and their collective response ultimately determines whether the intended safety and traffic-flow benefits are achieved.

2.4.4. Mixed Traffic and Market Penetration Rate Effects

Mixed traffic, in which autonomous, connected, partially automated, and human-driven vehicles share the same infrastructure, is expected to remain the dominant operating condition during a prolonged transition period [114,119]. It may also include pedestrians, cyclists, motorcyclists, and public-transport users, so cooperative-control strategies need to be evaluated under heterogeneous rather than idealized, fully connected conditions. The market penetration rate (MPR) of connected and autonomous vehicles has a direct, non-linear influence on system performance. At low MPR, benefits are generally confined to local platoons, individual interactions, or specific traffic disturbances. At medium MPR, cooperative effects extend to merging, lane changing, and intersection discharge. At high MPR, coordinated strategies such as platooning, speed harmonization, and cooperative traffic management become substantially more effective [110,116].

Recent reviews indicate that CAVs can improve congestion, road capacity, traffic stability, safety, and emissions, although the size of these benefits depends strongly on penetration rate, communication capability, traffic demand, and interaction with human-driven vehicles [110]. A recent meta-analysis similarly found that safety benefits remain comparatively limited at low MPR and become more substantial at higher penetration levels [120]. Human behaviour adds further complexity, because drivers may follow, trust, or anticipate automated vehicles differently depending on experience, expectations, and familiarity with the technology. Mixed traffic should therefore be understood as both a technical control problem and a socio-technical interaction problem [121,122].

MPR-focused studies cover the system level more broadly than studies of individual manoeuvres, but they say less about why a specific interaction succeeds or fails. Reviews such as [110] compare several traffic conditions, performance indicators, and deployment scenarios, and the meta-analysis in [120] gives a stronger basis for estimating the overall relationship between MPR and safety effects, although pooled findings mix different automation capabilities, communication assumptions, traffic compositions, road geometries, and definitions of safety. Manoeuvre-level studies explain interaction mechanisms more clearly but are usually restricted to narrow scenarios. Robust conclusions therefore need both: microscopic interaction studies to validate cooperative behaviour and traffic-level experiments to quantify its network consequences [121,122].

2.4.5. Traffic-Flow Optimization and Evaluation

Cooperative control should be evaluated with system-level indicators, not ego-vehicle tracking performance alone. Relevant indicators include headway, speed variance, string stability, and shockwave propagation for car-following and platooning; gap acceptance, conflict frequency, discharge rate, and delay for merging and lane changing; and travel-time reliability, congestion spillback, emissions, and throughput at the network level [111,123]. A controller that performs well for the individual vehicle does not necessarily improve the behaviour of the whole traffic stream.

The evaluation objectives can also conflict. Shorter headways increase capacity but may reduce perceived safety or passenger comfort, smoother eco-driving may conflict with travel-time minimisation in periods of high demand, and efficiency gains for automated vehicles may transfer delay or inconvenience to human-driven vehicles, pedestrians, cyclists, or public transport. Cooperative control should therefore be judged on a combination of stability, safety, delay distribution, comfort, emissions, throughput, and fairness rather than average speed or throughput alone [124,125].

Controller-centred and traffic-centred evaluations complement each other. The former give precise measures such as tracking error, spacing error, control effort, and string stability, but may miss congestion spillback, network delay, emissions, or how benefits

are distributed. The latter capture these wider consequences, but aggregate improvements can hide uncomfortable, inefficient, or unsafe individual interactions. A controller may be locally stable while shifting delay or risk onto other road users, and an apparent network-level gain may rest on assumptions that are hard to reproduce in real traffic. Comparative evaluation should therefore report manoeuvre-level safety and comfort alongside network-level efficiency and distributional outcomes, under matched traffic demand, MPR, communication, and human-behaviour assumptions. Section 2.4.6 and Table 2 compare the evidence type, operating conditions, and evaluation scale of the studies discussed here.

Table 2. Comparative summary of representative cooperative-control studies and their principal limitations.

