

Review

Survey on Key Performance Indicators for Evaluating the Impact of Autonomous and Connected Vehicles on Traffic Flows and Mobility Services

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Abstract

The introduction of Connected and Autonomous Vehicles (CAVs) into the existing traffic system represents one of the greatest challenges of modern road traffic engineering. Beyond their role as active traffic participants, CAVs can also be regarded as mobile (floating) sensors, effectively turning the vehicle fleet itself into a distributed, city-wide and motorway-wide sensing infrastructure. The transition from fully human-driven vehicles to fully autonomous vehicles will take decades, giving rise to a prolonged mixed-traffic period in which vehicles with different levels of automation share the same road space. This paper analyses the parameters and measures used for evaluating the throughput, environmental impact, and safety of traffic networks at different CAV penetration rates. It further reviews studies that rely exclusively on data collected from CAVs acting as mobile sensors, examining data-aggregation and traffic-state-estimation methods used to reconstruct macroscopic traffic parameters such as flow, density, headway, and speed. Additionally, measures for evaluating specific use cases for CAVs including mobility-on-demand services and their cost comparison with human-driven taxi operations are also addressed. The energy and emissions implications of CAV deployment, including the added burden of sensing hardware and system-level rebound effects, are also examined. Based on the synthesis performed, a set of representative CAVs penetration rates is proposed as a standardised framework for future mixed-traffic flow evaluations.

Keywords: connected and autonomous vehicles; floating car data; mobile traffic sensors; probe vehicle data; market penetration rate; surrogate safety measures; mobility on demand; traffic state estimation



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1. Introduction

The development of autonomous driving technologies and vehicle-to-vehicle (V2V), as well as vehicle-to-infrastructure (V2I) communication, has over the past decade fundamentally changed the perspective on planning and managing road traffic systems. Autonomous vehicles (AVs) and connected autonomous vehicles (CAVs) are anticipated to significantly improve traffic safety, increase the capacity of road infrastructure, reduce congestion and fuel consumption, and enhance travel comfort [1–3]. The expected benefits arise primarily from the ability of CAVs to travel with shorter headways, track the leading vehicle more precisely, react faster to changes in traffic flow, and coordinate manoeuvres such as lane changing and motorway merging.

Beyond their role as active traffic participants, CAVs equipped with advanced sensor suites can simultaneously function as mobile probe vehicles, continuously sampling the surrounding traffic state. Equipped with Global Navigation Satellite System (GNSS) receivers, onboard cameras, radar, and LiDAR sensors, they can be treated as mobile or floating sensors embedded directly in the traffic flow [4,5]. Unlike fixed infrastructure sensors, which observe traffic at discrete, stationary locations (an Eulerian perspective), each probe vehicle continuously reports its own movement trajectory—position, speed, acceleration, and the relative spacing and speed of surrounding vehicles—yielding a Lagrangian, vehicle-centred view of the traffic state [6,7]. This mobile-sensing paradigm is the foundation of Floating Car Data (FCD) and Floating Car Observation (FCO) techniques, and it becomes increasingly relevant as the Market Penetration Rate (MPR) of CAVs grows [8].

The complete replacement of Human-Driven Vehicles (HDVs) by autonomous vehicles will occur gradually, creating a prolonged mixed-traffic period in which vehicles with different levels of automation share the same road space [9–11]. The MPR has been shown to affect throughput and safety in a nonlinear and often inconsistent manner, depending on the infrastructural context, the applied car-following model, and the level of connectivity [12–14]. Traffic flow throughput is traditionally described through the fundamental diagram (flow, density, average speed), while safety is increasingly assessed through surrogate safety measures derived from microsimulation trajectories or real vehicle data—most prominently Time-To-Collision (TTC), Time Exposed TTC (TET), Time Integrated TTC (TIT), and Post-Encroachment Time (PET) [1,12]. Each measure has specific strengths and limitations: TTC captures immediate conflict severity but assumes constant velocities; PET better describes crossing conflicts; TET and TIT quantify cumulative risk exposure at the cost of losing information about individual critical events.

Existing research shows that the relationship between MPR and safety or mobility indicators is not monotonic. Low to moderate penetration rates (10–50%) may produce only modest improvements or even temporary deterioration of certain indicators, whereas significant benefits are achieved above 70–80% [1,10,12]. The aim of this review is to systematically compare the parameters and measures used to evaluate CAV impact across four domains: mixed-traffic safety and throughput, traffic state estimation from probe data, environmental and energy impacts, and mobility-on-demand (MoD) effectiveness. Based on the synthesis, a set of representative MPR levels is proposed as a standardised evaluation framework.

2. Materials and Methods: Search Strategy and Study Selection

The research approaches for this survey study are explained by a PRISMA-informed literature search and screening process [15]. The PRISMA process is adapted for a narrative/scoping synthesis rather than a fully registered systematic review. This is done given the methodological heterogeneity of the four domains within this study; (i) estimation of throughput and safety in traffic flow with a combination of CAV and human-driven vehicles, (ii) traffic state estimation using vehicle probe data, (iii) energy and environmental impacts, and (iv) effectiveness of autonomous mobility-on-demand. It is important to mention that the PRISMA analysis does not take into account the survey papers and studies used in Section 8.

During the preparation of this manuscript, the authors used the generative Artificial Intelligence (AI) tool Claude; model Sonnet 5 (Anthropic, San Francisco, CA, USA) to assist in exploring and screening the relevant literature, as well as to support the formatting of selected figures, equations, text passages, and tables. All AI-generated content and

suggestions were carefully reviewed and edited by the authors to ensure scientific accuracy and compliance with academic standards.

2.1. Information Sources and Search String

Searches were conducted in Google Scholar and Scopus scientific databases for records published between 2012 and July 2026. Foundational methodological references predating this window (e.g., [16]) were retained irrespective of publication date due to their continued use as the analytical basis for current traffic-state-estimation methods. The search string combined terms for the technology, the traffic context, and the four evaluation domains, e.g.,

“connected and autonomous vehicle” OR “autonomous vehicle*” OR “CAV” OR “AV”*
AND “traffic flow” AND “mixed traffic flow” AND “market penetration rate” OR
“penetration rate” AND (“surrogate safety measure” AND “time-to-collision” AND*
“traffic state estimation” OR “floating car data” OR “probe vehicle” OR “autonomous*
mobility-on-demand” OR “energy consumption” AND “vehicles emissions” OR “vehicle
platoons”) AND “key performance indicators”

Reference lists of retrieved articles were additionally hand-searched (backward snowballing) to identify further eligible studies. Regulatory and institutional grey literature (UNECE/WP.29 regulations, McKinsey, ARK Invest, Goldman Sachs Research, VTPI, and U.S. DOT ITS Joint Program Office material) was identified separately through targeted searches of organisational repositories rather than the bibliographic databases above, and was included only where it supplied quantitative cost or policy benchmarks not available in the peer-reviewed literature.

2.2. Eligibility Criteria

Records were included if they: (i) were peer-reviewed journal articles, peer-reviewed conference proceedings, or authoritative grey literature/regulatory documents; (ii) were published in English; (iii) addressed at least one of the four review domains listed above in the context of CAVs, AVs, or mixed CAV-HDV traffic; and (iv) reported at least one quantifiable KPI, parameter, or evaluation method relevant to traffic throughput, safety, probe-based state estimation, energy/emissions, or mobility-on-demand performance. Records were excluded if they: (i) were not accessible in full text; (ii) addressed only vehicle-level control or perception algorithms without traffic-flow-, fleet-, or network-level KPIs; (iii) were duplicate or preprint versions of an included peer-reviewed publication; or (iv) were editorials, non-peer-reviewed blog posts, or opinion pieces without original data or synthesis.

2.3. Study Selection Process

Two reviewers independently screened titles and abstracts against the eligibility criteria; disagreements were resolved by discussion with a third reviewer. Full texts of records passing this stage were then assessed for eligibility using the same criteria. The process is summarised in Figure 1.

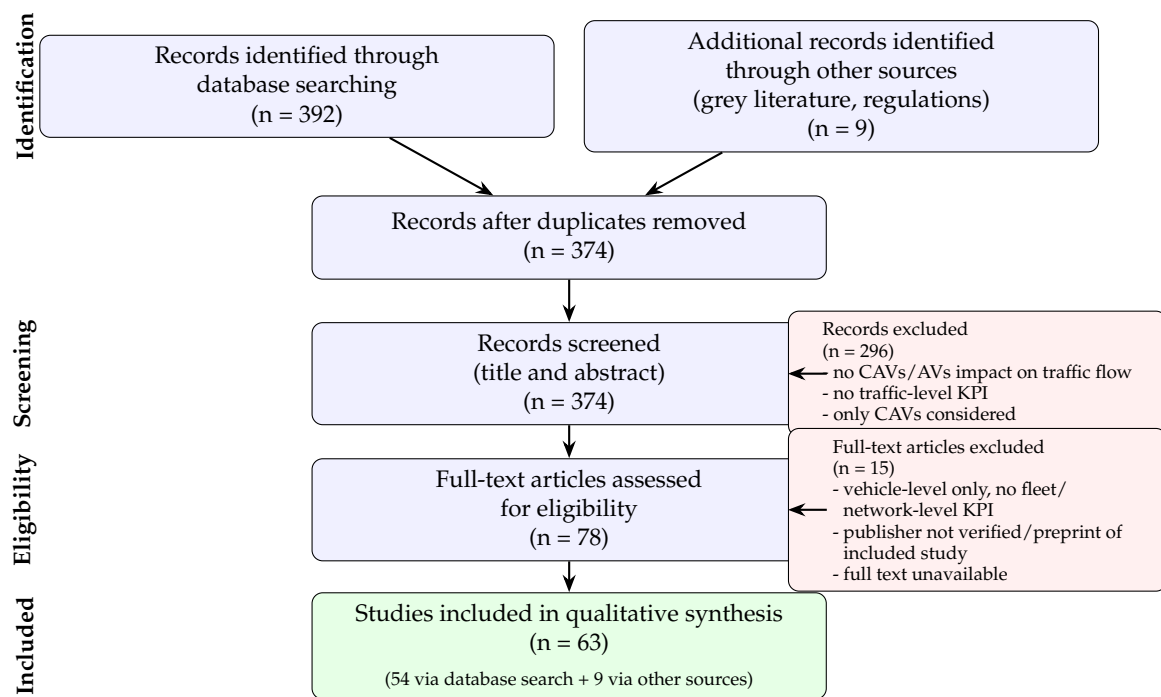


Figure 1. PRISMA flow diagram summarising the identification, screening, eligibility assessment, and inclusion of studies synthesised in this review.

