electronics

Review

Impacts of Connected and Automated Driving: From Personal Acceptance to the Effects in Society: A Multi-Factor Review

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Abstract

This systematic literature review explores the impacts of autonomous and connected mobility systems on sustainable road transportation. The evaluation process involves a multifaceted analysis, encompassing the assessment of their capacity to mitigate accidents, energy consumption, emissions, and urban traffic congestion. As a novel approach, this paper analyses the parameters of user acceptance of technology and how these are reflected in the overall impacts of automated and connected driving. Thus, based on a behavioral intention to use the new technology model, we aim to analyze the state of the art of the overall impacts that may be correlated with individual interests. To this end, a multi-factor approach is applied and potential interactions between factors that may arise are studied in a holistic and quantitative assessment of their combined effects on transportation systems. This impact assessment is a significant challenge, as numerous factors come into play, leading to conflicting effects. Since there is no significant penetration of vehicles with medium or high levels of automation, conclusions are often obtained through simulations or estimates based on hypotheses that must be considered when analyzing the results and can lead to significant dispersion. The results confirm that these technologies can substantially improve road safety, traffic efficiency, and environmental performance. However, their large-scale deployment will critically depend on the establishment of coherent regulatory frameworks, infrastructural readiness, and societal acceptance. Comprehensive stakeholder collaboration, incorporating industry, regulatory authorities, and society, is essential to successfully address existing concerns, facilitate technological integration, and maximize the societal benefits of these transformative mobility systems.

Keywords: automated and connected mobility; acceptance; impact; safety; consumption; emissions; traffic

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1. Introduction

The transportation sector is of critical importance in modern society, exerting influence on economic activities, urban development, and environmental sustainability. However, conventional road transportation systems confront serious challenges, including escalating traffic congestion, increasing energy consumption, and significant greenhouse gas emissions, alongside persistent safety concerns stemming from human error. In response to these challenges, road mobility is currently undergoing an unprecedented transformation.

Intelligent transport systems (ITS) aim to address the inefficiencies and negative effects caused by mobility, and more specifically, but not exclusively, in road transport.

These negative effects include accidents, environmental impact, energy consumption, productivity losses, and lack of user satisfaction, among others. In this context, technological development is driving the development of vehicles with increasingly high levels of automation (mainly level 4) [1]. The introduction of sophisticated assistance systems, especially in the case of passenger cars [2] allows vehicles to perform more complex operations autonomously. In this context, recent works have proposed intersection-based distributed routing schemes supported by vehicular fog computing to enhance the reliability and delay performance of V2V communications in complex urban scenarios [3]. These innovations hold great promise in addressing significant contemporary challenges, including road safety, traffic congestion, energy consumption, and environmental sustainability [4–8]. On the other hand, connected vehicles employ a range of communication technologies, including Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), and Vehicle-to-Everything (V2X), to enable real-time information exchange. This facilitates effective cooperation among vehicles in various traffic scenarios. Research has consistently demonstrated the substantial benefits of smart traffic management systems, including improved traffic flow, reduced congestion and enhanced roadway capacity.

However, the introduction of vehicles with higher levels of automation still presents barriers that must be overcome. These barriers include various aspects [9]:

- Technical, to improve perception and decision-making capabilities in more complex scenarios.
- Economic, since some of the components of perception and decision-making systems are still expensive within the price of the vehicle.
- Regulatory, necessary to ensure the safety and robustness of vehicle operation, as well as to establish possible changes in traffic rules in the event of the coexistence of autonomous and traditional vehicles.
- Social acceptance, both among users of these vehicles and among users of other vehicles or pedestrians.

Within this framework, in the case of acceptance aspects, social changes are proposed that may be slower, less predictable, and more difficult to directly influence. Therefore, the gradual introduction of driver assistance systems is advocated, as low acceptance could slow the advancement of the technology's deployment [10]. There are several studies that attempt to assess the most determining parameters for user acceptance of this new technology. Acceptance is inevitably linked to expectations about how the vehicle performs and what impact that performance may have on users.

However, people's individual motivations are not always aligned with the broader interests of society, so some objectives fall closer to one pole than the other (Figure 1). Thus, there are analyses of the potential impacts of the introduction of autonomous and connected vehicles on aspects such as safety, fuel or energy consumption, environmental impact, traffic congestion, among others, but not all of these impacts are perceived with the same level of relevance by users when defining their attitude toward autonomous vehicles (in fact, in many studies, some impacts are ignored, and only those related to safety are considered). Furthermore, it has been observed that there is no correlation between the perception of impacts and their quantification, which could slow the social acceptance of technology. This fact, in turn, could hinder progress at other levels [11,12]. In fact, the effective deployment of new technologies requires positive acceptance that eliminates potential social barriers that impede or delay their introduction. Therefore, new technologies must generate user trust and add value to their expectations. However, the overall effects are not clearly perceptible at the individual level, and this situation can lead to slow deployment or even poor interaction in mixed traffic scenarios. Therefore, the correlation between individual and social interests, both for users of autonomous vehicles and other road users, can lead to an optimization of the mixed traffic scenario.

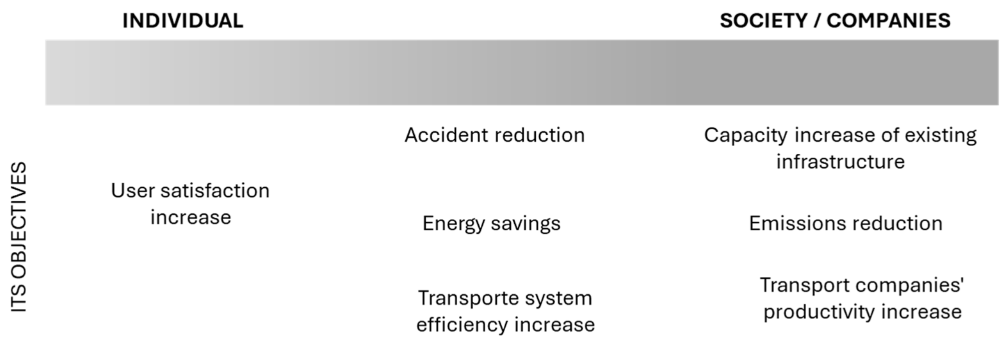

Figure 1. Individual and collective interests in the impacts of ITS.

This work is intended to fill multiple gaps highlighted by previous studies. While several studies have examined the potential of autonomous, connected, and shared vehicles, most have done so in an isolated way or with limited scope; few have provided a holistic and quantitative assessment of their combined effects on transportation systems [13]. This research addresses this issue by providing an integrated evaluation of how these technologies can collectively reduce accidents, fuel consumption, emissions and traffic congestion, while also reshaping fleet composition, economic dynamics and infrastructure requirements. Furthermore, the current literature tends to overlook the societal dimension of technological adoption. Thus, this integrated approach helps to bridge the gap between technical assessments and individual and societal expectations, providing practical insights for policymakers, industry and urban planners.

Therefore, this paper analyses the parameters of user acceptance of the technology and how these are reflected in the overall impacts of automated and connected driving. Thus, based on a behavioural intention to use the new technology model, we aim to analyse the state of the art of the overall impacts that may be correlated with individual interests. To this end, a multi-factor approach is applied and potential interactions between factors that may arise are studied. Although there are various literature reviews on connected and automated driving [14], this study introduces as a novel factor the user perspective and multifactorial vision of the impacts with respect to the works that deal with some partial aspects individually, both impacts and technological. It should be noted that the study is limited to automated and connected driving in road transport, excluding applications in sectors such as construction, agriculture, or the military, whose impacts are very specific and on which some reviews have been found [15].

This paper is organized as follows: Section 2 presents the method for carrying out the literature review. Section 3 explores the main factors users consider when adopting automated and/or connected mobility solutions. Section 4 provides an overview of the correlation between individual motivations and social impacts that could show main gaps and discrepancies in both interests. Section 5 presents the systematic literature review across the main performance dimensions (road safety, traffic efficiency, energy consumption, emissions and collateral effects). Finally, Section 6 includes some results discussion and Section 7 concludes the study and outlines future research directions.

2. Literature Review Method

The Systematic Literature Review (SLR) begins with a study of the variables that stand out in the acceptance of automated and connected driving by users from an individual perspective. This analysis distinguishes between conclusions reached from real vehicle tests or simulators and those derived from the analysis of surveys, studies, or statistical models. From there, the correlation between individual variables and collective impacts is explored. The SLR quantifies the reported impacts of autonomous (AV) and connected (CV) mobility on the following five performance dimensions: (i) road safety; (ii) traffic flow and capacity; (iii) energy and fuel consumption; (iv) tailpipe and greenhouse gas emissions; and (v) system-level effects, economic indicators, and collateral impacts.

The review followed an explicit protocol inspired by PRISMA guidelines. It was conducted in major academic databases, with a particular emphasis on Scopus, complemented by specialized journals and other relevant sources. In addition to database searches, we applied forward and backward snowballing based on key articles identified in the initial query. Predefined combinations of keywords related to autonomous and connected vehicles (e.g., 'autonomous vehicle', 'self-driving car', 'connected vehicle', 'CAV', 'cooperative driving') and each performance dimension (e.g., 'safety', 'crash', 'traffic flow', 'capacity', 'energy consumption', 'fuel use', 'emissions') were used to carry out searches. Some examples of search string used are: ("autonomous vehicle" OR "self-driving" OR "connected vehicle" OR "shared mobility" OR "shared vehicle") AND ("consumption" OR "emissions" OR traffic OR "safety" OR "VKT" OR "vehicle kilometers traveled" OR "fleet" OR "economy" OR "public acceptance" OR "barrier"). Only peer-reviewed journal articles and full conference papers in English addressing road transport were considered. Records were screened in two stages (title/abstract and full text) against the inclusion criteria, which required that the study quantified at least one of the selected performance indicators for AV/CV scenarios. Exclusion rules discarded conceptual papers without quantitative results, studies not focused on road transport and duplicates. A basic quality appraisal was conducted based on the clarity of the scenario definition, the appropriateness of the methods adopted, and the transparency of the reported metrics and numerical results. Studies that failed to report essential methodological information or quantitative outcomes were excluded from the synthesis.