Study	Focus and Evidence	Main Strength	Limitation for Generalisation
[111]	CACC, car-following, and traffic stability	Connects vehicle-level interactions with string stability and traffic-flow performance.	The reported benefits depend on behavioural, penetration-rate, and communication assumptions.
[112]	Field experiment on stop-and-go waves	Provides real-world evidence that a small proportion of automated vehicles can damp traffic disturbances.	The controlled ring-road setting does not represent open networks, complex lane changes, or unreliable communication.
[115]	Feedback control in nonlinear mixed traffic	Provides a controller-level mechanism for using automated vehicles as mobile traffic-control agents.	Transfer to real traffic depends on model accuracy and sensing, actuation, and behavioural assumptions.
[117,118]	Cooperative merging and multi-lane coordination	Extends cooperation to anticipatory gap creation and coordinated longitudinal–lateral decisions.	Structured scenarios and assumed compliance may underrepresent uncertain or opportunistic human behaviour.
[110]	Review of CAV traffic impacts	Compares safety, capacity, stability, congestion, and emissions across operating conditions.	Heterogeneous methods and assumptions limit conclusions regarding the performance of individual controllers.
[120]	Meta-analysis of MPR-related safety effects	Synthesises the magnitude and penetration-rate dependence of reported safety benefits.	Pooled effects may conceal differences in automation capability, connectivity, traffic scenarios, and safety measures.
[121,122]	Human interaction, trust, and anticipation	Makes the behavioural and socio-technical dimensions of mixed traffic explicit.	Human responses vary across populations, experience levels, traffic contexts, and automated-driving behaviours.

2.4.6. Comparative Synthesis of Existing Work

Table 2 compares representative studies from this section by focus, evidence type, principal strength, and limitation. Experimental and control-oriented studies give relatively direct evidence for specific cooperative mechanisms, whereas reviews and meta-analyses cover traffic conditions, penetration rates, and performance measures more broadly; the evidence is therefore strongest when both types are considered together, rather than when a single study is generalised to all mixed-traffic and connectivity conditions.

2.4.7. Challenges and Future Perspectives

Several challenges remain despite the potential of cooperative control to improve traffic safety and efficiency. Reliable V2V communication cannot be guaranteed in real-world conditions, because of latency, packet loss, limited range, cybersecurity risks, inaccurate messages, and inconsistent interoperability across manufacturers. Cooperative benefits also depend strongly on market penetration rate, particularly when most surrounding vehicles are human-driven or non-connected. Controllers must remain robust to heterogeneous human driving and reconcile local vehicle safety with system-level efficiency: conservative policies may increase safety margins but reduce capacity, whereas more assertive coordi-

nation may improve traffic flow while increasing perceived risk or reducing comfort for human road users [110,114,121,122].

The limitations summarized in Table 2, together with the dependencies illustrated in Figure 6, point to four research gaps. First, results are hard to compare across studies because traffic demand, MPR definitions, communication assumptions, human-driver models, and safety measures differ. Second, many controllers are evaluated only under nominal scenarios, leaving little evidence on communication loss, failed negotiations, unexpected human responses, and rare critical interactions. Third, behavioural planning is less mature than state exchange, trajectory generation, and low-level control, particularly regarding whom to cooperate with, when to yield, when to abandon a negotiation, and how to behave predictably toward non-connected road users. Fourth, average system-level benefits may hide delay, risk, or discomfort shifted onto human-driven vehicles or vulnerable road users.

Future research should therefore prioritise communication-aware CACC, distributed cooperative decision-making, human-driver prediction, traffic-aware behavioural and motion planning, and multi-objective optimization under partial connectivity and mixed autonomy. Evaluation frameworks should combine standardized manoeuvre-level stress tests with network-scale experiments, vary MPR and communication quality explicitly, include heterogeneous human responses, and report safety, efficiency, comfort, emissions, and fairness together rather than optimizing a single measure [124,125]. Cooperative control can then be understood as a transition layer between vehicle-level autonomy and infrastructure-supported autonomous mobility, with cooperative decision-making and behavioural planning bridging exchanged information and safe, socially compatible vehicle motion.

2.5. Infrastructure-Based Control

Smart infrastructure, combining sensing, communication modules, and centralized processing, enables continuous monitoring of traffic participants and roadway conditions [5]. In a critical scenario, it can assist connected and automated vehicles by providing perception data beyond the range of onboard sensors, generating suggested trajectories, or intervening directly in longitudinal and lateral dynamics to improve safety and operational performance [5]. The interaction between automated vehicles and smart infrastructure falls into two broad categories: maneuver coordination and direct control of vehicle dynamics.

2.5.1. Infrastructure-Based Maneuver Coordination

For maneuver coordination, smart infrastructure is typically installed at critical locations such as urban intersections, highway merging zones, and accident-prone areas. Using infrastructure-based sensors and Vehicle-to-Infrastructure (V2I) and Infrastructure-to-Vehicle (I2V) communication, it can perceive the traffic environment, monitor connected and non-connected road users, receive the intended maneuvers of connected vehicles, and predict the future trajectories of all participants [5]. It can then transmit warning messages and trajectory recommendations to connected automated vehicles to improve traffic flow and efficiency and reduce collision risk [126].