3. Surrogate Safety Measures and Proposal of Representative Penetration Rates of CAVs in Mixed Traffic Flow

Traditional road safety studies rely on historical crash records, which are unsuitable for evaluating emerging technologies such as CAVs where real-world crash data are statistically insufficient [17]. Modern traffic safety research therefore relies on Surrogate Safety Measures (SSMs), derived from microscopic vehicle trajectories, which estimate how close interacting vehicles come to a potentially hazardous situation [18]. Since traffic conflicts occur orders of magnitude more frequently than crashes, SSMs provide richer datasets for statistically meaningful safety evaluations.

3.1. Mathematical Definitions of SSMs

Time-to-Collision (TTC) is the most widely used SSM for longitudinal vehicle interactions, representing the remaining time before a collision if both vehicles maintain their current speeds:

$$TTC = \frac{x_l - x_f - L}{v_f - v_l}, \quad (1)$$

where x_l , x_f are the positions of the leading and following vehicles, L is the leading vehicle length, and v_l , v_f their velocities. TTC is defined only when $v_f > v_l$; otherwise $TTC = \infty$. Situations with $TTC < 1.5$ s or $TTC < 2.0$ s are typically classified as critical.

Time Exposed TTC (TET) measures the cumulative duration during which TTC remains below a predefined threshold TTC_{crit} , capturing sustained exposure to unsafe conditions rather than isolated critical events:

$$TET = \sum_{i=1}^N I(TTC_i < TTC_{crit}) \Delta t. \quad (2)$$

Time Integrated TTC (TIT) extends TET by weighting each conflict interval by its severity, so that extremely small TTC values contribute disproportionately:

$$TIT = \sum_{i=1}^N \left(\frac{1}{TTC_i} - \frac{1}{TTC_{crit}} \right) I(TTC_i < TTC_{crit}) \Delta t. \quad (3)$$

Post-Encroachment Time (PET) applies to crossing trajectories, measuring the temporal separation between two vehicles passing through the same conflict area:

$$PET = t_{entry,2} - t_{exit,1}, \quad (4)$$

where $t_{exit,1}$ is when the first vehicle leaves the conflict area and $t_{entry,2}$ when the second enters. Values below 1–1.5 s are generally considered critical. Unlike TTC, PET is a retrospective measure.

Deceleration Rate to Avoid Collision (DRAC) estimates the minimum braking required to prevent a collision:

$$DRAC = \frac{(v_f - v_l)^2}{2d}, \quad (5)$$

where d is the available spacing. Complementary throughput measures include space headway $SH = x_l - x_f - L$ and speed standard deviation σ_v , which together with SSMs provide a complete picture of mixed-traffic performance.

All SSMs must be computed in post-processing from trajectory data; none are directly available as simulation outputs. Table 1 summarises availability in three widely used simulators. The FHWA Surrogate Safety Assessment Model (SSAM) is the de facto standard post-processing tool, automatically identifying and classifying conflicts from trajectory exports of VISSIM, AIMSUN, PARAMICS, and compatible platforms, though its accuracy depends on trajectory temporal resolution and predefined thresholds may require adjustment for highly automated scenarios.

Table 1. Availability of surrogate safety measures in commonly used microscopic traffic simulators.

Safety Measure	VISSIM	SUMO	AIMSUN
TTC, TET, TIT, PET, DRAC, σ_{TTC}	Post-proc.	Post-proc.	Post-proc.
Space headway, speed variance	Direct	Direct	Direct
Vehicle trajectories, positions, speeds, acceleration	Direct	Direct	Direct

3.2. Proposed Representative CAV Penetration Rates

Based on the reviewed literature and the observed thresholds at which significant changes occur in throughput and safety, Figure 2 illustrates the proposed six-level MPR framework for future microsimulation-based and field evaluations. Applying this range in combination with a consistent set of throughput measures (speed, flow, density) and safety measures (TTC, PET, TET, TIT) would enable direct comparability of results across studies.

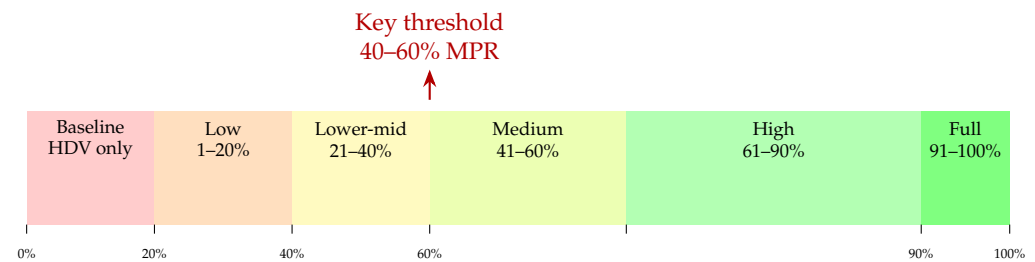


Figure 2. Proposed representative CAV penetration rate. The 40–60% range represents the critical threshold at which CAVs begin to dictate ambient traffic flow rather than merely adapting to it.

3.3. Emerging and Learning-Based Risk Indicators

Classical KPIs remain attractive for their interpretability and rigid closed-form definitions. Simultaneously, they share two limitations that become more pronounced in heterogeneous, long-horizon CAV settings. First, most conventional safety KPIs, TTC and DRAC are defined for pairwise, largely longitudinal interactions between vehicles and assume constant velocity or acceleration over a short horizon. This limits their ability to capture interaction-wise risk that unfolds over several seconds in dense mixed traffic flow. Second, fixed critical thresholds (e.g., $TTC < 1.5$ s) calibrated using data captured in traffic flow with HDVs may not generalise to CAV behaviour. They can operate safely at shorter nominal gaps than a human driver would tolerate. Recent literature has proposed several directions to address these limitations.

Generalised surrogate safety measures. Because TTC is defined only along the single closing axis between a leader and a follower, with $v_f > v_l$ required in Equation (1), it cannot represent conflicts that unfold at an angle, such as merges, crossings, and simultaneous multi-vehicle interactions common at CAV-managed intersections. Generalised formulations instead represent risk as a scalar potential field generated jointly by every vehicle surrounding a subject vehicle i [19,20]:

$$U_i(t) = \sum_{j \neq i} k_j \exp\left(-\frac{\|\mathbf{p}_i(t) - \mathbf{p}_j(t)\|^2}{2\sigma_j(v_j)^2}\right) g(\theta_{ij}), \quad (6)$$

where $p_i(t)$ and $p_j(t)$ are the two-dimensional positions of vehicle i and a neighbouring vehicle j , rather than only their longitudinal coordinates. The $\sigma_j(v_j)$ is a speed-dependent field decay parameter that elongates the field of a fast-moving vehicle along its heading, k_j scales the field intensity by vehicle class or its mass; and $g(\theta_{ij}) \in [0, 1]$ weights the contribution of vehicle j by the approach angle θ_{ij} between i and j . Thus, lateral and crossing conflicts remain represented even though they would be assigned $TTC = \infty$ under the classical pairwise, longitudinal definition. A vehicle is flagged at risk once $U_i(t)$ exceeds a calibrated threshold. This is the same role that $TTC < 1.5$ s plays for the classical measure, but the value is now aggregated over every vehicle in range rather than a single designated leader. Study conducted by Del Re and Olaverri-Monreal [19] demonstrates this generalisation empirically. It is based on a use-case with three-vehicle lane-change scenarios. Thus, the ranking of the riskiest interaction can shift once a trailing vehicle beyond the immediate leader is admitted into the comparison.

Proximity-resistance and risk-propagation. A second family of methods models how risk introduced at one vehicle-to-vehicle interaction spreads to neighbouring vehicles in the same traffic flow. This is a more comprehensive evaluation methodology of traffic flow safety compared to treating each pairwise conflict of following vehicles in isolation. A representative recursive formulation expresses the risk carried by vehicle i at time t as a

weighted combination of its own instantaneous conflict risk and the risk inherited from its upstream neighbours [21,22]:

$$R_i(t) = \alpha r_i(t) + (1 - \alpha) \sum_{j \in \mathcal{N}(i)} w_{ij}(t) R_j(t - \tau_{ij}), \quad (7)$$

where $r_i(t)$ is a locally computed risk term (e.g., derived from TTC_i , $DRAC_i$, or $U_i(t)$ from Equation (6)) and $\mathcal{N}(i)$ is the set of vehicles upstream of vehicle i whose braking or lane-change behaviour can influence it. Furthermore, the τ_{ij} is the propagation delay between j and i ; and $\alpha \in [0, 1]$ balances local against inherited risk. The propagation weight $w_{ij}(t) \in [0, 1]$ increases as the gap and reaction-time buffer between i and j becomes smaller. Equivalently, $(1 - w_{ij})$ can be read as the resistance that spacing, deceleration capability, or a CAV's compensating manoeuvre offers against inbound risk. It is a mechanism that proximity-resistance approaches make explicit [23]. A study conducted by Wang et al. [21] instantiates this idea directly for motorway settings. The results of this study demonstrate how a spatio-temporal deep learning model shows that the conflict risk triggered by a single sudden deceleration or lane change propagates backwards through several following vehicles in a structured and learnable pattern. The study conducted by Liu et al. [24] models a vehicle platoon as a time-delayed communication graph and derive closed-form value-at-risk expressions. It shows that the risk of a cascading collision between a pair of vehicles depends explicitly on the Laplacian spectrum of the V2V communication topology, the propagation delay, and how sparsely prior failures are distributed along the platoon of vehicles. They further show that a single long-range communication edge can lower cascading risk more effectively than adding local connections. This offers a graph-design analogue to the resistance term $(1 - w_{ij})$ in Equation (7). It is not merely proximity but the topology of vehicles' configurations modelled by the V2V communication network, that influences how far an initial safety risk event propagates.