In summary, studies were included if they met the following conditions:

- Focused specifically on autonomous, connected, or shared vehicles.
- Addressed at least one of the impacts considered in this review: energy consumption, emissions, traffic, safety, vehicle-kilometers traveled (VKT), vehicle fleet size, economic impacts, collateral effects, barriers, or public acceptance.
- Reported quantitative and comparable results.
- Peer-reviewed scientific publications.
- Written in English or Spanish.

Studies were excluded when they presented one or more of the following characteristics:

- Absence of quantitative results (e.g., conceptual articles or technological development papers without impact assessment).
- Non-academic or purely divulgative content.
- Restricted access preventing full-text analysis.
- Studies focusing exclusively on technical system development without addressing impacts.
- Studies dealing only with public acceptance. These papers were used solely to support the state-of-the-art section on acceptance but not included in the quantitative impact review.

Overall, the search and screening process resulted in a final dataset of 150 studies that met all inclusion criteria and were included in the review. The bibliographic compilation was carried out iteratively across the selected databases and complementary sources, with duplicates and clearly out-of-scope items being removed during the process. Intermediate counts at each screening step were not systematically logged during the original compilation of the database, which is a limitation in terms of PRISMA-style reporting.

The final set of selected documents was classified into one or more predefined impact categories, depending on the scope of each study. The following information was extracted for each included document: bibliographic metadata; study design; geographical and contextual scope; scenario assumptions (e.g., automation level, penetration rate, and traffic composition); outcome metrics (e.g., % change, g/km, veh/h, and s/veh); and numerical results. Firstly, records were consolidated into a global evidence table summarising the corpus (ID, reference, method, context, scenario, metrics and headline quantitative results) and then split into category-specific tables regarding the selected dimensions. In terms of data synthesis, a structured descriptive approach was adopted rather than a meta-analytic one. For each performance dimension, studies were grouped by methodology type (field or real-world experiments, road tests, test-track trials, driving simulator studies, microscopic/macroscopic traffic simulations, analytical scenario analyses and survey-based investigations) and by key scenario parameters, such as automation level, connectivity features, penetration rate and network context. Simulation-based studies (microscopic/macroscopic traffic simulations and analytical scenario analyses), controlled experiments (test-track trials, driving simulator studies and instrumented-vehicle field tests) and real-world on-road observations were treated as distinct strata of evidence, as were stated- or revealed-preference surveys. These strata were not pooled into a single quantitative indicator or combined through numerical weighting. Instead, they were synthesized separately, with explicit references in the tables and narrative to the underlying study type. Within each stratum, the effect sizes reported in the original studies were used to directly construct ranges of percentage change (minimum–maximum) and representative values, which are reported in the tables and discussed in the text. Due to the significant differences in modelling assumptions, baseline conditions and performance indicators, no statistical modelling was performed, and variance and confidence intervals were not calculated across studies as these would not be comparable. Instead, dispersion is conveyed through the reported ranges and by highlighting divergent results where they occur. Furthermore, simulation-based projections and real-world experimental evidence were kept distinct in classification and interpretation. The tables explicitly reflect the methodology of each study and the narrative synthesis distinguishes between results obtained under controlled or simulated conditions and those derived from real-world deployments. Survey-based evidence is also used to complement the characterization of behavioral responses and user acceptance. This separation avoids artificially merging structurally different evidence bases and allows emphasis to be placed on cases where experimental findings confirm or qualify the outcomes suggested by simulations.

3. Connected and Automated Vehicles Acceptance Parameters

Public acceptance of autonomous, connected, and shared vehicles has emerged as a critical research domain, as successful deployment depends not only on technical maturity but also on user trust and societal readiness. Acceptance has been studied from two perspectives: surveys that allow us to identify the main influencing variables, their relative relevance and possible correlations, and track or road tests that measure variables characteristic of users or possible changes in their perception after trying out new technologies.

The survey-based approach has been widely discussed in literature. A summary can be found in [16], where the biases identified in 91 surveys related to the acceptance of automated vehicles are analyzed. Survey-based studies across Europe indicate optimism regarding ecological and safety benefits, tempered by persistent concerns about privacy and cybersecurity [17–20]. In China, trust and social influence, particularly among younger users, are stronger determinants of acceptance [21–23], while in the United States, age significantly differentiates interest, with younger respondents showing higher willingness to adopt new mobility solutions. Refs. [24,25] place special emphasis on differences in acceptance regarding gender. Using a survey of 400 respondents and a mixed logit model, recent evidence shows that single-user autonomous vehicles are generally preferred over shared autonomous vehicles, and that autonomous technology may provide only limited benefits for shared transport, with younger users being more willing to adopt both SAVs and single-user AVs than older individuals [26].

Complementary qualitative approaches, including interviews and expert think tanks, reveal ambivalence among stakeholders, balancing efficiency and comfort with regulatory and ethical challenges [27–29]. Unlike previous studies focused on vehicle users, ref. [30] focuses on the study of the perception of other users with whom the vehicle interacts.

Experimental evidence confirms that direct exposure to AVs through simulators, real-world test drives, or pilot programs increases trust, reduces perceived risks, and improves comfort, especially among initially skeptical users [10,31–34]. It has also been shown that acceptance of automated driving increases if the user is provided with information on aspects of how the system works [35,36]. Beyond the statements of the users after the tests, it is worth highlighting the study [37] in which user monitoring is introduced. Physiological responses are measured, and less positive affectivity is observed in autonomous driving compared to traditional driving, while excitement did not differ between the two conditions. Overall, literature converges on the central role of trust, risk perception, and safety in determining adoption. In this sense, the adaptation of the decision-making parameters of assistance and automation systems has been proven to be a key factor [11,12,38].

Table 1 presents a summary of factors that influence user acceptance of autonomous vehicles.

Table 1. Factors Influencing Public Acceptance of Autonomous Vehicles.

Factor	Situation	Relevant Studies
Trust	Trust is critical for acceptance, particularly in regions where social influence also plays a significant role. Initial trust can improve with direct experience and exposure.	[10,21,22]
Risk Perception	High risk perception can significantly decrease acceptance. Experiments show that perceived risk decreases with increased exposure to AV technology, though it varies across regions.	[31,32,39]
Perceived Usefulness	Perceived usefulness, especially in terms of ecological benefits and traffic efficiency, generally supports acceptance, though it can be outweighed by concerns about safety and privacy.	[16,17,29]
Privacy Concerns	Privacy remains a significant concern, particularly in Europe, where data security issues are frequently highlighted. This concern is a major barrier to widespread acceptance.	[16,21,27]
Social Influence	Social influence, particularly from younger demographics, positively affects acceptance. Social media and peer opinions play an important role.	[17,20,31]
Technological Readiness	Technological readiness is crucial in regions where legal frameworks and technological infrastructure are closely tied to public acceptance.	[40,41]
Comfort	Comfort, both in terms of physical experience and perceived ease of use, influences acceptance. Direct experience, such as test drives, can improve comfort and willingness to adopt AVs.	[25,42–44]
Safety Perception	Safety perception is one of the most significant factors. While AVs are often seen as potentially safer, concerns about system reliability and pedestrian safety persist.	[21,29,45]

Additionally, several studies can be identified that address the new role of the driver in automated vehicles and how the interaction between the vehicle and users can be improved [46,47].

In summary, studies highlight trust, perceived risk, perceived usefulness, and demographic characteristics as the most determining factors for the adoption of these new technologies. Furthermore, to a much lesser extent, they emphasize the importance of considering broader impacts, such as mobility, cost, and environmental benefits, beyond safety, which has traditionally been prioritized. In summary, studies on the acceptance of automated driving do not consider certain variables relevant, such as energy consumption, which may be related to pollutant emissions, or the reduction in travel time, a variable related to traffic efficiency. This highlights that users have a clear bias towards aspects such as safety and comfort, but do not associate autonomous and connected vehicle technology with other consequences.

4. Correlation Between Individual Motivations and Social Impacts

As reflected in the study of individual motivations, these tend to focus on safety, increased mobility opportunities for certain groups, or ease of use. In this sense, based on a behavioural intention to use model, the factors that are typically considered include perceived ease of use, perceived risk, and perceived usefulness. The latter encompasses all direct or indirect impacts that a user may consider in their decision-making process. However, other global impacts are not usually considered, although they are mentioned in some cases, such as in [48,49].

At this point, the differences become clear between the internal cost borne by the agent causing the inconvenience, which affects their decision-making, and an external cost that is not borne by that agent and does not influence their decision or does so to a very limited extent. Finally, the social cost encompasses the sum of costs that affect all agents in society, such as users, businesses, public administrations, etc. But, for effective implementation of the technology, personal and group objectives must be aligned, as well as how they interact.

Figure 2 shows the interaction between individual expectations and social impacts. The impacts of autonomous and connected vehicles are much broader in scope, and there is a direct relationship between effects that become visible at the individual level and global impacts. Thus, there is a correlation between the risk perceived by users and road safety. Similarly, the social effects of traffic, energy consumption, and pollutant emissions are directly linked to individual aspects such as travel time (more efficient and organized traffic should reduce travel times) and cost (fuel or electric recharge). Regarding travel time, the individual perspective adds an additional dimension which is not considered at a global level: time use. Similarly, traffic management is linked to infrastructure, and the introduction of automated and connected driving entails modifications to that infrastructure modifications, both physical and digital. Finally, the new mobility possibilities that these technologies open for users have implications for modal split, public transport, and transport-related sectors, with economic consequences that must be considered. This correlation motivates a detailed analysis on impacts of connected and automated driving given that the effects at the individual level, if proven sufficiently positive, can catalyze greater technology penetration and, therefore, global benefits. It is also relevant at this point to analyze why users do not significantly appreciate other impacts besides those related to safety and comfort.