The ETSI Technical Committee on Intelligent Transport Systems (ITS) has recently introduced a pre-standardization study for the Maneuver Coordination Service (MCS), which aims to establish a unified framework for cooperative maneuvers. Within it, agreement-seeking is the process of evaluating and accepting cooperation agreements among participating entities. The study addresses two concepts: vehicle-to-vehicle (V2V) cooperation agreement seeking, and I2V maneuver coordination with roadside infrastructure [127].

In V2V agreement seeking, the MCS can be initiated in two ways. A subject vehicle may request cooperation from one or more target vehicles, disseminating its intent and a cooperation request, which may require several sequential exchanges to complete the maneuver. Alternatively, a target vehicle may proactively assist one or more subject vehicles by broadcasting its intent and a cooperative offer, with coordination then proceeding through iterative message exchanges. The framework defines two trajectory types: reference trajectories, which communicate intended plans to other vehicles, and requested trajectories, which seek assistance when the subject vehicle cannot resolve a situation alone, for example when its desired trajectory is blocked by a vehicle with higher precedence [127].

In I2V coordination, a roadside unit (RSU) initiates the service. RSUs typically have superior situational awareness because they combine multiple infrastructure-based sensors with information from other road users [128]. The RSU identifies target vehicles and recommends coordinated maneuvers to achieve mobility objectives, and these recommendations are communicated to the relevant connected vehicles, which may reply with their intended trajectories or an explicit confirmation. Collective action begins only when all relevant connected vehicles accept the proposed maneuver, and once they agree, each vehicle remains responsible for executing its own maneuver at all times [127].

2.5.2. Infrastructure-Based Remote Operation

Smart infrastructure may also take a temporary role in controlling vehicle dynamics through remote operation. Highly automated vehicles may rely on remote assistance for complex scenarios that exceed their operational design domain, such as previously unseen situations, post-collision environments, or partially or fully obstructed roadways [129]. Remote operation can also compensate for limitations or failures in onboard localization, perception, or decision-making. In these cases, a remote operator or infrastructure-based control system provides direct control inputs to guide the vehicle safely until it can resume autonomous operation or reach a safe state [130].

Communication latency is the primary limitation of remote operation, since it directly affects real-time responsiveness and safety. Delays arise from signal propagation, network congestion, packet processing, and routing within the communication infrastructure [131]. Most current deployments connect vehicles to remote operation centres over public 4G or 5G networks, which offer high bandwidth and wide coverage but can still introduce variable latency and reliability problems, particularly in congested urban areas or regions with limited coverage. Roadside units offer a way to address this. They can be placed at critical locations such as Operational Design Domain (ODD) transition zones, construction sites, and complex intersections, where remote assistance is most likely to be needed. A dedicated low-latency wireless link between the vehicle and the remote operation centre then reduces transmission delay and dependence on public cellular networks, allowing human remote operators or automated cloud- or edge-based assistance systems to intervene more effectively with trajectory guidance, decision support, or direct control of longitudinal and lateral dynamics.

2.6. Human-Centered Control

Human-Centered Control (HCC) is an emerging paradigm in intelligent transportation systems and autonomous vehicle (AV) research that places the vehicle occupant at the centre of control design. Traditional vehicle control has focused on safety, stability, and efficiency, whereas HCC also accounts for passenger perception, physiological response, cognitive state, and, above all, subjective comfort when making driving decisions. As automation features such as adaptive cruise control, lane-change assistance, and regenerative braking spread, drivers are becoming passengers. This shift raises new challenges, including trust

in automation, situational awareness, and user acceptance [132,133]. Future vehicle control must therefore optimise vehicle dynamics and human well-being together if it is to deliver genuinely user-centric mobility.

A key motivation for HCC is motion sickness, which could limit the adoption of AVs once occupants no longer control the vehicle. Roughly one in three people is affected by motion sickness [134]. It arises from a sensory conflict between the visual, vestibular, and proprioceptive systems, and is aggravated when occupants read, browse on a phone or laptop, or otherwise engage in non-driving activities [135,136]. The literature links low-frequency vehicle motion, excessive lateral acceleration [137], and abrupt trajectory changes [138–140] to sickness in passengers. This has motivated motion-aware control strategies that mitigate sickness-inducing dynamics through trajectory optimisation, motion planning, speed regulation, and steering control.