Learned risk scores. Rather than a hand-specified formula, this class of methods trains a model f_θ to map a trajectory-derived feature vector directly to a continuous safety risk value:

$$\hat{r}_i(t) = f_\theta(\mathbf{x}_i(t)), \quad \theta^* = \arg \min_{\theta} \mathbb{E} \left[c(y_i) (\hat{r}_i(t) - y_i)^2 \right], \quad (8)$$

where $\mathbf{x}_i(t)$ collects the recent speeds, gaps, accelerations, and lateral offsets of vehicle i and its neighbours. The y_i is a risk label, e.g., derived from a near-miss or crash outcome. Furthermore, the $c(y_i)$ is a cost weight that up-weights the rare high-risk labels. The study conducted by Hu et al. [25] implements this cost-sensitive formulation with a semi-supervised deep model. This model is trained on naturalistic vehicle trajectories, letting f_θ exploit both the sparse labelled crash-adjacent events and the abundant unlabelled driving behaviour in between. Because $\hat{r}_i(t)$ can encode interaction patterns among several neighbouring vehicles simultaneously, this can potentially capture the same multi-vehicle, non-longitudinal effects targeted by Equation (6). This can be done without requiring the field parameters $k_j, \sigma_j, g(\theta_{ij})$ to be specified a priori.

Comparison-based (ordinal) learning. Most recently, comparison-based approaches have been proposed to mitigate a practical obstacle shared by all learned-risk approaches. The reliable absolute risk labels y_i are scarce, because crashes are rare and near-miss severity is itself uncertain to clearly identify and classify. Rather than regressing an absolute safety risk value as in Equation (8), these methods learn a risk-ranking function directly from pairwise supervision. This is typically done by minimising a margin-based ranking loss over a set of ordered pairs $\mathcal{P}$:

$$\mathcal{L}_{rank} = \sum_{(i,j) \in \mathcal{P}} \max \left(0, m - (\hat{r}_i - \hat{r}_j) \right), \quad \text{for each pair with } y_i \succ y_j, \quad (9)$$

where $y_i \succ y_j$ denotes that moment i is judged riskier than moment j , and $m > 0$ is a margin enforcing separation between the two predicted scores. One example is ordering the relative danger of two moments in a safety-critical sequence. Such pairwise orderings are considerably easier to obtain than calibrated absolute risk values. Furthermore, they are derived from the temporal progression within near-miss events and the measured contrasts between the dangerous and normal vehicle interactions [26].

Fully learned replacements of surrogate safety measures. A further, more recent direction goes beyond augmenting SSMs with an additional propagation or ranking term. It aims to replace them outright with an end-to-end learned risk indicator. A study conducted by Jiao et al. [27] proposes the Generalised Surrogate Safety Measure (GSSM). It is a data-driven indicator that learns collision risk directly from large-scale naturalistic driving data without requiring any crash- or near-crash labelled datasets. These datasets contain thousands of real-world crashes and near-crashes. Thus, the trained model can report both higher detection accuracy and earlier warning times than conventional SSMs such as TTC.

In a related direction, study conducted by Zou et al. [28] introduces the RiskProp, a risk-propagation model trained using only the collision frame in dash-cam video. This is a single moment that can be reliably labelled. A future-frame regularisation loss then lets the model propagate risk backward in time from that frame to earlier ones. This removes the need for manually annotated onset labels, i.e., the exact moment a situation starts becoming dangerous, which hand-specified propagation formulations such as Equation (7) normally require as training input.

The study conducted by Liu et al. [29] propose RiskNet approach. It couples a field-theoretic interaction risk model, conceptually related to the generalised potential field of Equation (6), with a graph-neural-network-based multimodal trajectory predictor. It computes a probabilistic risk forecast rather than a single deterministic score. Together, these studies point to a broader shift from hand-specified propagation and ranking mechanisms toward risk indicators that are learned end-to-end and validated directly against real-world crash outcomes. The main drawbacks of those approaches are reduced interpretability and a strong dependence on the scale and quality of the naturalistic or dash-cam datasets used for training those models. For CAV evaluation specifically, this class of indicators is a natural complement, rather than a replacement of conventional safety KPIs [30]. TTC, PET and DRAC remain useful as standardised, comparable traffic network-level KPIs, while learned and ordinal safety risk indicators are designed for capturing long-horizon, interaction-aware risk within an individual CAV's own decision-making loop.

4. Analysis of Safety and Traffic Throughput Evaluation Parameters in Traffic Flows with Different Penetration Rates of Autonomous Vehicles

The integration of CAVs into modern transportation networks requires systematic evaluation using validated safety and efficiency indicators. This section compares empirical and simulation-based studies evaluating SSMs such as TTC and PET alongside throughput indicators including average speed, flow rate, and travel time delay under varying CAV penetration rates. A study conducted by Hamadneh and Esztergár-Kiss [31,32] demonstrates potential travel time reductions achievable through innovative CAV driving strategies.

Table 2 synthesises key findings. Quantitative values are illustrative, synthesised from ranges reported across the reviewed literature; individual studies report varying figures depending on simulation environment, car-following model, and penetration rate increment.

Table 2. Synthesis of key findings across four representative studies. For each study, the Safety Indicators and Throughput Indicators columns report the surrogate safety measure and traffic performance metric most commonly used in that study’s traffic network context. All changes in percentages are expressed relative to a 0% CAV (conventional HDV-only) baseline. The underlying studies have different test frameworks such as non-aligned penetration-rate increments. Thus, the values at the three representative breakpoints (low, medium, full deployment) are interpolated and represent order-of-magnitude estimation consistency with each study’s reported trend.

Study	Traffic Network	CAV %	Safety Indicators	Throughput Indicators
Ye & Yamamoto [33] (2019)	Motorway	20%	Critical TTC (<1.5 s) −15%	Speed +4%, flow +6%
		50%	Critical TTC −42%	Speed +12%, flow +18%
		100%	Critical TTC −75%	Speed +25%, flow +45%
Makahleh et al. [34] (2025)	Urban	10%	PET +5%	Delay −8%, queue −6%
		50%	PET +30%	Delay −35%, queue −40%
		100%	PET +85%	Delay −72%, queue −88%
Ye & Yamamoto [35] (2018)	Motorway	30%	DRAC −18%	Headway −20%, capacity +15%
		60%	DRAC −45%	Headway −45%, capacity +32%
		100%	DRAC −80%	Headway −70%, capacity +60%
Park et al. [36] (2021)	Combined/hybrid	20%	$\sigma_{TTC} +10\%$	Travel time −5%, $\sigma_v -12\%$
		50%	$\sigma_{TTC} +35\%$	Travel time −12%, $\sigma_v -38\%$
		100%	$\sigma_{TTC} +65\%$	Travel time −22%, $\sigma_v -70\%$

Table 3 presents the advantages and disadvantages of the principal safety and throughput indicators. This table clearly presents use cases for when each KPI can be used in evaluating CAVs’ impacts on traffic safety and throughput.

Table 3. Advantages and Disadvantages of Specific Safety and Throughput Indicators.

Indicator	Advantages	Disadvantages
TTC	Intuitive; widely adopted; sensitive to immediate braking events; suitable for longitudinal car-following analysis.	Assumes constant velocity; does not capture lateral risk (e.g., cut-ins).
PET	Ideal for crossing conflicts and intersection safety; no trajectory extrapolation required.	Retrospective only; less useful for continuous motorway analysis [37].
Mean speed & σ_v	Correlates directly with travel time efficiency; lower σ_v indicates reduced shockwave formation.	High speed does not guarantee safety; aggregation obscures local bottleneck anomalies.
Space headway & flow rate	Reflects both micro- and macroscopic capacity gains.	Short headways increase HDV driver anxiety; requires stable V2V communication.

Three cross-cutting observations emerge from the reviewed literature. First, benefits are non-linear: at low penetration (10–30%), the traffic stream remains dominated by HDV behaviour and improvements are marginal—PET improves by only 5% at 10% MPR in urban networks [34]. A threshold effect consistently appears between 40% and 60% MPR, at which point CAVs begin to dictate ambient flow, causing critical TTC events to drop by 42–45% on motorways [33,35].

Second, network type matters fundamentally: motorway environments respond fastest (up to 60% capacity increase at 100% MPR [35]), while urban networks require near-total automation to replace cycle-based signal control and achieve the observed 72% reduction in intersection delay [34]. In combined networks, V2I communication yields a 70% reduction in speed variance at full penetration [36].

Third, the reviewed evidence suggests that the classical safety-throughput trade-off described in traditional traffic theory may be substantially hindered, though not eliminated. Several simulation studies with high-MPR of CAVs report that their deterministic reaction times enable them to reduce TTC/PET and maintain smaller headways. This result coincides with the 45–60% increase in capacity at the maximum MPR of CAVs in these traffic network configurations [33,35]. This finding should be interpreted with caution, as it is derived primarily from traffic microsimulation under idealised assumptions about sensing and communication. Thus, they may not generalise to traffic networks with imperfect V2V communication reliability or heterogeneous driver behaviour [38].