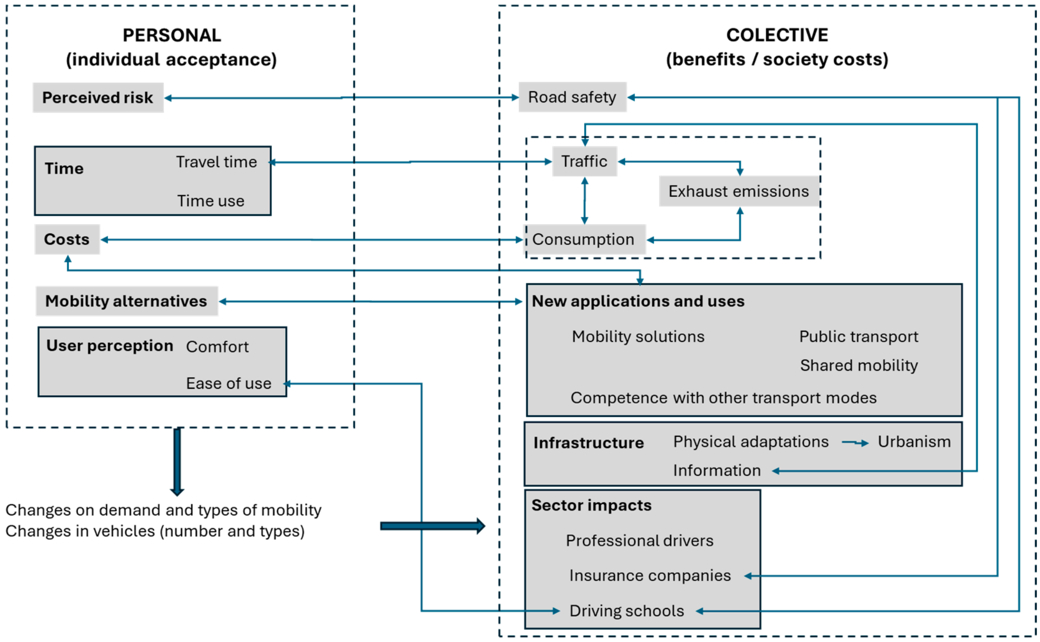

Figure 2. Correlation between factors related to individual acceptance of automated and connected driving and overall socioeconomic impacts.

5. Social Impacts of Connected and Automated Vehicles

The following section presents an analysis of the literature regarding the global impacts of autonomous and connected mobility. Specifically, the following dimensions are considered: (i) road safety; (ii) traffic flow and capacity; (iii) energy and fuel consumption; (iv) tailpipe and greenhouse gas emissions; and (v) system-level effects, economic indicators, and collateral impacts.

5.1. Impact on Road Safety

Safety is a critical aspect in the development and adoption of AVs. These vehicles promise to reduce accidents and save lives by eliminating human errors and improving decision-making in dangerous situations. However, to achieve reliable autonomous mobility, it is essential to evaluate the reliability and effectiveness of autonomous driving systems. In this regard, a complex and controversial line of work is underway to ensure the appropriate legal and ethical conditions for the deployment of this technology [50–52]. A Comparative Approach. Within this framework, one of the key aspects is defining the conditions and tests necessary for highly automated vehicles to operate in mixed traffic alongside conventional, manually driven vehicles [53–55].

In general terms, connected and automated vehicles eliminate human errors resulting from distractions, fatigue, misjudgements, etc. [56–59]. Furthermore, onboard sensors provide greater awareness of the environment, quantifying variables that a human driver can only assess qualitatively. Additionally, automated driving guarantees greater compliance with driving regulations.

On the other hand, despite the potential of AVs to enhance road safety, numerous challenges related to regulatory frameworks, liability determination, and public trust persist [20,21,60,61]. It must be considered that the introduction of technological advances is not exempt from operational glitches. Similarly, the information handled by these vehicle systems differs in some cases from that used by a human driver, and decision-making may be different. This makes the interaction between autonomous and non-autonomous vehicles a challenge, as conflicts can arise during driving. Finally, a major effort is being made to deploy effective and robust measures to guarantee the cybersecurity of these systems, which are particularly vulnerable if they have external information channels.

The evidence base indicates substantial potential safety gains when dominant human-error modes are removed or mitigated (Table 2): eliminating general human error yields ≈ 14–94% accident reduction [62–67]; targeting alcohol/distraction/fatigue achieves ≈ 40–90% [68,69]; addressing perception/incapacitation errors contributes ≈ 34% [70]. Partial cooperative systems already show modest but positive improvements (~7%) [7], while prevention/avoidance functions reach 82–100% success in controlled evaluations [71]. Ref. [37] estimates a reduction of up to 41% in heavy vehicle accidents thanks to the implementation of low levels of automation (levels 1 or 2 according to [1]) and connectivity (driver alerts, adaptive cruise control, assisted braking systems, etc.).

Table 2. Summary of Safety Impacts on Accident Reduction.

Factor	Accident Reduction (Safety Improvement)	Ref.
Elimination of human error	14.17–94%	[58,62–66]
Alcohol, distractions, drugs, fatigue	40–90%	[67,68]
Elimination of perception & incapacitation errors	34%	[69]
Cooperative systems	7%	[70]
Accident prevention & avoidance functions	82–100%	[7]

However, most of the studies focus only on eliminating human errors and distractions, often overlooking potential machine errors, such as software perception failures or connectivity issues. To address this gap, the following analysis includes experimental studies that simulate or detect various possible accidents involving AVs, assessing the current reliability of these technologies. Overall, while the studies indicate significant advancements in AV technology, they also reveal that reliability varies greatly depending on the level of automation and specific system capabilities. Level 5 systems show near-complete reliability under controlled conditions, whereas lower levels of automation still face challenges, particularly in unexpected scenarios or when human intervention is required. This suggests that while fully AVs are nearing operational readiness, further development is essential to ensure consistent safety and reliability across all driving conditions.

Reliability results (Table 3) are heterogeneous and level dependent. A Level 5 stack (Waymo) avoided 100% of reconstructed fatal collisions when substituting for the initiating human driver and 82% when reacting to human-initiated events [7]. In contrast, advanced Level 2 vehicles testing (Tesla Model 3) revealed variable monitoring/alert performance with missed alerts in a non-trivial fraction of runs (≈51–67%) [4]. Simulation and proving-ground studies often report satisfactory (≈100%) outcomes [7,72,73], but population-level demonstration of failure rates requires very large exposure (≈275 million miles for reference targets) [6]. Field datasets for Level 3 systems show mixed detection/reaction (3/26 cases) [74] and statistically significant associations between autonomous miles and disengagements/incident rates [68,75]. Finally, driverless operations still exhibit occasional interventions (~1 per 8244 km) even in structured ODDs [74]. According to [76], only when a penetration of more than 50% of automated vehicles with level 4 is achieved, will the reduction in accidents be significant, but not with lower penetration rates.

Despite the great potential in safety, it is observed that large theoretical benefits require robust, ODD-aware implementations and exposure-normalized evaluation. Priorities include (i) driver-monitoring/HMI standards for L2/L3 to prevent misuse and overtrust; (ii) cooperative infrastructure (V2I/V2X) to reduce conflict rates; (iii) transparent incident/disengagement reporting; and (iv) scenario-based testing that stresses perception edge cases and degraded connectivity. Within such a framework, L4/L5 in constrained ODDs appears closest to delivering consistent safety gains, while L2/L3 still presents non-negligible variability that justifies conservative human-in-the-loop designs.

Table 3. Summary of Key Findings in AV Testing and Reliability.

Automation Level [1]	Description	Location	Results	Reliability	Ref.
Level 5	Waymo fatal collision scenarios (reconstruction)	Chandler Arizona	Avoided all collisions when replacing the driver who initiated the crash; prevented 82% when reacting to the human initiator's actions	100%; 82%	[7]
Tesla Model 3 (advanced Level 2)	Road tests (monitoring/alerts)	Triangle, North Carolina	High variability in monitoring/alert metrics; 50% of tests no alert/assistance; 50% no alert despite obstacles	86%; 51%; 67%	[4]
Partial	Collision-avoidance model (simulation)	Simulated scenarios	Satisfactory	100%	[37]
Complete	Simulation (Udacity & NVIDIA model)	Simulated road	Satisfactory	100%	[77]
Complete	Collision-avoidance system (10 experimental cases)	INSIA, Madrid	Satisfactory	100%	[72]
Complete	Route-planning algorithm (5 scenarios)	Madrid, A3 road	Satisfactory	100%	[73]
Complete	Statistical safety & reliability analysis	United States	To reach reference failure rates: ~275 million miles (≈12.5 years with 100 vehicles)	95% (target confidence)	[6]
Level 3	Accident-report analysis of AV tests	California	Autonomous tech detected/reacted in 3 of 26 cases	11.54%	[74]
Level 3	Factors influencing disengagements & accidents	California	Strong positive correlation (0.73) between accidents and autonomous miles ($p < 0.01$)	1 accident/47,148 km	[78]
Level 4	Tesla Autopilot tests (overview)	China & USA	Human baseline: 1.18 fatalities/160,000,000 km;	5 fatal incidents total	[67]
Level 5	Waymo tests without human backup	Arizona	Human intervention once every 5128 miles (8244 km)	Improved performance and reliability	[74]

It is essential to continue developing technology for safe and reliable autonomous mobility. Studies show varied results in different test scenarios. In simulations, success rates of 100% were achieved in avoiding collisions, but higher levels of automation presented challenges in detecting and reacting to close collisions. Although level 5 vehicles have shown significant improvements in real-world conditions, further research is needed to ensure their safety in all driving situations.