Comfort-oriented trajectory planning for aggressive manoeuvres has become a major research focus. Algorithms for motion planning during high-speed lateral manoeuvres were proposed in [139] and validated in later work [141]. More recent studies move away from conventional time- and energy-optimal path planning toward human-centered planning that minimises jerk, lateral acceleration, and rapid directional changes such as repeated turns [140,142]. Smoother motion improves ride comfort and also builds trust and perceived safety [143], which has led to comfort metrics being built into predictive control and motion planning frameworks for AVs.

Advances in sensing allow controllers to respond to the occupant as well as the vehicle. Heart rate, skin conductance, eye movement, and head motion can be monitored in real time with wearable and vision-based sensors [144], and these signals can be used to estimate discomfort, stress, and susceptibility to motion sickness during a journey. Adaptive controllers can then modify speed profiles, lane-change planning, and route selection in response, tailoring the journey to the comfort and sickness sensitivity of each occupant.

AV interiors add a further dimension. Future vehicles are expected to feature flexible cabin layouts, including face-to-face seating, lounge-style interiors, and rotating seats, intended to improve social interaction and productivity [145]. As noted in [136], however, these non-traditional configurations may make passengers more susceptible to motion sickness because the body orientation relative to the direction of motion changes substantially. Interior design therefore cannot be treated as an isolated problem, and vehicle-cabin co-design approaches are being explored. One example combines deep learning with computational fluid dynamics to predict cabin temperature, which supports both monitoring of sickness levels and adjustment of driving style, and helps return the cabin to comfortable conditions [146].

What remains is a framework that allows such interactions to be implemented. Human-in-the-Loop (HITL) methodologies are a natural candidate. They incorporate human preferences and direct feedback in real time, so that occupants are no longer passive recipients of the driving system but part of its decision-making loop [147]. HITL frameworks can personalise driving style, adapt acceleration profiles, shape car-following behaviour, and keep lane changes to a minimum to reduce sickness. They can also apply smart motion planning, such as that investigated in [138–140], to ease repeated cornering according to individual preference. Personalisation is also a key factor in public acceptance of AVs [133].

In HITL architectures, occupant states such as physiological responses are captured continuously and integrated with vehicle decision-making, going beyond conventional controllers that rely solely on environmental and vehicle-state information. Recent studies [143,144,147] indicate that including physiological measurements improves perceived comfort, trust, and acceptance, and ultimately helps mitigate motion sickness. This will

matter more as drivers become passive occupants who, with less authority over the vehicle, are more prone to sickness.

Figure 7 shows an example HITL framework for occupant-centric AV control. Occupant data are first collected using multimodal sensing, including wearable devices, cameras, eye trackers, inertial sensors, and seat-embedded monitoring. These measurements are processed into occupant-state estimates by human-state algorithms [148], which feed the supervisory layer of vehicle decision-making, for example Model Predictive Control (MPC) or Artificial Intelligence (AI) decision modules. The resulting decisions adjust motion planning and lane-change behaviour [141], steering smoothness, and speed control, among others. These actions in turn shape vehicle motion outputs such as acceleration, jerk, yaw motion, and ride dynamics, which change the occupant state. Because individuals differ in physiological sensitivity, with some responding quickly and others slowly, Machine Learning (ML) and adaptive control techniques are needed to personalise the control actions. The loop is closed by feeding the updated occupant state back into the HITL, typically for comparison with the initial state.

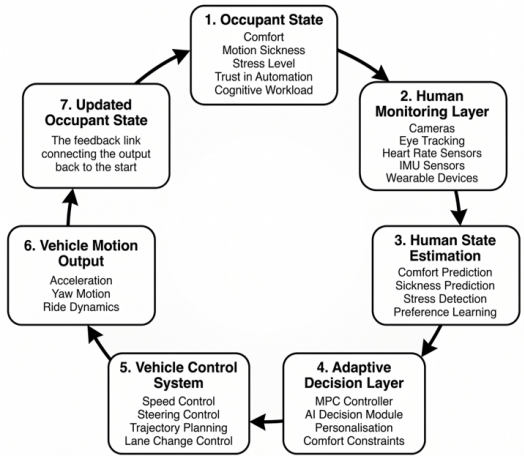


Figure 7. Example of a Proposed Human-in-the-Loop Framework for Occupant-Centric Autonomous Vehicle Control.