4.1. Impact of CAVs Penetration Rates on Traffic Throughput and Safety

The exact percentages of CAVs penetration rates differ slightly in different studies. It is possible to identify 3 possible regimes in which these penetration rates can be located. These can be considered as HDV-dominated, transitional, and saturated. Thus, fixed numeric bins cannot be specified for the penetration rates of CAVs in investigated studies. These categories can be considered as a common MPR sampling grid.

- Low penetration (1–39%)—"HDV-dominated" regime. At this range, CAVs are a small minority of the traffic flow, so it is still governed by conventional human car-following behaviour. A CAV's improved reaction time or spacing control only benefits its own immediate interactions, not the traffic network as a whole. This is the reason why studies report only marginal gains here (PET +5% at 10% MPR).
- Critical mass (40–60%)—"transition" regime. This range introduces measurable benefits for overall traffic flow. Literature explicitly names it as a "threshold effect". This implies that CAV-to-CAV interactions (e.g., platooning, chained V2V responses) become frequent enough to start dictating the overall traffic flow patterns, rather than being isolated events lost inside HDV-dominated interactions.
- Dominant penetration (61–100%)—"saturation" regime. Dominant percentage of CAVs over HDVs represents the scenario that enables investigation of the full potential of CAVs' impact on overall traffic flow KPIs. The 100% MPR in this regime is present in every investigated study. This use case is useful as a reference ceiling scenario—maximal potential of this technology even though it is not a realistic deployment scenario.

It is possible to conclude that these broad regimes corresponds with the three possible states of traffic flow which can be seen in the density-flow fundamental diagram. Where Low penetration rate corresponds with the free flow state, Critical mass regime with a bistable traffic state, and Dominant penetration with a saturated (congested) traffic state.

4.2. Implications for Design of Control Algorithms

The conventional use of the investigated KPIs is as metrics for post-processing evaluation of traffic flow safety and throughput. Beyond this conventional role, surrogate safety measures are increasingly embedded directly in the algorithmic design of CAV control subsystems such as perception, planning, and general traffic control. In reinforcement-learning-based decision-making algorithms, TTC and DRAC-type metrics are commonly used as reward surrogates that penalise trajectories passing through the high-risk regions. The study [39] explicitly contrasts such conventional TTC-based reward with a proposed short-horizon predictive Safety Potential term. This study reporting that the latter yields higher success rates and fewer collisions than a TTC-based reward in a roundabout scenario. In optimisation-based motion planning, the same indicators reappear as explicit risk constraints or planning costs. The study [40] embeds driving risk assessment based on the TTC directly into the cost function. It improves the Driving Risk Field (DRF) model. This

is done by replacing the traditional artificial potential fields by integrating TTC, vehicle geometries (using elliptical boundaries), relative velocities, and directional attributes of obstacles, road boundaries, and pedestrians into a unified spatial-temporal risk gradient.

PET- and TET/TIT-type KPI metrics serve an analogous role in vehicle-to-vehicle interaction-based planning. This is especially important at conflict points such as intersections and merging points on motorways, where they are used to numerically evaluate the effectiveness of all possible CAV manoeuvres for a particular traffic scenario and road geometry [41]. Recent work on CAV safety control, such as ref. [42], illustrates this same shift toward embedding classical surrogate safety measures within the control/planning loop itself. Those studies set the KPIs discussed in this survey along this design-versus-evaluation axis of CAVs control subsystems. Thus, it suggests that their relevance to CAV research extends into the essential parts of their driving control algorithm design. In most cases, investigated KPIs are an integrative part of cost functions and behavioural constraints within optimisation-based control algorithms.

5. Macroscopic Traffic Parameters Approximated from Data Collected by Connected and Autonomous Vehicles

Building on the safety and throughput context established above, a distinct and rapidly growing body of literature works exclusively with trajectories reported by probe vehicles present in the traffic stream, without access to infrastructure-based detectors. Every equipped vehicle is treated as a mobile sensor sampling the surrounding traffic state, and the central problem becomes how to reconstruct macroscopic, Eulerian parameters—flow q , density k , space-mean speed $\bar{v}_s$ —from an inherently sparse set of Lagrangian observations at partial, often unknown, penetration rates. This creates two coupled challenges: the aggregation problem (converting asynchronous trajectory samples into consistent macroscopic quantities) and the penetration-rate problem (correcting for partial fleet observation) [8,43].

Eddie's generalised definition of traffic flow variables—expressing flow and density as functions of total travel distance and time within a space-time region—remains valid for sub-sample trajectories and serves as the foundational tool across nearly all reviewed studies [16]. Two main families of estimation methods build on this foundation. The first combines probe trajectories with macroscopic flow models (e.g., the Lighthill-Whitham-Richards model) within Kalman-filtering or adaptive-smoothing frameworks to fill in the traffic state between sparse observations [4,44]. The Mobile Century field trial demonstrated that even a few percent MPR of GPS-equipped probes suffices to reconstruct freeway travel times with accuracy comparable to dense loop-detector networks when combined with an ensemble Kalman filter [5]. Lagrangian state estimators formulated in vehicle coordinates propagate probe information more efficiently since the estimation grid moves with the flow [7]. The second family avoids an explicit flow model and instead exploits the vehicle-conservation (continuity) equation directly: onboard spacing measurements combined with overtaking counts allow section-wide density and flow to be estimated without a known penetration rate [6,8]. This approach is particularly suited to CAVs, which already carry the forward-sensing hardware needed for spacing measurement as part of their driving function. Probe data has also been applied to estimate queue lengths at signalised intersections via shockwave propagation [43].

Table 4 summarises the main aggregation method families with their output parameters, approximate minimum MPR requirements, and principal references. Two general conclusions emerge. First, reconstruction accuracy improves non-linearly with MPR: below a few percent, model-based fusion is required; above roughly 10–15%, conservation-law-based and data-driven methods become reliably self-sufficient [6,8]. Second, the transition from CAVs as traffic participants to CAVs as traffic sensors is primarily a data-processing

rather than a hardware challenge—the onboard sensing already required for autonomous driving is sufficient for probe data collection.

Table 4. Data-Aggregation Methods for Deriving Macroscopic Traffic Parameters from Probe Vehicle Data (or CAVs). Minimum MPR values are synthesized thresholds based on investigated studies which uses the same aggregation method. It condenses accuracy versus MPR curve (error metrics, MPR sampling points and different traffic network) into a single representative threshold—the approximate penetration rate at which the reported reconstruction error drops to an acceptably low/stable level in that study.

Aggregation Method	Principle/Output Parameters	Approx. Min. MPR	Key Reference(s)
Edie’s generalised definitions	Total travel distance and time within a space-time window $\rightarrow$ flow q , density k .	Any	[16]
Kalman-filter/adaptive-smoothing	Fuses probe trajectories with a macroscopic flow model (LWR) to reconstruct the full spatio-temporal speed/density field.	$\sim 2\text{--}5\%$	[4,5,44]
Lagrangian state estimators	Estimation grid in vehicle coordinates; propagates probe information along the flow direction.	$\sim 5\text{--}10\%$	[7]
Conservation-law/spacing-based	Onboard spacing and overtaking counts with the continuity equation $\rightarrow$ density and flow without known MPR.	$\sim 5\text{--}15\%$	[6,8]
Shockwave/queue-based	Last probe joining a queue + shockwave propagation $\rightarrow$ queue length and intersection delay.	$\sim 10\text{--}20\%$	[43]
Machine-learning/data-driven	Maps sparse probe features (speed, spacing, flow) to macroscopic ground-truth using training data.	Variable	[8]

$\rightarrow$ denotes “is used to derive/yields”; it links the inputs available from probe-vehicle data (left of the arrow) to the macroscopic traffic parameters obtained through the aggregation method (right of the arrow).

6. Methods for Evaluating the Impact of Autonomous Vehicles on Energy Usage in Road Traffic Environments

Beyond their sensing and throughput roles, CAVs are promoted as a pathway toward lower-emission road transport through smoother longitudinal control, V2V/V2I-enabled eco-driving, and cooperative platooning. At the same time, the sensing and computing hardware adds electrical load, weight, and drag that partially offset these gains, and system-level effects-induced demand, fleet repositioning, modal shift—can erode vehicle-level improvements at the network scale.

6.1. Methodological Approaches for Assessing CAV Energy and Emissions Impacts

The studies reviewed in this section do not share a single assessment methodology. Instead, four broad approaches are used, each answering a different question and each carrying different limitations; the Method column of Table 5 identifies which of the four produced each reported figure.

Field (empirical) measurement. A small number of studies instrument real vehicles, through onboard fuel-flow sensors or OBD-II loggers, and compare consumption between automated and human-driven operation on matched routes and traffic conditions, or track disengagement-corrected energy use over real operational mileage [45–47]. This approach has the highest external validity, since it captures real driver/controller behaviour, sensor duty cycles, and traffic conditions as they actually occur, but sample sizes are typically small (single vehicles or short truck platoons over limited trial periods), limiting statistical generalisability to network-wide or fleet-wide claims.

Microscopic traffic simulation coupled with instantaneous fuel/emission models. The majority of reviewed studies [48–57] follow a two-stage pipeline: a microscopic traffic simulator (e.g., VISSIM, SUMO) generates second-by-second vehicle trajectories—speed, acceleration, and inter-vehicle spacing—under a specified car-following/lane-changing logic and CAV market penetration rate. These trajectories are then passed through an instantaneous fuel-consumption or emissions model that converts kinematic state into second-by-second fuel use and pollutant output (CO_2 , HC, NO_x , CO), which is then aggregated over the simulated network and time horizon. This approach is the only one able to isolate the specific effect of CAV penetration rate and control logic on network-level energy outcomes, since MPR can be varied as a controlled parameter, but the results are only as reliable as the calibration of both the car-following model and the emission model to real driving/vehicle data, and idealised communication/sensing assumptions in the traffic simulator can inflate the estimated benefit relative to field conditions.