In this context, radar-based perception has gained increasing relevance in autonomous driving due to its robustness under adverse environmental conditions and the impact that different data representations have on detection and tracking performance [79]. Building on this sensing capability, recent studies demonstrate that ultrasonic radar in-the-loop testing combined with Bayesian accelerated methods significantly improves the efficiency and realism of automatic parking system validation, narrowing the gap between simulation and real-world performance and directly addressing the limitations observed in high-level automation safety assessment [80]. Beyond perception and testing, human-like behavior modeling approaches based on inverse reinforcement learning have shown superior accuracy in reproducing lane-changing spatiotemporal features, contributing to safer and more socially compliant autonomous driving strategies [81]. In parallel, probabilistic behavior recognition methods that incorporate driver preview characteristics and lateral vehicle dynamics enable earlier and more accurate prediction of target vehicle maneuvers, thereby strengthening decision-making and control capabilities in autonomous driving systems [82]. More recently, interaction-aware trajectory prediction frameworks based on transformer architectures and uncertainty quantification have further improved safety in motion planning by explicitly modeling bidirectional AV–HDV interactions and propagating prediction uncertainty into the planning process [83]. Taken together, these advances highlight a clear convergence between robust perception, human-centered behavior modeling, and interaction-aware prediction as key enablers for reliable and safe autonomous driving.

5.2. Impact on Traffic Efficiency

The study of traffic effects is fundamental to understand how connected and automated mobility can influence road efficiency and flow. Overall, it is observed that vehicle automation and its penetration on roads have a significant impact on various aspects of transportation. Studying the impacts on traffic efficiency is complex because it involves numerous factors of very different kinds. Quantitative studies consistently demonstrate that autonomous, connected and shared mobility can have a significant impact on the performance of traffic on freeways, interurban corridors and signalized urban networks. In this way, automated and connected driving should provide better traffic organization and more appropriate route selection, both at the individual level and in terms of traffic flow organization from control centres. Furthermore, efficient driving provides a reduction in sudden acceleration and deceleration and better speed management. Even if penetration is not complete, the driving style of autonomous vehicles could favourably influence that of other users. However, it is necessary to evaluate the implications of the coexistence of different levels of automation (and, therefore, decision-making strategies). Along the same lines, the formation of platoons could provide better traffic reorganization. From the social perspective of usage expectations, these solutions are estimated to favour a growth in shared mobility and, therefore, a foreseeable increase in occupancy, although this may also result in greater demand for mobility, less use of public transport, or the use of private vehicles for longer journeys.

On the other hand, traffic efficiency has a clear and direct relationship with travel time, as it will be reduced if congestion is reduced or routes are chosen more effectively. Regardless of these factors, what is clear is that the use of automated and connected driving should result in a reduction (and potentially elimination) of parking time and better use of time by users who can perform other tasks while traveling.

The studies were categorized by facility type, analysis scale and metric. Facility types included freeways, interurban corridors and signalized urban networks. Analysis scales included link, corridor or network. These studies rely on simulation-based evidence, including microscopic simulations (e.g., intersections, lane-level interactions) and macroscopic simulations conducted at the city or network scale.

Metrics included capacity ($\text{veh}\cdot\text{h}^{-1}\cdot\text{lane}^{-1}$), average speed ($\text{km}\cdot\text{h}^{-1}$), delay and travel time ($\text{s}\cdot\text{veh}^{-1}$), queue length/density, and throughput/flow ($\text{veh}\cdot\text{h}^{-1}$). Table 4 summarizes the overall put the text here distribution of evidence, mapping the direction of effects by factor (e.g., cooperative adaptive cruise control/platooning, cooperative merging, connected/adaptive signal control, intersection reservation/priority, network-wide coordination/eco-routing, parking/curb management, shared autonomous vehicle dispatch/ride-pooling).

Table 5 summarizes the overall effects (ranges and percentage changes) of each factor on various traffic-related metrics, as reported in the analysed articles, providing a comprehensive overview of how different technologies and strategies can impact traffic efficiency and flow alongside the key scenario assumptions (automation level, penetration, compliance and demand). In this sense, it is relevant to observe that some studies propose connectivity solutions in a global way, while others focus on specific applications such as platooning or operation at intersections, for example.

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Table 4. Traffic Flow and capacity of automated, connected, and shared vehicles.

AV Level [1]	Factors	Conditions	Road Capacity	Travel Time	Delay Time	Average Speed	Traffic Flow	Ref.
Full	Platooning	Interurban highway	−35%			48%		[84]
		Highway	−21%			37%		
Full (4–5)	Connectivity, cooperation, eco-driving	Urban + Highway		−16%/−20%/−56%/−80%				[76]
Full	Energy efficiency, release of heat	Urban simulation (Singapore)	350%	−61%				[85]
Full	Micro traffic model	Highway corridor in Porto		+10%/+13%				[86]
Full	Platooning, eco-driving, eco-routing	Congested traffic		−15%/−30%/−60%		8–13%		[66]
Full	Congested traffic	5.3 km highway (Auckland, NZ)	88%	−26%			Free flow	[87]
Full	CAV	Endless highway 1 lane					15–40%	[56]
Complete	Cooperative systems	Intersection with optimized signaling			−91% (at intersection)			[5]
Full	Vehicle distance, speed oscillations	CV: 90–100 km/h; AV: 80 km/h	1.8–3.2%	−10.1%/−21.9%/−23.0%/−26.7%	−26.0%/−34.4%/−63.7%/−74.2%			[63]
Partial/Full	Private vehicle	50% CAV; 100% CAV	12%/77%					[88]
Full	Less incidents, better traffic flow	Exclusive lane for CAV		−30%				[89]
Full	Vehicle sharing	90% sharing		−60%				[90]
Partial	Eco-routing (E2ECAV)	Traffic in Toronto (Canada)		−40.7%		32% (average speed)		[91]
Advanced Level 3	Speed control at intersections	Optimistic case		−35%	−60%	163%		[92]
Full	Platooning	Increased reaction speed	8–13%	−25%		250–500%		[67]
Full	Carsharing	Increased capacity, increased trips	50%				0.5–2%	[93]
Partial	Cooperative systems	Annual time savings 2B hours		−3%				[70]

Table 5. Overall Effects of Various Factors on Traffic Metrics.

Factor	Capacity Increase	Travel Time Reduction	Delay Reduction	Average Speed Increase	Traffic Flow Increase	Reference
Platooning	1.8 to 13%	−10.1 to −35%	−25 to −74.2%	48% to 37%	100 to 500%	[63,67,90]
Connectivity & Cooperation	12 to 77%	−3 to −60%	−16 to −80%	—	15–40%	[56,70,88]
Cooperative CAV at Intersections	—	−35%	−60––91%	—	163%	[5,92]
Eco-driving & eco-routing	35%	−15 to −60%	—	8 to 13%	32%	[20,65,91]
Traffic Congestion	+88%	−26%	—	—	Free flow	[87]
Carsharing	+50–100%	—	−0.5 to −60%	—	—	[90,93]
Efficient Traffic Models	+350%	+10% to −61%	—	—	—	[86]
Accident Reductions	—	−4.5 to −30%	—	—	—	[66,89]

In this sense, autonomous mobility could offer advantages in terms of road capacity, travel time, and traffic flow. Capacity gains are consistently reported on freeways under cooperative adaptive cruise control (CACC) and platooning, with double-digit improvements at moderate penetration and larger gains as penetration rises (string-stability maintained). In signalized urban networks, a reduction in delay and travel time has been observed when connected/adaptive signal control and cooperative intersection management are active [5,92]. The magnitude of this reduction can reach tens of percent, with the upper end occurring under high CV/AV penetration and coordinated corridors. These factors contribute the most to enhancing overall traffic efficiency by substantially increasing capacity, reducing travel time delays, and improving traffic flow [56,70,88]. Platooning emerges as a promising technique to reduce congestion on interurban roads and highways, with reductions in travel time up to 35% in interurban road and 21% in highway, respectively [84].

Additionally, connectivity and cooperation between vehicles also show a clear trend in reducing congestion in urban areas and roads. This additional information provides alternatives for optimizing the management of critical sections such as intersections [94].

Studies highlight that the combination of AVs with eco-driving can lead to notable reductions in travel time [91], reaching up to 80% in highways [56] and 91% in intersections [5] in delay time, under full penetration rate and complete automation and connectivity, depending on the degree of penetration of these vehicles. This solution also provides considerable improvements in capacity. These strategies facilitate better vehicle communication and coordination, which are essential for smoother traffic flow.

Furthermore, parking and curb management have been shown to curtail cruising time and modestly increase speeds. Eco-driving and eco-routing contribute to moderate improvements in traffic metrics, particularly in reducing travel time and increasing average speed [20,65,91].

It is important to mention that the degree of penetration and the combination of technological and traffic management factors strongly influence the results [20]. The implementation of cooperative merging/ramp control has been demonstrated to reduce merge delay and increase ramp throughput in settings characterized by demand constraints. Network-wide coordination and eco-routing have been demonstrated to reduce the share of congested links and raise average network flow, so traffic congestion management strategies result in substantial capacity increases and travel time reductions, often achieving free-flow conditions [5].

In the context of shared-mobility operations, ride-pooling and dispatch optimization have been shown to reduce vehicle-hours/kilometers per passenger. Car-sharing and efficient traffic models demonstrate benefits in capacity improvement and delay reduction [91,94], although their impact on travel time varies. Car-sharing helps reduce the number of vehicles on the road, alleviating congestion, while efficient traffic models provide valuable insights into traffic management. However, it should be noted that empty miles have the potential to offset link-level improvements if not effectively managed.

Overall, these systems have been shown to improve capacity and reduce traffic delays [95,96], but, despite these clear benefits, the widespread adoption of these technologies faces obstacles concerning infrastructure investment, interoperability standards, and data privacy [66,97–102]. The research indicates that implementing a combination of these strategies, with a focus on platooning and connectivity and cooperation technologies, can lead to significant enhancements in traffic efficiency and congestion reduction, but the benefits derived from such measures are non-linear in nature, exhibiting sensitivity to factors such as traffic composition, compliance levels, and the employed control strategy. The presence of a mixed fleet, characterized by a range of vehicles with different levels of penetration, has the potential to attenuate the gains achieved. Additionally, the induced demand generated by such measures may partially erode network-level improvements, underscoring the need for a nuanced and holistic approach to network management. As with emissions, values should be treated as comparative indicators rather than directly comparable estimates due to methodological heterogeneity.