Taken together, these developments mark a shift from vehicle-centric driving systems toward occupant-centric mobility management, in which physiological responses, psychological factors, comfort requirements, and environmental stimuli are integrated into the control architecture. The goal is AVs that are safe and efficient and that also respond to human needs and well-being. Future work in HCC and HITL is likely to centre on predictive comfort models, multimodal sensing, personalised adaptation strategies, and vehicle-interior co-design that supports the HCC experience in future AVs.

3. Digital Twins, Simulation and Experimental Validation

3.1. Digital Twin Technologies

A digital twin is a virtual representation of a physical vehicle or infrastructure asset that is continuously updated with real-world data, enabling bidirectional synchronization between the physical and virtual domains. For autonomous vehicles, digital twin frameworks have been proposed to address safety and security across the vehicle lifecycle, with data collection, processing, and analytics identified as the core stages of a standardized vehicular digital twin architecture [149]. Digital twins have also been positioned as a development paradigm for the entire autonomous driving software stack, supporting the move from design to deployment through continuously synchronized virtual and physical vehicle models [150].

Work at finer and coarser scales extends this concept. At the vehicle level, a real-time multi-physics digital twin of an autonomous off-road vehicle has been validated against physical vehicle dynamics and hydraulics, supporting both mechanical development and visual perception tasks through synchronized simulation and real-world data [151]. At the traffic and infrastructure scale, edge-based frameworks distribute computation between vehicles, roadside units, and edge servers to improve the responsiveness of digital twin-based coordination [152]. Cyber-physical simulation platforms built on digital twin principles have been used to optimize dedicated lanes for connected automated vehicles, linking vehicle-level behaviour to infrastructure-level planning [153], and automatic traffic modelling can construct digital twins of real traffic environments without manual scenario authoring [154]. Within the framework proposed in this paper, these technologies support the modelling, simulation, monitoring, prediction, and validation functions at the core of Figure 3, connecting vehicle-level, safety-critical, cooperative, and infrastructure-based control.

3.2. Simulation-Based Development and Validation

Simulation provides a safe, repeatable, and cost-effective means of developing and evaluating control strategies before physical testing. Digital twin-assisted simulation has been applied to car-following scenarios, where synchronized virtual and real vehicle models are used to evaluate longitudinal control under realistic traffic interactions [155]. LTE-V2X-based digital twin test methods allow safety testing under connected communication conditions, tying simulation-based validation to the communication constraints discussed in Section 2.4 [156].

Scenario-based simulators built on open urban driving environments have been used to evaluate specific vehicle-level functions. Deep reinforcement learning-based obstacle avoidance, for example, has been developed and evaluated in an open-source urban driving simulator, showing the value of simulation for training and validating learning-based controllers under repeatable obstacle configurations [157]. Simulator-based studies have also examined driver take-over behaviour during transitions between autonomous and manual control, using gaze focalization and vehicle state data to assess situational awareness during handover [158], which informs the trust- and acceptance-related considerations of Section 2.6.

Simulation is particularly valuable for the safety-critical and cooperative layers of Sections 2.2 and 2.4, because emergency manoeuvres, fault scenarios, and multi-vehicle cooperation can be evaluated systematically across a wide range of traffic conditions and communication assumptions without exposing vehicles or road users to risk. Its conclusions are nonetheless bounded by the accuracy of the underlying vehicle, sensor, and traffic models, which motivates hardware-in-the-loop testing to close the gap between simulated and physical performance.

3.3. Software-in-the-Loop and Hardware-in-the-Loop Testing

Software-in-the-Loop (SIL) and Hardware-in-the-Loop (HIL) testing sit between pure simulation and full-scale vehicle trials. In SIL testing, the complete control software stack runs against a simulated vehicle and environment, allowing algorithmic verification under controlled, repeatable conditions before any hardware is involved. HIL testing goes further by placing actual vehicle controllers, sensors, or actuators in the simulation loop, which exposes the software to real timing constraints and hardware-specific behaviour while vehicle and environment dynamics remain simulated. HIL platforms combining dynamic path planning with Model Predictive Control have been used to validate self-driving and automated parking functions for electric vehicles, integrating an electric power steering

system, pedal actuators, and an onboard processing unit within a virtually rendered test field. Adaptive Model Predictive Control strategies for the coupled longitudinal and lateral dynamics of connected and automated vehicles have likewise been validated through hardware-in-the-loop experiments, extending earlier processor-in-the-loop testing toward more realistic actuator and communication conditions [159].