Life-cycle assessment (LCA). Two studies [58,59] apply a cradle-to-grave LCA framework, following the general ISO 14040/14044 [60,61] structure: energy and GHG emissions are quantified across the manufacturing phase (including the sensing/compute hardware bill of materials specific to automation), the use phase (operational energy consumption), and end-of-life, combined into a single life-cycle total. This is the only approach capable of capturing the embodied-emissions cost of the sensing and computing hardware that enables both automation and the mobile-sensing role of CAVs discussed in Section 5, but it depends on manufacturer reports or modelled bill-of-materials data for the automation hardware, which is not independently verifiable and varies significantly with the specific sensor suite (e.g., LiDAR-heavy vs. camera-primary configurations) assumed.

Literature-based synthesis. A final group of studies [62–65] do not generate new primary data but instead aggregate results across many category (i)–(iii) studies to identify overall ranges or net effects (e.g., the 60–80% MPR optimal window reported by [62]). These are valuable for identifying cross-study patterns and bounding plausible net effects, but inherit the heterogeneity of their underlying sources: since the primary studies they draw on differ in vehicle type, network context, simulation platform, and system boundary (vehicle-level vs. network-level vs. full life-cycle), the resulting ranges should be read as order-of-magnitude indicators rather than directly comparable point estimates.

Because these four approaches answer different questions—operational energy use under real conditions (i), the isolated marginal effect of MPR under controlled simulation (ii), full embodied and operational impact (iii), and cross-study net-effect bounds (iv)—the percentage changes reported in Table 5 are not directly interchangeable, and this review does not treat them as such.

Table 5. Environmental and energy impacts of CAVs relative to HDVs.

Study	Network	CAV MPR	Method	Indicator(s)	Key Impact
Zhang et al. [45]	Urban	Single-vehicle	Field	Fuel (L/100 km)	HDV mode 5.6–14.7% more fuel; up to 60% under high σ_v
Yao et al. [48]	Motorway	0–100%	Sim	Fuel; HC, NO _x , CO	Up to 40.58% fuel and 24–38% emissions reduction at 100%
Zhao et al. [49]	Urban	0–100%	Sim	Fuel; emissions	Up to 32% reduction; largest at signalised intersections
Ferrarotti et al. [52]	Urban (roundabout)	10–100%	Sim	Energy; emissions	Monotonic decrease for both AVs and HDVs as penetration increases
Vrbanić et al. [50]	Motorway (VSL)	0–100%	Sim	Fuel; electric energy	Energy-based VSL reduces combined use; largest gains at low-moderate MPR
Ge et al. [51]	General	0–100%	Sim	Network emissions	~20% reduction at 100%; non-linear with MPR
Hua et al. [55]	Urban motorways	Varying	Sim	Fuel	Progressive fuel reduction as MPR increases
Xiong et al. [56]	Motorway	30–70%	Sim	Fuel; CO ₂ ; throughput	Dedicated lanes: throughput +5–10%, fuel −1–3%
Tu et al. [47]	Motorway	Empirical	Field	VSP-based energy	<10% saving on expressways; disengagement adds 8–40% on arterials
Mohammed & Horváth [65]	General	Literature	Review	Aggregate fuel	Fleet-level savings reversed; up to 42% increase under high demand
Zhang et al. [53]	Urban (platoon)	Platoon	Sim	Energy; emissions	Up to 61.26% energy and 56.23% emissions reduction (trailing vehicle)
Irshayyid & Chen [54]	Motorway	Platoon	Sim	Energy; jerk	Up to 76.7% energy and 50% jerk reduction via RL cooperative merging
Gawron et al. [58]	Vehicle (LCA)	N/A	LCA	Primary energy; GHG	Sensing hardware +3–20%; net ~9% LCA reduction with savings
Onat et al. [59]	Fleet (LCA)	N/A	LCA	GHG (full LCA)	21.2% lower operational; up to 40% higher manufacturing; net ~8% higher
Massar et al. [62]	Review	60–80% optimal	Review	GHG	Eco-driving −35%; induced travel +41.24%; peak at 60–80% MPR
Taiebat et al. [63]	Review	Literature	Review	Energy; GHG; VKT	Wide uncertainty; net positive or negative depending on MPR and shared mobility

6.2. Vehicle-Level Effects: Eco-Driving and Platooning

The primary fuel-saving mechanism is smoother longitudinal control. Zhang et al. [45] showed through field experiments that switching a vehicle to human-driven mode increased fuel consumption by 5.6–14.7% at 20–40 km/h and by up to 60% under high speed fluctuation, suggesting that reducing speed variance is the key efficiency factor. Chen et al. [57] found that AVs consistently outperform HDVs in energy consumption in route-guidance scenarios, the benefit of which arising from driving behaviour rather than route choice.

Simulation studies report substantial but scenario-dependent savings. Yao et al. [48] found up to 40.58% fuel reduction at 100% CAV penetration on an 8.5 km motorway, with 24–38% reductions in HC, NO_x, and CO. Zhao et al. [49] found the largest gains at signalised intersections (up to 32% fuel reduction), confirming that stop-and-go urban environments offer greater eco-driving potential than free-flowing motorways. Vrbanić et al. [50] demonstrated that a Q-learning VSL controller using electric CAVs as actuators reduced combined fuel and electric energy use across all tested penetration rates, with the largest relative gains at low-to-moderate MPR. Ge et al. [51] found a non-linear, approximately 20% network-wide emissions reduction at 100% CAV penetration. Ferrarotti et al. [52] observed a monotonic decrease in energy consumption and emissions for both AVs and surrounding HDVs as AV penetration increased from 10% to 100% in a roundabout scenario, confirming a spillover benefit onto conventional traffic.

Cooperative platooning consistently yields the largest energy savings through aerodynamic drag reduction and shockwave suppression [66,67]. Early truck-platooning field tests demonstrated 14% fuel savings for a three-truck platoon [46]. Zhang et al. [53] found up to 61.26% energy reduction for the trailing vehicle in a bus-car urban platoon. Reinforcement-learning cooperative merging reduced platoon energy by up to 76.7% and jerk by up to 50% [54]. Across the broader literature, realistic platoon savings cluster in the 8–18% range [64].

Not all evidence points to unambiguous savings. Tu et al. [47] found early-stage AVs achieved less than 10% energy saving on expressways, while frequent disengagement events on urban arterials added 8–40% extra energy consumption. Mohammed & Horváth [65] caution that individual-vehicle savings may be reversed at fleet level once increased travel demand from AV adoption is included.

6.3. System-Level Effects: Hardware Burden and Rebound

The sensing and computing hardware enabling mobile sensing capability is itself a source of added energy and embodied emissions. Gawron et al. [58] found that Level-4 CAV sensing subsystems increase vehicle primary energy use and GHG emissions by 3–20%. When operational savings are incorporated into a full life-cycle model, the net effect is approximately a 9% life-cycle reduction. Onat et al. [59] modelled autonomous electric vehicles from cradle to grave and found 21.2% lower operational emissions but up to 40% higher manufacturing emissions, with the full life-cycle balance showing autonomous EVs emitting approximately 8% more GHGs than non-autonomous counterparts once rebound effects were included. Taiebat et al. [63] similarly conclude that the net effect of automation on energy use spans from large net reductions under optimistic high-penetration shared-mobility scenarios to net increases dominated by induced demand.

Authors in [55,62] synthesised the literature and found that eco-driving and platooning contribute up to 35% emissions reduction, while induced travel contributes up to 41.24% increase, with the maximum net emissions reduction estimated within the 60–80% AV penetration window-consistent with the threshold effects identified in Sections 3 and 4.

Table 5 summarises quantitative findings across the reviewed environmental studies.

Figure 3 represents a graphical representation of the minimal and maximal ranges within which the CAVs impact energy consumption relative to the HDVs. It is based only on the studies that take into account the vehicle-level effect. The Low/High comparison shows that reported eco-driving and platooning benefits are highly scenario-dependent. They ranging from marginal single-digit gains (Xiong et al. [56] reports 1–3%; while Zhang et al. [45] field study reports 5.6–14.7%) to substantial reductions exceeding 60% for cooperative platooning of vehicles (Zhang et al. bus-platoon, 61.26%; Irshayyid and Chen, 76.7%), confirming that aerodynamic and shockwave-suppression effects in platoons dominate over simple longitudinal smoothing at the single-vehicle level. Most simulation-based studies which report a low bound of 0% is direct implication of testing the case with 100%-MPR scenarios rather than a genuinely reported extreme value.

Only two studies fall entirely on the negative side of the axis. The first of them is Tu et al.'s disengagement-affected arterial driving (−40 to −8%). The second one is Mohammed et al. study with fleet-level reversal (−42% point estimate). They both illustrate that operational disruptions and induced-demand effects can outweigh the eco-driving gains measured at the vehicle level. Together, the results underscore the asymmetry induced by idealised simulation conditions, which cluster toward large positive savings. The sparse field-based study is the only source of net-negative outcomes in this study.

The most used KPI for fuel and energy consumption with CAVs in almost all investigated studies is direct comparison with traffic scenarios with only HDVs. Thus, all studies represent the inclusion of various percentages of CAVs as direct improvement over traffic flow with the same traffic load but only with HDVs. In this direction, CAVs are considered as mobile traffic actuators that can improve overall traffic safety and throughput [68–70].