5.3. Impact on Consumption (Fuel/Energy)

The adoption of AVs is expected not only to revolutionize the way we travel but also to have a significant effect on the energy efficiency of transportation. Studies demonstrate that increased automation and penetration of AVs have significant potential to decrease energy consumption in transportation [103]. Connectivity between vehicles and cooperative systems improves coordination and communication, reducing energy consumption by optimizing traffic flow and avoiding inefficient congestion. Additionally, the use of platooning techniques, where vehicles follow closely and coordinate electronically, has high potential to reduce energy consumption. Vehicle sharing is an effective strategy to reduce the total number of cars in circulation, thus decreasing energy consumption in transportation. Eco-driving practices also contribute to fuel consumption reduction and consequently, energy consumption in transportation. Furthermore, intelligent route selection systems and variable speed regulation can optimize routes and minimize energy consumption, especially in congested situations.

Quantitative findings on energy/fuel use were harmonized by boundary (tank-to-wheel, TTW, vs. well-to-wheel, WTW, where available), scale (vehicle vs. network), facility type (freeway, interurban, signalized urban), and metric (e.g., $L{\cdot}100\ km^{-1}$, $MJ{\cdot}km^{-1}$, $Wh{\cdot}km^{-1}$, % change vs. baseline). Table 6 maps the distribution of evidence by factor.

Table 6. Energy consumption of automated, connected, and shared vehicles.

Automation Level	Penetration Rate	Factors	Effect	Energy Consumption	Ref.
Complete	100%	AV efficiency/AV electric/SAV + EV	Reduction	20%; 50%; 75%	[58]
High	High	Vehicle weight reduction	Reduction	5–10%	[104]
Complete		Platooning	Reduction	20.0%; 1.50%	[105]
Complete			Reduction	8–23%	[90]
Complete	Unitary effects	Platooning, traffic efficiency, parking efficiency, security, vehicle weight	Reduction	80%; 50%	[106]
Partial/Complete	Low/High	VKT/VMT increase/reduction	Increase/Reduction	14.5%; 2–34%	[107]
Complete	10%/90%	Platooning, eco-driving, eco-routing	Reduction	25–30%	[65]
Partial/Total	High	Private vehicles	Increase/Reduction	8.90%; 64%; 205.00%	[88]
High	High	Speed increase	Increase	13.9%/mile; 7–22%	[108]
High	Unitary effects	Connectivity	Reduction	13%	[109]
High	High	Eco-driving	Reduction	10–20%	[104]
High	Unitary effects	Eco-driving	Reduction	5%	[105]
Partial	Unitary effects	90% carsharing	Reduction	25%	[90]
Complete	High	Progressive acceleration	Reduction	23%	[90]
High	High	Eco routing	Reduction	12%	[104]
High	Unitary effects	Velocity control/Self-parking	Reduction	5–7%; 40%	[108]
High	100%	Eco-driving	Reduction	62%	[110]
Partial & Complete	35%/15%	Traffic reduction	Reduction	10–45%	[111]
High	High	Cooperative ITS; Heavy vehicles; Eco-driving; Velocity control	Reduction	31%; 20%	[92]
High	Unitary effects	CACC; Efficient driving; lighter vehicles; electrification	Reduction	15–33%; 91%	[92]
High	100%	Carsharing; efficient driving; lighter vehicles	Reduction	10–15%	[67]
Complete	100%	Traffic reduction	Reduction	83%	[87]
Complete	100%	Cooperative systems in junctions	Reduction	75%	[5]
Complete	Full	Speed increase	Increase	5.13%	[112]
Partial	100%	Cooperative systems	Reduction	1.2%	[70]

Table 7 summarizes the effects of different factors on energy consumption in transportation. It shows that platooning, shared vehicles, traffic efficiency improvements, eco-driving, and connectivity systems generally lead to reductions in energy usage, with varying degrees of impact depending on the specific implementation.

The estimations highlight a consistent pattern of energy savings across operational and network interventions, with platooning and eco-driving providing 5–31% (up to 23% for platooning alone) through smoother longitudinal control and reduced aerodynamic drag. For instance, high penetration rates of highly automated vehicles (Level 3 or higher) can achieve up to 20% energy savings through platooning [104], while simulations in urban environments highlight a more modest reduction of 1.5% due to increased travel distances [105].

Table 7. Effects of various factors on energy consumption.

Factor	Effect	Energy Consumption (Interval)	Ref.
Platooning	Reduction	1.5–23%	[90,104,105]
Shared vehicle	Reduction	25–75%	[58,105,106]
Traffic efficiency	Reduction	10–60%	[104,108,111]
Eco-driving & efficient driving	Reduction	5–31%	[63,90,92,104,110]
Route selection	Reduction	5–25%	[65,104,108]
Variable speed	Reduction	5–33%	[92,108]
Connectivity & cooperative systems	Reduction	1.2–75%	[5,70,113]
Impact of vehicle usage	Increase	24–205%	[88,106,107]
	Reduction	2.3–64%	[88,107]
Speed increase	Increase	5%	[112]

Traffic-efficiency measures and connectivity/cooperative systems exhibit broader ranges 10–60% and 1.2–75%, respectively, reflecting heterogeneity in penetration, compliance, facility type, and controller design. The 75% reduction [5] applies only to highly optimized intersections with short durations, as shown in simulations using intelligent traffic signals and cooperative cruise control. In contrast, broader studies with real-world applications show more modest reductions, such as 2–6% with full automation [113] or 1.2% with partial automation [70]. This variability highlights how different scenarios, from localized systems to large-scale deployments, influence the results.

Eco-routing/route selection contributes 5–25% savings by avoiding congested and stop-and-go regimes; similarly, variable-speed strategies yield 5–33% reductions by flattening acceleration profiles. At the system level, shared-vehicle scenarios report 25–75% energy reductions per passenger-km when pooling rates are high and empty-vehicle kilometres are controlled. A smaller but systematic increase appears with higher cruising speeds (+5%) [114], consistent with known speed–consumption relationships.

Finally, the impact of vehicle usage on energy consumption is highly variable, ranging from a 205% increase to a 64% reduction depending on the scenario [107]. These extreme values reflect different fundamental assumptions about the deployment of automated mobility. Scenarios reporting substantial increases in energy use usually involve a high level of privately owned autonomous vehicles (AVs), low travel costs in general, significant mileage with no passengers (e.g., repositioning and empty cruising) and considerable demand for private vehicles, or a shift away from public transport and active travel. Conversely, scenarios reporting significant reductions tend to assume fleet-based operation with high pooling rates, explicit constraints on empty-vehicle kilometres, and strong integration with mass transit. This means that higher occupancy and reduced redundant mileage outweigh rebound effects. Privately owned autonomous vehicles (AVs) can significantly increase energy use due to longer distances travelled and induced demand, where vehicle hours travelled (VHT) increased by 74% and fuel consumption increased by 66–87% under different technology adoption rates. However, according to this study, introducing a tax per mile on empty trips could reduce VHT by 13% and fuel consumption by 15–20%. In conclusion, while automation improves efficiency per vehicle, the overall increase in usage due to convenience and accessibility may offset energy savings, highlighting the importance of shared mobility and trip management policies. In this sense, shared mobility should optimize vehicle occupancy rates, so these solutions have demonstrated significant reductions in fuel consumption, achieving environmental improvements [114–118]. Nevertheless, social acceptance, behavioural changes, and regulatory barriers continue to pose challenges for widespread implementation [119–121].

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Overall, these results indicate that control-oriented and connectivity-enabled strategies reliably reduce energy consumption, while operational choices that elevate non-productive mileage or cruising speeds can offset or reverse gains. Reported values should be interpreted as comparative indicators, not directly comparable estimates, given differences in boundaries (TTW vs. WTW), fleet/powertrain mix, penetration, and network context across studies.

5.4. Impact on Exhaust Emissions

The study of emissions has become increasingly critical, particularly in the context of modern urban environments. With the rapid growth of cities and the corresponding rise in vehicular traffic, the issue of emissions has taken centre stage in efforts to improve air quality and public health. In large metropolitan areas, the concentration of vehicles leads to elevated levels of greenhouse gases (GHGs) and pollutants such as nitrogen oxides (NOx) and particulate matter (PM). These emissions have direct consequences for both environmental and human health. Elevated GHG levels contribute to climate change, while pollutants like NOx and PM are linked to respiratory diseases, cardiovascular conditions, and premature deaths. It should also be noted that the impact on polluting emissions is strongly correlated with other impacts such as fuel or energy consumption, improved traffic efficiency in general, or the influence on the use of mobility alternatives (for example, increased mobility, a percentage reduction in the use of public transport, etc.). In this section, the results of the collected set of studies on emissions is explored, analysing the most relevant factors influencing greenhouse gas and pollutant emissions in the transportation sector.

Studies were harmonized according to analytical boundary (tailpipe vs. well-to-wheel, where available), scale (vehicle vs. network level), facility type (freeway, interurban and signalized urban) and metric (e.g., $g \cdot km^{-1}$, % change vs. baseline). Non-exhaust emissions (e.g., brake and tyre wear) are reported separately where available. Table 8 includes the overall distribution of evidence, collating the outcomes of all reviewed articles and indicating the direction of the effect on emissions (increase or reduction) and the specific pollutants assessed (e.g., CO_2, NOx, PM, VOC).

A compact synthesis is provided in Table 9, which groups studies by intervention (e.g., eco-driving, platooning, connectivity/ITS, parking efficiency, electrification and ridesharing) and reports effect sizes (ranges/percentage changes) together with the relevant measurement boundary (tailpipe versus well-to-wheel). Generally, most studies indicate greenhouse gas (GHG) reductions of tens of percent when efficiency improvements, connectivity and electrification dominate. Increases are reported in unfavourable scenarios, such as aggressive driving profiles, added mass/auxiliary loads, elevated non-exhaust emissions, high computational/ancillary energy or empty-mile effects. For interpretability, values should be treated as comparative indicators rather than directly comparable estimates given the methodological and contextual heterogeneity across studies.

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Table 8. Emissions impacts of automated, connected, and shared vehicles.