3.4. Vehicle Validation

Following simulation and hardware-in-the-loop testing, autonomous vehicle technologies must be validated on physical platforms under realistic conditions. Simulation offers a safe and cost-effective framework for controller development and safety assessment, but experimental testing remains essential for evaluating sensor uncertainty, actuator dynamics, communication delay, environmental disturbance, and model mismatch, which are difficult to reproduce fully in virtual environments.

Full-scale studies have demonstrated advanced control in practice. The authors of [160] validated a learning-based model predictive control framework on a Toyota Supra performing aggressive manoeuvres near the limits of handling, and their results highlighted the importance of real-world data collection and adaptation for reliable control under highly nonlinear conditions. Cooperative driving has also been tested on connected vehicle platforms: the authors of [5] demonstrated cooperative adaptive cruise control, emergency braking, and cut-in handling with heterogeneous platoons, confirming the potential of cooperative control for stability and safety in mixed traffic.

Infrastructure-assisted functions have been validated on connected vehicles and smart infrastructure. The authors of [5,104,108] proposed an infrastructure-based trajectory planning framework for vulnerable road user collision avoidance under sensor occlusion. It was evaluated experimentally on the ANTON automated vehicle platform with a roadside installation of cameras, LiDAR, and radar. Field tests showed that collision-free avoidance manoeuvres could be generated, transmitted, and executed in real time, highlighting the potential of cooperative perception and infrastructure-assisted decision-making for connected and automated vehicles.

Scaled platforms offer a cost-effective route to rapid prototyping and controller verification. The authors of [87] developed a 1:3.33 over-actuated scaled vehicle with independent steering, braking, and driving actuators, and reported strong agreement between simulation and physical testing, supporting the use of scaled platforms to validate control algorithms before full-scale deployment.

3.5. Challenges and Future Perspectives

Despite progress across simulation, SIL/HIL, and physical validation, several challenges remain for digital twin-based development. First, model fidelity bounds the reliability of simulation-based conclusions: discrepancies between simulated and real sensor noise, actuator dynamics, and traffic behaviour can mask failure modes that appear only in physical testing [151]. Second, keeping the physical vehicle and its digital twin consistently synchronized across the vehicle's operational lifetime, rather than only during discrete test campaigns, remains computationally and logistically demanding, particularly for fleets or edge-distributed infrastructure [152]. Third, digital twin-based safety and security architectures must be extended to handle evolving cyber-physical threats as vehicles become more deeply networked with roadside and cloud infrastructure [149]. Finally, results from scaled research vehicles, full-size prototypes, and infrastructure-assisted environments must be reconciled through consistent modelling assumptions so that conclusions transfer reliably between scales [92].

4. Integrated System-Level Model and Cross-Cutting Outcomes

The five control layers reviewed in this paper are not independent research domains. They are coupled components of a single autonomous mobility system, as shown in the multi-level framework of Figure 3. Each layer passes information to its neighbours and receives control feedback from them, so the flow runs from the dynamics and actuation of the ego vehicle up to traffic-level and human-centered outcomes. Vehicle-level control (Section 2.1) supplies the trajectory-tracking capability on which the other four layers (Sections 2.2–2.6) build, and human-centered control closes the loop through the comfort, trust, and acceptance of the road users the system serves.

Digital twin and system integration technologies (Section 3) are not an additional control layer. They act as connective infrastructure that supports modelling, simulation, monitoring, and validation across all five layers (Figure 3). Because the same vehicle, sensor, and environment models can be reused from early simulation through software- and hardware-in-the-loop testing to physical validation, a control strategy developed at one layer, such as a fault-tolerant controller from Section 2.2 or a cooperative merging strategy from Section 2.4, can be assessed for its effect on the other layers before deployment.

The framework is organised around the five control objectives introduced in Section 2: safety, efficiency, sustainability, comfort, and equity and accessibility. No objective belongs to a single layer; each emerges from their interaction. Safety depends on tracking accuracy (Section 2.1), fault-tolerant and emergency-manoeuvre capability (Section 2.2), cooperative and infrastructure-assisted perception beyond onboard sensor range (Sections 2.4 and 2.5), and on human-centered design that fosters appropriate trust rather than overreliance (Section 2.6). Efficiency and sustainability depend on vehicle-level energy management, the flow-smoothing effect of platooning and cooperative adaptive cruise control, and infrastructure-level routing and signal optimisation, but are bounded by the comfort requirements of the human-centered layer, which limit how aggressively speed and trajectory profiles can be optimised. How much of this potential is realised under mixed traffic depends on market penetration (Section 2.4.4). Improved user experience reflects motion-sickness mitigation and personalised, trust-calibrated driving styles (Section 2.6). Social benefit and equity require that capacity gains from cooperative control do not come at the expense of other road users, an issue raised in the traffic-flow evaluation of Section 2.4.5.