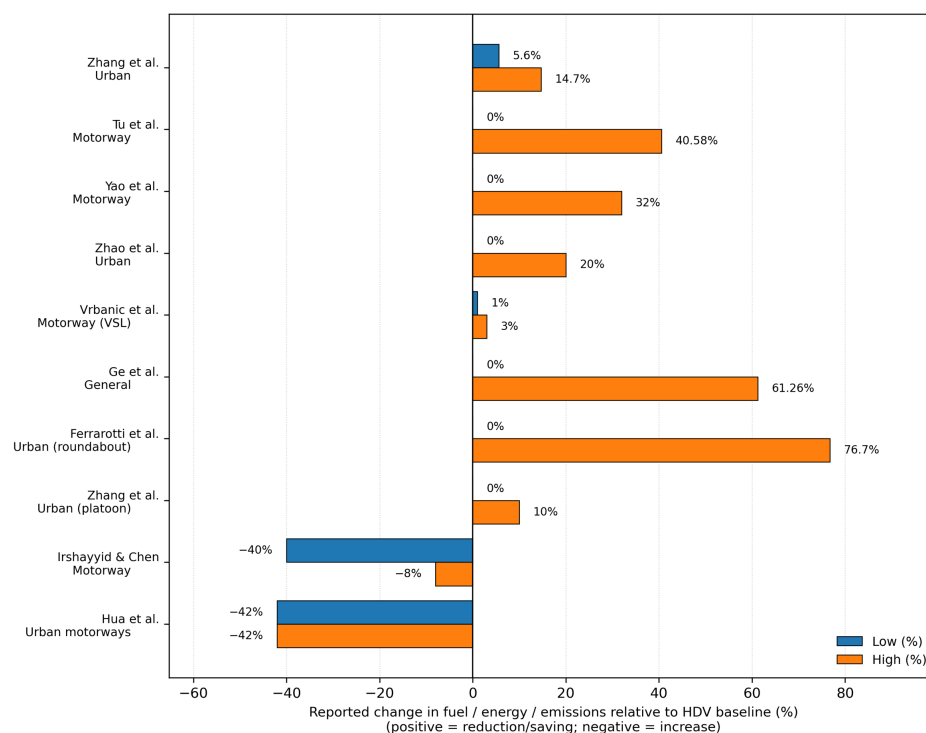


Figure 3. Reported CAV energy and fuel impacts across the studies, which take into account vehicle-level effects compared to HDV [45,47–55].

6.4. Implications for the KPI Taxonomy

Taken together, these two contributions illustrate the multi-level nature of platooning-related KPIs relevant to this survey: control-level indicators (spacing error, string stability, robustness to disturbances) determine whether a platoon can be maintained re-

liably under realistic heterogeneity and noise, while flow-level indicators (capacity, oscillation/shockwave metrics, safety) determine the traffic-level benefit of doing so once deployed at scale in mixed traffic. A KPI framework for CAVs that omits the control layer risks attributing flow-level gains to platooning strategies that may not be robustly realisable in practice, while a framework that omits the flow layer risks overlooking the fact that platoon-level stability does not automatically translate into network-level benefit, particularly at low MPRs or without complementary measures such as dedicated lane management.

7. Key Performance Indicators for Evaluating Mobility-on-Demand Systems Based on Autonomous Vehicles

MoD services have evolved substantially with the introduction of CAVs, creating operational paradigms that differ fundamentally from conventional human-driven taxi services. Assessing such systems requires a framework that captures operational efficiency, cost structure, safety performance, and environmental impact simultaneously [71]. This section reviews and compares the principal KPIs used in the literature to evaluate MoD effectiveness, with particular focus on the contrast between autonomous mobility-on-demand (AMoD) fleets and human-driven taxi services.

7.1. Operational and Cost KPIs

The core operational KPIs for MoD systems are passenger waiting time, fleet utilisation rate, service rate, detour ratio, and VKT [72,73]. Waiting time—the elapsed time between a trip request and vehicle arrival—is the primary metric for fleet sizing. Fagnant & Kockelman [74] showed through agent-based simulation that a single SAV can replace 9–11 CDVs while maintaining waiting times below one minute under static demand. Atlanta microtransit studies reported 7–10 min average waiting times for human-driven services with marginally lower values for autonomous configurations at equivalent fleet sizes [75]. Fleet utilisation—the proportion of vehicles actively serving passengers or en route—is the key economic KPI for operators; a review of ten AMoD case studies found that shared autonomous fleets allow 88–93% of CDVs to be eliminated with 83–97% parking space reductions [76], though empty kilometres increase by 6–15%. Alonso-Mora et al. [77] demonstrated a 98% service rate in New York City with a fleet of 2000 high-capacity vehicles, reducing the required fleet to 15% of the conventional taxi fleet, with a detour ratio below 1.1. AMoD systems are approximately six times more likely to satisfy demand than equivalent CDV fleets [76]. Zhang et al. [78] showed that poor rebalancing policy can increase total VKT by over 20%, highlighting the importance of distinguishing fleet-level from vehicle-level efficiency [79,80].

Labour costs represent approximately 60% of total operational costs in conventional taxi operations [81]. Bösch et al. [82] found that AV taxi services are cheaper than human-driven taxis at most urban densities, with public transit competitive only in the highest-density environments. Table 6 summarises representative cost estimates. Current robotaxi services operate at approximately 4.57 €/km, projected to decline to 0.75 €/km by 2035 [81]; human-driven taxis are estimated at 1.14–1.71 €/km [82]; at scale, shared autonomous platforms could reach 0.14–0.29 €/km [83]. Autonomous vehicle taxis have been projected to exceed the lifetime costs of human-piloted vehicles by approximately 49% in near-term scenarios due to acquisition costs, but the societal cost of human-piloted services was found to be 34% higher when crash-related costs and productivity losses are included [84]. Goldman Sachs Research projects depreciation costs dropping from 0.20 €/km in 2025 to 0.09 €/km by 2040 [85].

Table 6. Representative Cost Estimates for MoD Service Models. Cost figures are directly reported from the cited source for each row (converted from USD/mile using 1 mile = 1.609 km, 1 USD = 0.92 EUR, mid-2025).

Service Model	Cost [€/km]	Driver Cost Share	Source/Horizon
Human-driven taxi (current)	1.14–1.71	~60%	Bösch et al. [82] (2018)
Ride-hailing (current)	0.86–1.43	~55–60%	McKinsey [81] (2022)
Privately owned AV (current)	0.38–0.57	0%	ITS-DOT [79] (2018)
AV taxi (current, at-scale)	2.86–4.57	0%	McKinsey [81] (2022)
SAV (pooled, near-term)	0.34–0.57	0%	Litman [80] (2021)
Privately owned AV (2035)	0.17–0.29	0%	ITS-DOT [79] (2018)
Robotaxi (2035 projection)	0.75	0%	McKinsey [81] (2022)
SAV (at-scale, long-term)	0.14–0.29	0%	ARK Invest [83] (2020)
AV truck (2025)	3.51	0%	Goldman Sachs [85] (2025)
AV truck (2030 projection)	1.08	0%	Goldman Sachs [85] (2025)
Human-driven truck (2025–2030)	1.49–1.60	~40%	Goldman Sachs [85] (2025)

7.2. Safety and Environmental KPIs

The primary safety KPIs in the MoD context are conflict rate per vehicle-kilometre, injury incident rate, and fatality rate. CAV conflicts were found to be reduced by 66.7% at a 70% market penetration rate, even accounting for unreliable V2V communication [86]. Empirical robotaxi data indicates injury or fatality incidents approximately once per 1.3 million km vs. once per 560,000 km for HDVs, suggesting AVs are approximately 2.3 times safer under current operating conditions [81]. Environmental KPIs for AMoD systems—CO₂ per passenger-kilometre and energy per trip—improve through more efficient driving profiles and reduced idling [87], but are sensitive to induced demand, which can negate per-kilometre gains if total trip volume increases substantially (see Section 6).

Table 7 presents a structured comparison of key effectiveness KPIs across representative MoD studies.

Table 7. Comparison of Effectiveness KPIs across MoD Studies with CAVs and Human-Driven Vehicles.

Study	Context	Fleet Reduction	Waiting Time	Key Finding
Fagnant & Kockelman (2014) [74]	SAV sim., Austin TX	10:1 vs. CDV	<1 min	1 SAV replaces 9–11 CDVs; waiting time primary sizing metric
Alonso-Mora et al. (2017) [77]	Ride-sharing, NYC	Fleet → 15% of taxis	2.7–2.8 min	98% service rate; detour ratio < 1.1; delay < 100 s
Bösch et al. (2018) [82]	Cost analysis, CH	N/A	N/A	AV taxi cheaper than human taxi; driver cost ~60% of total
Zhang et al. (2018) [78]	AMoD + EV, agent-based	Significant	Varies	VKT trade-off depends on pooling; poor rebalancing +20% VKT
Alotaibi et al. (2023) [76]	AMoD review, 10 cases	88–93%	Not standardised	Parking –83–97%; empty km +6–15%; AMoD 6× demand sat.
Auad et al. (2021) [75]	SAV microtransit, ATL	Human vs. SAV	7–10 min (human)	SAV maintains travel times; dispatching balances detour vs. wait
Islam et al. (2023) [88]	CAV use cases	N/A	N/A	Platooning and MoD as primary CAV use cases; V2V enables gap management
Sun et al. (2024) [87]	CAV, California	N/A	N/A	MoD integration reduces CO ₂ /pass-km; induced demand partially offsets

→ denotes “reduced to”; the required fleet size is reduced to the stated share of the conventional taxi fleet needed to serve the same demand.

Three consistent findings emerge. AMoD systems outperform human-driven fleets on utilisation, service rate, and cost per kilometre at scale, but the margin depends critically on demand density and dispatching quality. Waiting time advantages narrow at comparable fleet sizes, suggesting the primary AMoD competitive edge lies in cost structure rather than response speed. Environmental KPIs are inherently coupled to induced demand: a 10% reduction in per-kilometre emissions can be negated by a 10% increase in total trips, underscoring the need for system-level rather than vehicle-level environmental accounting.