Automation Level	Penetration Rate	Factors	Effect	GHG Emissions	Contaminants	Ref.
Full	100%	Platooning and eco-driving	Reduction	40–60%	GEI y NOx	[62]
Full	100%	Travel convenience	Increase	41.24%	CH_4, CO_2, N_2O	[122]
Full	100%	Platooning	Reduction	35.00%	CO_2 eq	[84]
Full (4–5)	—	Eco-Driving, connectivity, cooperation and vehicle increase	Reduction	24%	CO, NOx y VOC	[20]
Full	Variable	Shared, electric and automatized	Reduction	22–(+6)%	GEI	[123]
Full	High	Brake wear	Increase	30%	PM	[124]
Variable	High	Electrification complete	Reduction	90%	GEI	[85]
Full	10–30%	Traffic efficiency	Reduction	5%	CO_2	[86]
Full	100%	Cooperative systems on junctions	Reduction	85%	—	[5]
Full	Unitary effect	Efficient consumption/design; VMT reduction; vehicle park reduction	Reduction	63–82%; 34–43%; 13–20%	GEI; 0.58–0.94 t metrics	[106]
Partial	70%	Eco-routing (E2ECAV)	Reduction	18.95%	GEI	[91]
CAV level 4	Unitary effect	Platooning, eco-driving and connectivity	Reduction	9%	GEI	[125]
Full	High	Connectivity	Reduction	66%	CO_2	[89]
Full	100%	Traffic efficiency on junctions; velocity control; eco-driving	Reduction	13.8–39%; 10.2–44.6%; 31%	GEI	[59]
Full	100%	Change on mobility mode and carsharing	Reduction	40–60%	PM, NOx, CO, VOC GEI	[90]
Full	30% on interurban road	Conventional AV; Electric AV; SAV + EV; EV (efficiency)	Reduction	0.7%; 1.0%; 2%; 8%	NOx; CO_2; NOx y CO_2	[126]
High	—	Cooperative Intelligent Transportation; heavy vehicles	Reduction	3%	hasta 200 gCO_2	[113]
High	High	Adaptive Cruise Control (ACC) and V2I	Reduction	15–53%	—	[92]
High	100%	SAV; carsharing; lighter vehicles	Reduction	87–94%; 50%	—	[92]
High	—	Eco-driving	Reduction	19.1–30.9%	PM2.5	[127]
Full	100%	Eco-parking	Reduction	15.50%	SO_2 y CO_2	[128]
Partial	100%	Cooperative systems	Reduction	1.2%	Nox, CO, VOC y PM	[70]
Level 4	100%	Aggressive/cautious driving scenarios; electrification complete	Increase/Reduction	various (e.g., +35% to −61%; 90%)	CO_2 eq/km	[129]

Table 9. Effects of Various Factors on Emissions and Pollutants.

Factor	Effect	Emissions (Range)	Pollutants	Ref.
Platooning & eco-driving	Reduction	40–60%	GHG, NOx	[62,86,90,130]
Platooning	Reduction	60%	CO_2-eq	[131]
Eco-driving, connectivity, cooperation and increased vehicles	Reduction	24%	CO, NOx, VOC	[63]
Eco-routing (E2ECAV)	Reduction	43%, 19%	GHG, NOx	[91,110,132]
Traffic efficiency	Reduction	≈5%	CO_2	[132,133]
Parking efficiency	Reduction	24–90%	CO_2, SO_2, PM	[68,122]
Cooperative systems at intersections	Reduction	≈85%	CO_2	[66,132]
Sharing	Reduction	40–100%	GHG, CO_2	[66,84,96,122]
Shared, electric, and automated	Reduction	22– (+6)%	CO_2, NOx	[85]
Travel convenience	Increase	41.24%	CH_4, CO_2, N_2O	[90]
Vehicle weight (lower)	Reduction	≈50%	$PM_{2.5}$	[96,130]
Brake wear	Increase	30%	PM	[123]

It should be noticed that previous results include a wide methodological diversity: statistical analyses [57], LCA studies [122], simulations with varying penetration rates [20], and simplified analytical models [57]. These studies were grouped according to the pollutants examined and whether results referred to per-vehicle or fleet-level impacts, with particular attention to whether impacts were limited to the vehicle operation stage or to the full life cycle.

Platooning and eco-driving reduce GHG and NOx emissions by improving fuel efficiency [131]. According to [62,86,90,130], eco-driving and platooning reduce GHG emissions by 35%, but easier and faster travel could significantly increase GHG emissions by 41.24%.

Connectivity between vehicles and cooperative systems also decreases emissions by optimizing traffic flow and coordination. The unitary effect of connectivity results in a CO_2 reduction of 1,2% [70] but the global effect considering high penetration of high levels of automation could reach a CO_2 reduction of 66% [89].

The adoption of Shared Vehicles reduces emissions by decreasing the number of vehicles [66,84,96,122]. According to [97] the deployment of autonomous taxis (AT) in the U.S. by 2030 could reduce GHG emissions per mile by 87–94% compared to current conventional vehicles and by 63–82% compared to projected hybrid vehicles, with nearly a 100% reduction in oil consumption, even if total miles travelled, average speed, and vehicle size increase significantly.

Overall, GHG emissions are expected to decrease by approximately 40–60% [90]. The most significant reduction will come from the shift to shared vehicle mobility, though it is doubtful that people will give up the benefits of owning a personal car.

Electric Vehicles (EVs), especially when fully automated, reduce CO_2 emissions and other pollutants. A study on the effects of AVs and vehicle electrification using traffic micro simulation and emission modelling [129] found that aggressively programmed AVs reduce the emission factor by 26% and improve traffic conditions on highways, with less impact on streets with signalized intersections, while fleet electrification decreases emissions by over 90%, highlighting the need for both automation and electrification to effectively reduce emissions.

It is important to remark that these effects could be negative considering the worst-case scenarios. According to [123], for a realistic set of alternative mobility penetration scenarios of autonomous, electric, and shared vehicles, system CO_2 emissions range from a reduction of 22% to an increase of 6%, and NOx emissions range from a reduction of 35% to an increase of 5%.

Traffic optimization, including eco-routing, also contributes to further emissions reduction. Routing reduces average travel time, VKT, and GHG emissions in 43% and NOx in 18% [91], considering partial automation with 70% of penetration rate.

The level of automation and road penetration influences the impact of these factors. It is expected that higher levels of automation will lead to significant benefits in emissions reduction.

These studies demonstrate that autonomous mobility, especially when combined with approaches such as platooning, eco-driving, connectivity, and shared vehicles, can have a significant impact on reducing pollutant emissions and energy consumption, thus contributing to greater sustainability in the transportation sector.

However, it is also important to consider the potential increase in the overall use of AVs and their impact on total emissions to achieve a comprehensive understanding of their environmental effect. Therefore, it is essential to continue researching and evaluating the long-term impact of autonomous mobility to achieve a more sustainable and responsible transportation system. The impact on emissions is not clear, although a predominance of positive effects is noted. The wide range of reported greenhouse gas (GHG) impacts, from reductions of around 60% to increases of over 40% in certain scenarios, is largely driven by the interaction between vehicle technology, energy systems, and travel behavior. The most significant emission reductions tend to be associated with the combined deployment of low or zero-emission powertrains, high occupancy, eco-driving and platooning strategies, alongside a significantly decarbonized electricity mix. Conversely, emission increases tend to arise when efficiency gains are offset by higher VKT/VMT, low occupancy, substantial rebound effects or induced demand, or when the energy mix remains carbon-intensive or internal combustion powertrains continue to dominate. Therefore, the figures reported in the review should be interpreted as being conditional upon specific combinations of technology, fleet composition, energy mixes and policy measures rather than as unconditional forecasts of the most likely outcome.

5.5. System-Level, Economic and Collateral Impacts

The introduction of automated and connected vehicles also entails collateral impacts that encompass aspects such as mobility alternatives as an alternative, competition or complementary means to public transport, modifications in infrastructure and in the organization of the territory (both to favour the functioning of these vehicles because of their operation) and sectoral and economic impacts.

Thus, in relation to new mobility alternatives, options such as autonomous shuttles of different sizes depending on demand [134,135] and robotaxis [93] are emerging. Similarly, highly automated vehicles can offer mobility solutions to certain groups who previously had limited access, such as the elderly or people with disabilities. Robotaxi services can be cheaper than conventional taxis, although their deployment is still costly and complex, as their natural operating environment is city centres, which are very demanding on perception and decision-making systems. However, it should be noted that when this solution achieves high levels of penetration, it could become significant competition for conventional public transportation. While new technologies can complement conventional modes of transport in areas with low passenger demand (thus reducing the need to subsidize these services), their impact could be much broader, leading to significant increases in private vehicle use (with the inefficiencies that this entails) and potentially resulting in a more sprawling urban model.

Therefore, beyond safety, consumption, emissions and traffic flow, the literature consistently highlights further system-level impacts of autonomous and connected vehicles, notably on the vehicle fleet, Vehicle Kilometers Travelled (VKT/VMT), and the economy. Although these dimensions are not the primary focus of most studies, their implications are sufficiently significant to warrant dedicated consideration.

The reviewed studies highlight contrasting impacts of this kind of new mobility adoption on the vehicle fleet (Table 10). Connectivity, cooperation and eco-driving are generally associated with moderate increases in fleet size (5–26%) [20], as efficiency and accessibility stimulate additional demand. In contrast, carsharing scenarios consistently produce reductions, ranging from 10% to 33% depending on penetration, with maximum decreases of 33% at full adoption [136]. Private AV ownership tends to expand the fleet substantially, with estimates up to +60%, whereas household-level efficiency gains may limit the number of vehicles by around 9.5% [10]. The largest reductions are reported in shared autonomous vehicle (SAV) models, which may cut fleet size by up to 90%; integration of SAV with AVs and public transport can achieve similar reductions [67]. Overall, private-use scenarios are projected to increase fleet size, while shared and multimodal systems demonstrate the greatest potential for significant decreases.

Table 10. I pact of Penetration Level on Vehicle Fleet and Effects.