The system outcomes in Figure 3, namely safer roads, efficient traffic, lower emissions and energy use, improved user experience, and social benefit, therefore arise from the coordinated operation of all five layers rather than from any one of them. Autonomous vehicle control cannot be reduced to an optimisation problem confined to the ego vehicle. It is a multi-layer, multi-objective coordination problem: vehicle-level decisions propagate upward to affect traffic, infrastructure, and human experience, while system-level and human-centered requirements propagate back down to constrain lower-level controllers. This bidirectional coupling, shown by the information-flow and data/control-feedback arrows in Figure 3, is the organising principle of the framework proposed in this review and the basis for the trade-off analysis in Section 5.

5. Cross-Level Trade-Offs

The preceding sections show that the five layers often pursue objectives that pull against one another. This section draws together the three principal trade-offs identified in the review.

5.1. Comfort vs. Safety

Comfort-oriented vehicle-level and human-centered control conflicts with the priorities of safety-critical control. Classical vehicle-level controllers such as PID, LQR, and geometric path tracking are tuned for low tracking error and smooth motion under nominal conditions (Section 2.1). Once a hazard arises, however, Section 2.2 shows that this objective is overridden. Safety-critical control prioritises collision avoidance and stability even at the cost of hard braking, evasive steering, or operation at or beyond the tire-road friction limit illustrated in Figures 4–7. The operational timeline in Figure 2 captures this shift, with priority moving from comfort-oriented operation through the warning, hazardous, and mitigation zones, where comfort is subordinated to crash avoidance and, ultimately, injury mitigation.

The same tension appears in the human-centered layer (Section 2.6). Motion-sickness mitigation favours smooth trajectories, low jerk, and reduced lateral acceleration, which can conflict with the rapid, high-acceleration manoeuvres an emergency may demand. The Human-in-the-Loop framework in Figure 7 shows the coupling directly: acceleration, jerk, and yaw motion determine both the occupant's comfort state and the vehicle's safety margin, so adaptive decision layers must balance personalised comfort constraints against the demands of the driving scenario.

5.2. Comfort vs. Traffic Efficiency

The second trade-off, discussed in Section 2.4.5, lies between passenger comfort and system-level efficiency. Platooning and cooperative adaptive cruise control (Section 2.4.2) raise capacity and damp stop-and-go waves by holding shorter, more tightly coordinated headways than human-driven spacing would normally allow. As noted in Section 2.4.5, such behaviour can reduce perceived safety or comfort when human drivers, inside the automated vehicle or in surrounding traffic, are unprepared for it. Eco-driving strategies that favour smoother speed profiles can likewise conflict with travel-time minimisation when demand is high.

The conflict extends to the human-centered layer. The comfort, motion-sickness, and trust measures of Section 2.6 address the individual occupant, whereas the flow metrics of Section 2.4.5, including headway, string stability, and shockwave propagation, address collective performance. A strategy tuned only for network throughput may therefore erode the smoothness that human-centered control seeks to preserve. This is why, as argued in Section 2, efficiency and sustainability cannot be pursued independently of comfort.

5.3. Individual Vehicle vs. System-Level Objectives

The third trade-off, also raised in Section 2.4.6, separates the goals of the individual vehicle from those of the wider traffic system. A conservative policy, such as keeping a large safety margin when merging or changing lanes, protects the ego vehicle but reduces capacity and increases congestion for the traffic around it. More aggressive cooperative strategies that improve flow, conversely, can raise perceived risk or reduce comfort for the road users involved.

Mixed traffic (Section 2.4.4) compounds the problem. Because cooperative and infrastructure-based benefits depend strongly on market penetration, an individually rational policy, such as a highly conservative driving style, may deliver no system-level benefit until enough of the traffic stream can take part in coordinated behaviour. Efficiency gains for automated vehicles may also shift delay onto human-driven vehicles, pedestrians, cyclists, or public transport users (Section 2.4.5). Ego-vehicle metrics alone are therefore insufficient, and system-level indicators covering delay distribution, fairness, and safety across all road-user categories are needed to reconcile the two perspectives.