8. Discussion

This survey has reviewed four complementary dimensions of CAV evaluation. Several cross-cutting findings have implications for both research methodology and deployment policy. The MPR emerges as the single most consequential variable across all dimensions. Safety indicators (TTC, PET, DRAC), throughput metrics (capacity, speed variance, headway), probe data quality, and environmental performance all exhibit non-linear responses, with critical thresholds consistently reported in the 40–60% range. Below this threshold, CAVs adapt to HDV traffic rather than shaping it; above it, they begin to dictate ambient flow conditions, enabling the string stability, eco-driving coordination, and probe data density that unlock the larger benefits in the literature. Evaluation studies testing only a few penetration scenarios (e.g., 0%, 50%, 100%) may miss the region of fastest change. The six-level MPR framework in Figure 2 addresses this gap.

A persistent challenge is the lack of standardised evaluation protocols. Studies differ in SSM choice, critical thresholds, simulation platforms, car-following models, and network contexts, making direct quantitative comparison unreliable. As shown in Tables 2 and 5, this heterogeneity produces emissions estimates ranging from a 35% reduction to a 42% increase depending on system boundary assumptions. Standardising the evaluation framework using a consistent set of MPR levels, SSMs, and network contexts is a necessary precondition for meta-analytic synthesis and robust policy conclusions.

The mobile-sensing capability of CAVs is often treated as a costless co-benefit of automation. The environmental analysis in Section 6 challenges this: sensing hardware adds 3–20% to vehicle energy use and up to 40% to manufacturing-phase GHG emissions [58,59]. Meanwhile, meaningful traffic state reconstruction requires penetration rates above roughly 5–15% (Section 5). Together, these findings suggest an optimal deployment window—likely 15–40% MPR—where probe data quality is sufficient, and the fleet is not yet large enough for rebound effects to dominate. Turning to MoD evaluation, vehicle-level KPIs consistently favour AMoD at scale, but system-level KPIs—total VKT, induced demand, empty repositioning—frequently worsen, mirroring the gap between operational energy savings and life-cycle impact in Section 6. Both gaps point to the same lesson: CAV evaluation frameworks must account for second-order system effects to provide policy-relevant assessments.

Several limitations of the reviewed literature should be noted. Most safety and throughput studies rely on microsimulation rather than field data, and realism depends heavily on car-following model and calibration assumptions. MPR scenarios are typically imposed as fixed parameters, leaving transition dynamics unstudied. The interaction between CAV behaviour and HDV driver psychology—trust, risk compensation, adaptive behaviour—is rarely modelled explicitly. Large-scale empirical data on operational CAV fleet energy consumption remains scarce.

8.1. Impact of Regulatory Frameworks on Performance Indicators

It is worth noting how the KPIs considered in this work can be observed in the context of regulatory frameworks governing CAVs' operative deployment plans. Most

notably, those administered by the United Nations Economic Commission for Europe (UNECE) through the World Forum for Harmonisation of Vehicle Regulations (WP.29) and its Working Party on Automated/Autonomous and Connected Vehicles (GRVA) [89]. These regulatory frameworks do not define KPIs for specific mobility services or impact on traffic throughput and safety. Instead, they define compliance and safety-approval criteria evaluated at the level of an individual vehicle or subsystem, typically expressed as binary or threshold-based pass/fail requirements tied to a type-approval process:

- UN R157 (ALKS) mandates minimum performance thresholds for Object and Event Detection and Response (OEDR), transition-demand behavior, and minimum-risk manoeuvres, each evaluated under prescribed test scenarios rather than monitored as a continuous operational indicator [90].
- UN R155 and R156 define process-oriented compliance requirements—the existence and operation of a Cybersecurity Management System (CSMS) and a Software Update Management System (SUMS)—rather than quantitative security or reliability metrics [91,92].
- Complementary GRVA activities, such as the New Assessment/Test Method (NATM) and the Functional Requirements for Automated and Autonomous Vehicles (FRAV) initiative, are moving toward a scenario-based assessment paradigm in which safety is demonstrated against a curated set of critical scenarios rather than measured as an aggregate flow-level statistic [93].

In this sense, the regulatory view of performance is oriented toward demonstrating that a given CAVs, or a defined technical subsystem within it, satisfies a minimum safety and functional envelope before market approval in the context of service-level KPIs surveyed in this study. This emphasises the comprehensive effect of CAVs on traffic flow efficiency and mobility service quality. Regulatory compliance criteria act as boundary conditions (e.g., permitted operating speed, road type, sensor performance envelope) that constrain the operational implications within which the traffic-level KPIs discussed in this study can be meaningfully observed. Certification approaches inspired by other safety-critical domains, such as the nuclear sector, further illustrate this compliance-oriented framing of CAVs' performance [94].

8.2. Considering the Interactions Between CAVs and Vulnerable Road Users

The KPIs discussed in this study were selected primarily to evaluate interactions between CAVs and Human-Driven Vehicles (HDVs) at the level of traffic flow and mobility-service performance. Other road users, such as pedestrians and cyclists, jointly considered as Vulnerable Road Users (VRUs), have different interactions. Thus, they require a different set of KPIs. The main problem is the lack of a comparable communication channel between CAVs and VRUs to those used in vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) interactions. Characteristic VRU motion trajectories are less constrained by lane geometry, and their behaviour at crossings and shared spaces is comparatively harder to predict [95]. As a result, the literature on CAV-VRU interaction tends to rely on a partially distinct set of indicators.

The conflict and proximity-based surrogate safety measures (e.g., post-encroachment time, time-to-collision at crossings), pedestrian waiting and crossing time, and measures of communication effectiveness for external Human-Machine Interfaces (eHMIs) used by CAVs to signal intent to pedestrians and cyclists [96].

Among these, PET and TTC are the two most widely reported surrogate safety measures for CAV-VRU conflicts, since both can be extracted directly from trajectory data without requiring an actual near-crash to occur [97]. PET is a retrospective, purely temporal

measure defined as the interval between the moment a VRU (or the CAV) vacates a shared conflict point and the moment the other road user subsequently occupies that same point.

TTC, by contrast, is a proactive, instantaneous measure evaluated continuously as the CAV approaches a VRU's projected path. $TTC(t)$ is left undefined (or set to infinity) when the CAV is decelerating away from the conflict point, i.e., when the closing rate is non-positive. Because it is evaluated frame-by-frame rather than only at the moment of encroachment, TTC is better suited to capturing near-misses in which a VRU stops or hesitates before entering the CAV's path. The PET remains the more robust indicator once a crossing has actually taken place [97].

The same SSM framework extends to cyclists, though with important caveats. Cyclists travel at higher and more variable speeds than pedestrians, occupy a narrower and less predictable lateral footprint, and are more prone to abrupt evasive manoeuvres near intersections, all of which shift the distribution of critical PET and TTC values relative to pedestrian conflicts and reduce the transferability of pedestrian-calibrated safety thresholds to cyclist-CAV interactions [98].

A complementary, VRU-centred perspective models crossing behaviour directly as a gap-acceptance decision: given an available temporal gap G in the CAV/HDV traffic flow, a VRU is modelled as accepting the gap with probability,

$$P_{\text{accept}}(G) = \frac{\exp(\beta_0 + \beta_1 G + \sum_k \beta_k X_k)}{1 + \exp(\beta_0 + \beta_1 G + \sum_k \beta_k X_k)}, \quad (10)$$

where X_k denotes additional covariates such as crossing distance, waiting time, or number of already-waiting VRUs, and the β coefficients are fitted from observed crossing decisions [99]. In the context of CAVs, the covariate set can be extended to include eHMI-related variables (e.g., signalled yielding intent), which reframes gap acceptance as an outcome that CAV communication strategies can directly influence rather than a purely kinematic decision.

This last point connects back to eHMIs. The effectiveness of a given eHMI design is typically evaluated in terms of its influence on the VRU's crossing decision and reaction time, rather than through kinematic SSMs alone. Reviews of the eHMI literature report over seventy distinct eHMI concepts proposed to date, spanning light-based, textual, symbolic and projection-based modalities. Furthermore, note that perception and decision speed vary substantially across designs and are further moderated by scenario complexity (e.g., single-pedestrian versus multi-pedestrian crossings) [100]. This heterogeneity is one of the main reasons a single KPI set for CAV-HDV interaction cannot be transferred directly to CAV-VRU interaction.

8.3. Vehicle Platooning in the Context of CAVs and Framework for Their Efficiency Evaluation

Vehicle platooning is widely regarded as one of the key CAV capabilities, which utilises vehicle-to-vehicle (V2V) connectivity to form a coordinated and closely spaced group of vehicles capable of jointly improving road capacity, fuel efficiency, and safety [101]. A platoon typically consists of a leader vehicle, whose trajectory is either externally set or human-driven, and a set of follower vehicles that regulate their spacing and speed relative to their predecessor and/or the leader. It is enabled through a Cooperative Adaptive Cruise Control (CACC) architecture, which is essential for CAVs from a perspective of computing KPIs. The platooning main idea is to induce performance effects at two coupled levels: a control level, characterised by indicators such as spacing error, stability of spacing between vehicles in the platoon, and robustness to external disturbances; and a traffic-flow level, characterised by indicators such as capacity of the platoon, oscillation in vehicle speeds within the platoon, and safety in the context of the surrounding mixed traffic flow.

At the control level, the central challenge is maintaining a stable, minimal inter-vehicle spacing despite heterogeneity in vehicle dynamics, sensor noise, and external disturbances such as road slope, wind, and rolling resistance. The study [102] addresses this problem for a heterogeneous vehicle platoon operating under a predecessor-leader-follower topology, proposing a robust Static Output Feedback (SOF) controller that explicitly incorporates a Kalman-filter-based estimation of external disturbances in traffic flow. This line of work illustrates how control-level KPIs such as spacing error, disturbance mitigation, and provable string stability can be maintained even under vehicle-to-vehicle heterogeneity and imperfect sensing. This is a prerequisite for the reliable, large-scale platoon deployments assumed by most traffic flow level studies, which use the described KPIs in this study.