Factors	Penetration Rate	Effect	Fleet Impact	References
Connectivity, cooperation, eco-driving	20%; 50%; 80%; 100%	Increase	5%; 13%; 24%; 26%	[20]
Carsharing	50% shared 50% private	Reduction	10%	[65]
	100%	Reduction	25%	[106]
	100%	Reduction	28%	[89]
	100%	Reduction	33%	[136]
Private AV	100%	Increase	60%	
Fewer vehicles needed in households	100%	Reduction	9.5%	[10]
SAV	100%	Reduction	90%	[92]
	AV + SAV	Reduction	50%	
AV + SAV + Public transport	100%	Reduction	90%	[67]

The effect on VKT/VMT also shows contradictory trends depending on the influencing parameters considered (Table 11). Increases are typically linked to induced demand, migration from other transport modes, empty trips for carsharing or AV relocation, and greater accessibility, with estimates ranging from moderate values to substantial growth (+39–89%) under full SAV systems without public transport [137]. In scenarios with a high penetration of privately owned autonomous vehicles, these mechanisms become particularly pronounced: induced demand, longer average trip distances, zero-occupancy relocation and parking-search trips, and reduced use of public transport can collectively lead to substantial increases in VKT/VMT. Several studies have reported growth of up to approximately 89%. In these cases, reduced travel-time disutility and the need for empty repositioning trips can trigger a strong rebound effect that amplifies total vehicle travel.

Table 11. Impact of Various Factors on VMT/VKT.

Factors	Effect	VKT/VMT	Ref.
Migration from other modes of transport	Increase	15–59%	[137]
10% carsharing (empty trips)	Increase	8–10%	
100% SAV (without public transport)	Increase	39–89%	
Ridesharing	Reduction	10–25%	
Increase in road capacity	Increase	1–4%	
Empty private AV relocation	Increase	13.3%	[138]
—	Increase	14%	[136]
Social inclusion	Increase	2–10%	[109]
Increase in demand	Increase	50%	[139]
—	Increase	26%	
—	Reduction	12%	
Carsharing (empty trips)	Increase	13.3%	[138]
Carsharing	Reduction	27–43%	[106]
Ridesharing	Reduction	0–12%	[88]

Table 11. *Cont.*

Factors	Effect	VKT/VMT	Ref.
Transport costs	Reduction	7.9%	[140]
Increased road capacity and reduced travel time	Increase	4–8%	[65]
10% sales AV	Increase	20%	
50% sales AV	Increase	15%	
90% sales AV	Increase	10%	
—	Increase	13%	[105]
Platooning	Reduction	5% in urban roads	[84]
—	Increase	8% in highways	
90% penetration AV	Increase	26%	[92]
100% private AV	Increase	14%	[67]
100% Carsharing	Increase	12%	
100% Carpooling	Increase	6%	
Eco-routing (E2ECAV)	Increase	3%	[91]

Reductions are associated mainly with ridesharing, carpooling, and optimized sharing scenarios, which report decreases between up to 43% [61]. Some strategies, such as eco-routing, show minor increases (~3%) [89], while platooning produces mixed outcomes depending on road type (−5% urban; +8% highway) [90]. Overall, the evidence suggests that without strong integration of shared and collective transport, VKT/VMT is likely to rise, whereas pooling and multimodal strategies can counterbalance these effects.

Furthermore, the introduction of automated and connected vehicles has implications for the infrastructure, which must be adapted to facilitate the circulation of these vehicles, considering that even in their current state they have more limited capabilities than a human driver [141–144]. In the study [145], a feasibility study of road geometric design controls has been completed for fully autonomous vehicles, concluding that perception characteristics play a crucial role. In general, the modifications can be identified on two levels: physical changes and means of additional information. The former relates to geometric adaptations [146] such as curve radii, emergency stop zones, horizontal marking and vertical and temporary signals [147,148], simplification of intersections and roundabouts [149], improvement of pavement conditions [150] and ensure suitable external conditions (e.g., lighting). Furthermore, the goal of digital adaptations is to increase the information the vehicle acquires so it can reconstruct its situational awareness. This includes information such as precise and detailed digital maps, data from sensors in the infrastructure, and communication systems for exchanging information with the vehicles (based on the premise that high levels of automation can be achieved in connected vehicles). In this regard, classifications such as the Infrastructure Support Levels for Automated Driving (ISAD) proposed in the Inframix project have been developed [151]. This classification summarizes the digital support of the road facility to host vehicle automation. Five levels were introduced, from A (best support) to E (worst support). The most advanced state implies that the infrastructure can perceive, process, and send microscopic guiding information to vehicles to optimize the overall traffic flow.

Beyond the adaptations required for the operation of automated vehicles, their deployment is expected to impact spatial organization, primarily in urban environments. The anticipated reduction in the number of vehicles, coupled with the decreased need for parking spaces in complex areas and for extended periods, will free up space for vehicle circulation and parking, providing more space for pedestrians and businesses, with clear benefits for both pedestrians and businesses. It can be concluded that automated vehicles would encourage dispersed urbanization, reduce parking demand, and enhance network capacity [152].

Finally, economic impacts of AV, CV, and SV adoption are consistently reported as substantial, with benefits largely outweighing costs under most scenarios (Table 12). Accident reduction emerges as a primary driver of savings, estimated at up to 3% of GDP in Poland and $65.65 billion annually in Canada. Additional benefits include fuel savings of 11%, travel time reductions of 66%, and healthcare savings of approximately $3800 per capita annually. Cost savings at the vehicle level are also notable, with insurance, parking, and efficiency improvements valued at $2960–3900 per vehicle per year.

Table 12. Economic Impact.

Factors	Effect	Economy	References
Collision Reduction	Benefit	65.650 billion USD (Canada)	[130]
Fuel Savings	Benefit	11%	[96]
Travel Time Reduction	Benefit	66%	
Lower Accident Rate	Benefit	22%	
Parking Cost	Benefit	400–2600 USD/year per parking space	[90]
Accident Reduction	Benefit	3% of GDP in Poland	
Accident Reduction	Benefit	1232 USD/year per vehicle	[106]
Insurance, Parking Costs, Traffic Efficiency	Benefit	2960–3900 USD/year per vehicle	
Healthcare Savings	Benefit	3800 USD/year per American	[153]
Connection of New Vehicles	Annual Cost	3 Bn €	[70]
Infrastructure	Annual Cost	95 M€	
Related Time Savings	Annual Savings	10 Bn€ (2 billion h or 3% of total road time)	
Safety-Related Services	Annual Savings	3.5 Bn€ (7% fewer fatalities and injuries)	
Fuel Consumption and CO_2 Emissions	Annual Savings	1.6 Bn€ (Expected 1.2% reduction)	
NOx, CO, VOC, and PM Emissions	Annual Savings	33 M€ (Expected ±0.5% reduction)	

On the other hand, deployment of connected infrastructure and vehicle systems introduces recurring costs, including an estimated €3 billion annually for vehicle connections and €95 million annually for infrastructure upgrades. However, these expenses are counterbalanced by systemic benefits, such as €10 billion in time savings and €3.5 billion annually from enhanced safety services.

In summary, while initial investments in connectivity and infrastructure are significant, the literature converges on the conclusion that widespread deployment of AVs, CVs, and SVs has the potential to deliver net positive economic impacts, primarily through accident reduction, operational efficiency, and time savings.

From an economic standpoint, several business sectors are significantly impacted by the introduction of these technologies. On the one hand, the operation of commercial vehicles (primarily freight vehicles) could increase their productivity and competitiveness, addressing the current driver shortage and creating new job opportunities. These new professional profiles require a training process that will encounter difficulties in the transition from current positions to new ones, although it is estimated that the gradual introduction of technologies will favor this process. Furthermore, at a geostrategic level, peripheral regions will become more competitive as greater distances will pose less of an obstacle.

On the other hand, insurance companies will have to adapt to the new situation in which accidents will be less frequent, but with higher costs for material damages [154,155]. Furthermore, the responsibility would be transferred from the driver to the developer of the automated driving system, with the legal problems that this entails [51,52,156]. This transfer of responsibility in the event of an accident or incident has significant legal, commercial, and social implications, as it modifies the traditional model that has been used until now. Therefore, regulations must align with societal expectations. Furthermore, vehicle and automated driving system manufacturers will assume responsibilities that could hinder technological development.

Finally, driver training will need to be adapted to new technologies while there is still a need for user interaction with the vehicle, which has clear repercussions for driving schools and the driving license system. The need to reformulate the requirements, knowledge, and skills necessary to obtain a driving license must also be addressed. In fact, it seems reasonable that current drivers should undergo a refresher course, unlike the approach taken with the introduction of driver assistance systems, which receive scant attention in practical training.

6. Discussion

6.1. Analysis of Effect Ranges

First, a limitation of the study carried out must be considered. Reviewed literature reveals several recurring hypotheses that strongly influence the results. The numerical ranges reported in the tables should be interpreted as scenario-dependent responses rather than point predictions across all performance dimensions. Most simulation and analytical studies rely on stylized assumptions regarding demand levels, traffic composition, compliance with automated control strategies, baseline infrastructure, and, in the case of energy and emissions, the underlying powertrain mix and energy system. Reported benefits are often sensitive to parameters such as the penetration rate of automated and connected vehicles, the degree of sharing and occupancy, the aggressiveness of control algorithms, and the extent of induced demand. Under unfavorable combinations of these factors, several studies have shown that efficiency and environmental gains can be reduced or even reversed. While valuable, experimental and field evidence typically covers limited operational design domains, specific networks and relatively short observation periods. Survey-based studies, meanwhile, are subject to sampling and response biases. Consequently, the various methodological approaches should be considered as complementary perspectives rather than directly comparable estimators. The figures presented in this review should therefore be viewed as indicative ranges, subject to their respective assumptions and contexts, rather than definitive forecasts.

For example, numerous studies use scenarios of high or even total AV penetration (see Section 6.2), which maximize potential benefits but are not very representative of transition phases and mixed fleets, as is the case with energy and consumption assessments at the national or urban level [84,105,123], as well as various traffic and emissions simulation studies [5,85,89,90].