5.4. Synthesis

Across all three trade-offs, no single layer can resolve the tension alone. Safety-critical control cannot be designed without the comfort objectives of the human-centered layer, cooperative control cannot be tuned for throughput without the comfort and trust requirements of occupants, and infrastructure- and traffic-level coordination cannot be judged by ego-vehicle metrics. The five layers must therefore be treated as one coordinated, multi-objective system, as set out in Section 4.

6. Future Directions

Building on Sections 4 and 5, this section outlines emerging directions: human-aware control, safe reinforcement learning, a growing role for infrastructure, and an expanded use of digital twins in safety assurance, insurance, and energy management.

Human-centered control (Section 2.6) is expected to shift from a reactive paradigm to one in which occupant state, including comfort, motion sickness, stress, and trust, shapes control decisions in real time, as illustrated by the Human-in-the-Loop framework in Figure 7 [161,162]. A natural extension is to combine these occupant-state estimates with the safety-critical objectives of Section 2.2, so that intervention thresholds can be personalised rather than applied uniformly across passengers. Learning-based methods, particularly reinforcement learning, show strong potential for fault-tolerant control and emergency-manoeuvre adaptation under degraded conditions [4,81,108]. However, formal safety guarantees remain hard to establish, which limits certification. Future work is expected to focus on safe reinforcement learning that confines learned policies to verifiable safety envelopes, for example by combining them with the handling-limit monitoring of Section 2.2.1 or the constraint-handling structure of MPC reviewed in Section 2.1.

As the market penetration of connected and automated vehicles grows, infrastructure-based coordination is expected to matter more, because platooning and speed harmonisation become far more effective once enough of the traffic can participate [110,120]. This points to a gradual shift in control authority from vehicle-centric decisions toward infrastructure-mediated coordination at high-conflict locations, and reinforces the need for the partial-connectivity-tolerant strategies discussed in Section 2.4.6.

Digital twins are expected to move beyond the validation role described in Section 3 toward continuous, in-service safety assurance, monitoring proximity to fault conditions and handling limits throughout a vehicle's operational life rather than only during testing [149]. A second direction is insurance underwriting, where digital twin and microscopic traffic simulation can generate synthetic accident and loss distributions under counterfactual scenarios instead of relying on aggregate historical statistics. Recent actuarial work has demonstrated this by coupling microscopic traffic simulation with statistical loss modelling [163], linking the market-penetration effects of Section 2.4.4 to the equity objective of Section 2. A third direction is energy management, extending beyond vehicle-level control to powertrain, battery, and fleet-level optimisation. Digital twins of EV powertrains support battery health monitoring and degradation prediction [164], fleet-level twins have jointly optimised renewable generation, storage, and EV charging to cut operating energy costs [165], and vehicle-specific twins have compared powertrain configurations for energy use and range before physical prototyping [166].

Together, these directions point toward an integrated digital twin ecosystem spanning continuous safety assurance, insurance and risk modelling, and energy management, alongside human-aware control, safe reinforcement learning, and infrastructure-mediated coordination. Realising it will require architectures that can securely share state and risk information across manufacturers, insurers, energy providers, and infrastructure operators while preserving the safety, fault-tolerance, and human-centered principles

of Sections 2.2 and 2.6. This integration is expected to be central to the safe, efficient, sustainable, comfortable, and equitable mobility systems envisioned by the framework proposed in this paper.

7. Conclusions

This paper presented a comprehensive review of autonomous vehicle control through a unified multi-level framework comprising five interconnected layers: vehicle-level control, safety-critical control, cooperative control and traffic interaction, infrastructure-based control, and human-centered control, supported throughout by digital twin and system integration technologies. Rather than treating these domains as isolated fields of study, as is common in existing literature, this review has argued and demonstrated that autonomous vehicle control must be understood as a coordinated, multi-objective system in which decisions at one layer propagate to affect the performance, safety, and acceptability of every other layer.

Taken together, these findings support the central argument of this review: that safe, efficient, sustainable, comfortable, and equitable autonomous mobility cannot be achieved through the isolated optimization of any single control layer. Future research should therefore continue to move toward integrated, cross-layer architectures, combining robust classical control with learning-based adaptability, cooperative and infrastructure-supported coordination, and human-aware decision-making, validated through digital twin frameworks that span the full spectrum from simulation to real-world deployment. The multi-level control framework proposed in this paper is intended to provide a structured foundation for this integration, supporting the continued development of autonomous transportation systems that are simultaneously safe, resilient, efficient, and responsive to the needs of the people they are designed to serve.

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