Formally, the control-level spacing error is defined relative to a desired inter-vehicle spacing policy. Under the Constant Time-Gap (CTG) policy most commonly assumed in CACC platoons, the desired gap $d_i^{\text{des}}(t)$ of follower vehicle i with respect to its predecessor is defined by the equation:

$$d_i^{\text{des}}(t) = r_0 + h v_i(t), \quad (11)$$

where r_0 is a fixed standstill distance between vehicles in platoon, h is the CTG, and $v_i(t)$ is the speed of vehicle i . The spacing error is then $e_i(t) = d_i(t) - d_i^{\text{des}}(t)$, where $d_i(t)$ is the actual measured gap between vehicles in platoon. A platoon can be considered as (weakly) string stable if spacing errors do not increase as they propagate from the leader towards the tail of the platoon, i.e., if the transfer function $\Gamma_i(j\omega)$ relating e_{i-1} to e_i satisfies the following equation:

$$\|\Gamma_i\|_{\mathcal{L}_p} \leq 1 \quad \text{for all } i, \quad (12)$$

which formalises string stability in an $\mathcal{L}_p$ -gain sense and underlies the robust controller design used in studies such as [103]. This condition is precisely what allows small time gaps h to be used safely. Thus, without a string-stable controller, disturbances originating at the platoon leader would grow unboundedly downstream. This limits how small h can be chosen in practice and, consequently, how much capacity benefit a platoon can realise.

At the traffic flow level, the relevant question shifts from individual platoon stability to the aggregate effect of platooning vehicles in a mixed CAV-HDV environment. The study [104] addresses this scenario by proposing a hybrid control framework that combines a “catch-up”-based platoon coordination strategy with dedicated lane management for CAVs at multi-lane motorway on-ramps. It is evaluated through macroscopic simulation within a wide range of CAV MPRs. Their results show an increase in traffic flow capacity as MPR increases. The largest gains are observed when platoon control is combined with lane management rather than applied in isolation. Furthermore, disturbances in traffic flow and shock-wave propagation are also shown to be reduced under the hybrid framework, improving overall traffic stability. This work is representative of a broader body of literature examining how platoon length, lane assignment, and MPR can jointly affect the KPIs investigated to evaluate overall traffic flow safety and throughput.

The link between the control-level time gap h from Equation (11) and the resulting lane capacity can be illustrated with a simplified, idealised model. Treating a platoon of N vehicles as occupying an intra-platoon time gap $h_p \ll h$ between consecutive followers and a larger, uncoordinated inter-platoon gap h_g between successive platoons. The resulting lane capacity is approximately presented with the following equation:

$$C \approx \frac{3600 N}{(N-1) h_p + h_g} \quad [\text{veh/h}], \quad (13)$$

with h_p and h_g expressed in seconds. Equation (13) makes explicit that capacity gains from platooning are highly nonlinear respecting MPR and platoon size. In case of a fixed h_g ,

capacity only increases appreciably once N is large enough and if enough vehicles are equipped with the CACC system for the $(N - 1)h_p$ term to dominate. This qualitatively matches the simulation-based finding that CACC yields negligible lane-capacity change at low MPR but substantial gains once penetration reaches moderate-to-high levels [105].

At the traffic network level, the aggregate effect of increasing platoon of CAVs MPR p is often summarised through its influence on the macroscopic flow-density (fundamental diagram) relationship according to the following equation:

$$q(k; p) = k \cdot v_e(k; p), \quad (14)$$

where k is traffic density, q is traffic flow, and $v_e(k; p)$ is the equilibrium speed-density relationship. This equilibrium itself depends on p through the mix of CAV and HDV car-following behaviour present in the traffic flow. Both the shape and the critical density of $v_e(k; p)$ have been shown to shift favourably as p increases. This is the case since CAV/platoon strings reduce the stop-and-go oscillations in traffic flow that otherwise decrease vehicles throughput in mixed traffic flows [2]. This effect propagates from the level of a single road segment in the study [104] up to the traffic network level investigated in the study [106].

8.4. Implication of CAVs Evaluation on Public Policy and Urban Planning

Beyond their methodological and technical contributions, the KPIs investigated in this study carry direct application for public policy and urban planning. Investigated KPIs provide a quantitative basis for multi-phase public policies implemented to address the gradual increase of CAVs in traffic flow. Parallel traffic simulations can be conducted for an urban traffic network based on several MPR of CAVs. For each of those simulations, the same set of investigated KPIs is computed. The results can be used to plan the dedicated CAV lanes or platoon-priority corridors based on a minimum CAVs MPR threshold. Thus, in a simulated traffic network, an infrastructural expansion such as introducing additional traffic lanes on arterial roads for CAVs or transformations of existing traffic lanes into dedicated ones for CAVs can be tested based on investigated traffic throughput and safety KPIs at specific CAVs MPRs.

Similarly, mobility-service KPIs (e.g., service reliability, waiting time) are directly usable by transit authorities and city planners seeking to integrate CAV-based mobility services with existing public transport networks, curb space allocation, and first/last-mile connectivity planning. Safety-related KPIs, including surrogate safety measures for CAV-HDV and CAV-VRU interactions, offer a concrete evidence base for setting operational design domain restrictions, speed limits, or infrastructure redesign priorities (e.g., signalised intersection geometry, planning new dedicated crossings) in areas of mixed traffic flows. Translating these indicators into policy is not automatic. However, KPI thresholds derived from simulation or controlled deployment studies must be interpreted cautiously when used to justify regulatory or infrastructure decisions.

9. Conclusions

This survey has examined the key performance indicators used to evaluate the impact of CAVs on traffic flows and mobility services across four complementary domains: mixed-traffic safety and throughput, traffic state estimation from vehicle data, environmental and energy impacts, and Mobility-on-Demand effectiveness. Across all four domains, the synthesis performed confirms that a carefully selected and consistently applied set of KPIs, rather than any single indicator taken in isolation, provides the most reliable basis for comparing CAV impact across studies, network types, and penetration rates in traffic flows.

The MPR emerges as the single most consequential variable underlying every KPI reviewed. Safety indicators such as TTC, PET, and DRAC, throughput measures such as capacity, speed variance, and headway, probe-data reconstruction quality, and environmental performance all exhibit a markedly non-linear dependence on MPR, with the most rapid changes concentrated in the 40–60% range. Below this threshold, CAVs largely adapt to prevailing HDV traffic rather than shaping it.

For safety evaluation specifically, the reviewed KPIs indicate that TTC and TET are best suited to longitudinal motorway interactions, whereas PET remains the more appropriate indicator for crossing conflicts at intersections. Since none of these surrogate safety measures are available directly as simulation outputs, consistent post-processing is a necessary precondition for their use as comparable KPIs across studies. A closely related conclusion applies to the KPIs used to assess CAVs' mobile-sensing performance: below approximately 5–15% MPR, model-based Kalman-filter fusion of probe trajectories with macroscopic flow models is required, whereas above this range conservation-law-based and data-driven estimation methods become reliably self-sufficient. This confirms that the transition of CAVs from traffic participants to mobile traffic sensors is primarily a data-processing rather than a hardware challenge, and that estimation accuracy is itself a KPI that should be reported alongside CAV penetration rate in future studies which considers CAVs as mobile traffic sensors.

Environmental KPIs tell a more conditional story. Vehicle-level fuel and emissions savings can reach up to 40% at high MPR, but this benefit is partially offset by the added energy burden of sensing hardware (3–20% increase). The evidence synthesised here indicates that a net environmental benefit is most reliably achieved above 40–60% MPR, and only when high penetration is paired with shared-mobility deployment and low-carbon energy sources—underscoring that environmental KPIs must be tracked at the system level rather than the vehicle level alone. A parallel pattern holds for mobility-on-demand systems: the operational and cost KPIs reviewed show that autonomous fleets consistently outperform human-driven taxi services at scale, with required fleet size reduced by 88–93%, projected per-kilometre costs falling to 0.14–0.29 €/km, and Autonomous MoD fleets approximately six times more likely to satisfy demand than equivalent conventionally driven fleets. However, at the system level, total vehicle-kilometres travelled, and repositioning of vehicles without passengers across the fleet introduce trade-offs that can reduce some of these gains.

Future research should prioritise studies with large-scale implementations that combine CAV trajectory data, fixed-detector data, and crash records at currently achievable penetration rates (1–5%). Furthermore, advanced models of explicit HDV driver psychology and their adaptive behaviour in mixed traffic flow should be considered to enable application of the investigated KPI to a full system-level evaluation framework. Thus, covering a wide spectrum of traffic demands, modal shifts, fleet repositioning strategies, and CAV hardware-embodied energy consumption is essential to augment future evaluations beyond vehicle-level metrics toward policy-relevant, KPI-based assessments of CAV impact on traffic safety and throughput under different MPRs.

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Abbreviations

The following abbreviations are used in this manuscript:

AMoD	Autonomous Mobility-on-Demand
AV	Autonomous Vehicle
CAV	Connected and Autonomous Vehicle
CDV	Conventionally Driven Vehicle
DRAC	Deceleration Rate to Avoid Collision
FCD	Floating Car Data
FCO	Floating Car Observation
GHG	Greenhouse Gas
GNSS	Global Navigation Satellite System
HDV	Human-Driven Vehicle
LCA	Life-Cycle Assessment
MoD	Mobility-on-Demand
MPR	Market Penetration Rate
PET	Post-Encroachment Time
SAV	Shared Autonomous Vehicle
SSM	Surrogate Safety Measure
SSAM	Surrogate Safety Assessment Model
TET	Time Exposed TTC
TIT	Time Integrated TTC
TTC	Time-to-Collision
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
VKT	Vehicle Kilometres Travelled
VSL	Variable Speed Limit
VSP	Vehicle Specific Power

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