Some studies implicitly combine automation and electrification, attributing emissions reductions to AVs that largely depend on the adoption of electric vehicles and a low-carbon electric mix [58,85,123].

Certain methodological limitations are also common. Some studies use simplified emissions models based on average speed or aggregated functions, which restrict the representation of start-stop dynamics and real-world driving profiles [86,123,124]. Many studies focus on very specific networks (a highway lane, an intersection, or an urban area), which limits the generalizability of the results to other contexts.

The above conditions lead to a great disparity in the range of effects that must be analyzed in detail.

More specifically, several studies that evaluate impacts on safety or economic benefits assume very ambitious reductions in human error and accidents, without modeling in detail the new risks associated with cybersecurity, interaction with vulnerable users, or the long period of coexistence between AVs and conventional vehicles [65,68].

In this case, the wide interval associated with crash-reduction potential (14.17–94%) results from heterogeneous scenarios and metrics used across the reviewed studies. For example, the lower bound (14.17%) corresponds to a study estimating that AV deployment in the United States could prevent approximately 5500 fatal crashes annually [58]; therefore, the percentage refers only to the reduction in fatal crashes rather than total crashes. Other studies report reductions of around 50% at 10% penetration, increasing up to 90% at 90% penetration, illustrating how outcomes scale with fleet adoption levels [66]. Most remaining studies fall consistently within the 80–94% crash-reduction range when assuming high automation levels and near-full penetration, reflecting the proportion of crashes attributable to human error. Additionally, it should be clarified that one study isolates the contribution of alcohol, distraction, drugs, and fatigue (factors responsible for approximately 40% of crashes) and uses this to estimate the potential reduction in accidents if such human-related causes were fully eliminated by AV adoption [67].

Regarding traffic impacts, the variability observed in the summary table derives from the diverse simulation assumptions used across studies. For example, in the case of platooning, the reported capacity increase of 1.8–13% results from contrasting scenarios. Ref. [57] models full automation with penetration levels of 25%, 50%, 75%, and 100%, assuming reduced headways and smoother speed oscillations; under these conditions, road capacity increases by 1.8–3.2%, travel time decreases by 10–26.7%, and delay by 26–74%. In contrast, ref. [67] assumes 100% penetration, full automation, and improved reaction times under a platooning hypothesis, yielding higher capacity gains (8–13%), a 25% reduction in delay, and substantial improvements in flow stability (+250–500%). Study [6], also with full automation, high penetration, and connectivity, reports a 100% increase in traffic flow. Similarly, the range in eco-driving and eco-routing impacts reflects differing scenario assumptions. Ref. [66] (full automation, penetration levels of 10%, 50%, 90%) reports travel-time reductions of 15%, 30%, and 60%, while study [91], based on a real-world simulation of downtown Toronto with partial automation and 70% penetration, also assuming eco-routing, reports a 40.7% reduction.

In studies assessing efficient traffic-flow models, one study (urban Singapore, full automation, high penetration) reports a 61% reduction in travel time, whereas another (Oporto urban highway, full automation but only 10 to 30% penetration) assumes conservative AV behaviour (strict adherence to speed limits, larger safety distances, and secondary effects on conventional vehicles adapting to AV dynamics) leading to increased travel times of 10% during peak-hour congestion.

For energy consumption, the 1.5–23% range associated with platooning arises because the 1.5% reduction comes from a Chicago simulation with 100% penetration, where smoother driving reduces fuel use, but total distance travelled increases by 13% [105]. In contrast, studies assuming full automation and high penetration report reductions of 20% [104], or 8% for the lead vehicle and up to 23% for following vehicles due to aerodynamic and convoy-optimization effects [90].

For cooperative systems, the 1.2–75% interval results from differences in scope; some studies assess network-wide consumption and find modest savings (1.2%) [7], while others focus only on intersections, where eliminating stops and idling yields reductions of up to 75% [6].

Finally, the impact of vehicle use (VKT) spans –64% to +205%. Ref. [88] models both an optimistic scenario with minimal VKT and high efficiency (–64%) and a pessimistic scenario with maximal VKT and low efficiency (+205%). This widespread influence reflects uncertainty about user behaviour, whether AVs will lead to more sharing and fewer trips or, conversely, induce additional travel, shifts from public transport, and empty-vehicle movements.

As can be seen, the large disparity in the estimated results is often due to the hypotheses used in the studies. This disparity may explain why users do not have a clear perception of the impacts beyond safety (as is the case, since safety and comfort are the only parameters that are recurrently referred to in user acceptance analyses).

6.2. Effect of the Penetration Rate

The market penetration rate of autonomous or connected vehicles has consistently emerged as one of the most consequential. For example, traffic-simulation studies analyse roadway capacity, travel time, and delay across a range of penetration levels and point out relevant differences. However, as has been observed, many studies analyze the impacts from the perspective of full penetration of automation and connectivity technologies in the vehicle fleet but, to achieve scenarios of full automation and high penetration, it is essential to go through intermediate phases where different levels of automation coexist with human-driven vehicles. This mixed-traffic phase can be especially critical since it involves interaction between vehicles with very different characteristics, which can lead to a reduction in some impacts or even to the effects detected being the opposite of those estimated for full penetration due to the inefficiencies that may arise. In this context, several studies identify relevant barriers. Ref. [156] points to the coexistence of different automation strategies as an obstacle, emphasizing the need for differentiated measures for localized and generalized automation. It is also highlighted the unpredictable behavior of pedestrians and human drivers, and the complex coexistence of autonomous and non-autonomous vehicles, proposing improvements in the detection of unusual behaviors, learning from atypical scenarios, clear regulatory frameworks, vehicle-to-vehicle and vehicle-to-human communication, and smart infrastructure.

Regarding energy consumption, ref. [107] shows that with partial automation and low or high penetration levels, total consumption can increase by 14.5% and 24% due to the increased distance traveled by each vehicle. However, on a per-vehicle basis, partial automation can reduce consumption by up to 6.8% thanks to eco-driving [10], and even with low penetration, reductions of up to 10% are possible due to decreased traffic.

Regarding emissions, ref. [20] estimates reductions of 7%, 11%, 30%, and 24% for penetration levels of 20%, 50%, 80%, and 100%, respectively, considering the combined effects of eco-driving, connectivity, cooperation, and a greater number of vehicles. Additionally, ref. [56] projects that with partial automation and 70% penetration, eco-routing enabled by vehicle-infrastructure connectivity can reduce GHG emissions by 43% and NOx emissions by 18.58%, as well as decrease travel time by 40.7% in a realistic scenario simulated in Toronto. On an intercity highway, ref. [129] estimates that with full automation and 30% penetration, NOx reductions of 1.8% and CO_2 reductions of 0.7% are achieved.

Traffic simulations also reflect gradual benefits depending on the penetration level. Ref. [20] projects travel time reductions (urban environments and highways) of 16, 20, 56, and 80% for penetration rates of 20, 50, 80, and 100%, respectively, while [65], considering platooning, eco-driving, and route selection in congested scenarios, estimates reductions of 15, 30, and 60% for penetration rates of 10, 50, and 90%. Similarly, ref. [57] calculates travel time reductions of 10.1, 21.9, 23, and 26.7% and capacity increases of 1.8, 2.7, 2.9, and 3.2% for penetration rates of 25, 50, 70, and 100%, respectively.

Regarding safety, although many studies focus on scenarios of complete automation and total penetration, more realistic analyses exist. Ref. [65] estimates that accident reduction by eliminating human error can reach 50% with only 10% penetration and 90% with 90%. Ref. [70] indicates that under partial automation and 100% penetration, reductions of 7% are achieved thanks to cooperative systems. Finally, ref. [6], through collision reconstructions and simulations with Waymo, shows that with 50% penetration, the system can avoid most collisions (82%) and significantly reduce the severity of those that still occur.

Taken together, these studies demonstrate that the benefits associated with automation do not require full penetration scenarios to materialize. Even with low or intermediate levels of adoption, improvements are observed resulting from eco-driving, connectivity, cooperation, and the reduction of human error.

7. Conclusions

This study has provided an integrated assessment of the impacts of autonomous, connected, and shared mobility systems (AVs, CVs, and SVs). This impact assessment is a significant challenge, as numerous factors come into play, leading to conflicting effects. Since there is no significant penetration of vehicles with medium or high levels of automation, conclusions are often obtained through simulations or estimates based on hypotheses that must be considered when analysing the results and can lead to significant dispersion. The results confirm that these technologies can substantially improve road safety, traffic efficiency, and environmental performance. At the same time, evidence shows that large surges in VKT/VMT, driven by induced demand and trips in privately owned autonomous vehicles with no passengers, pose the main threat to these gains. These surges have the potential to offset or even reverse the net improvements in congestion and environmental performance.

However, their large-scale deployment will critically depend on the establishment of coherent regulatory frameworks, infrastructural readiness, and societal acceptance.

From a technical perspective, the evidence gathered in this review also points to several research directions regarding algorithms, system architectures and data flows. Future impact assessment and traffic management tools will require algorithms that explicitly couple vehicle-level control strategies (e.g., cooperative adaptive cruise control, eco-driving, dynamic ride-pooling and shared fleet management) with network-level indicators such as safety, congestion, energy demand and emissions, so that the trade-offs and feedbacks identified in the literature can be quantified in an integrated manner. This, in turn, calls for reference architectures that clearly allocate functions between in-vehicle controllers, roadside or edge units and cloud platforms, defining the associated V2X interfaces. At the data layer, harmonized and privacy-preserving data flows are needed to integrate high-frequency telemetry from vehicles and infrastructure with contextual information (e.g., land use, energy mix, demand patterns and user-acceptance data), enabling the training, validation and continuous monitoring of such algorithms under representative operating conditions.

From a policy perspective, several implications emerge. First, regulatory clarity is essential to address liability, safety certification, and data governance. The definition of international standards would mitigate the risk of technological fragmentation and accelerate interoperability across regions. Second, infrastructure investment is required to ensure both digital and physical readiness, ideally supported by public–private partnerships to reduce economic burdens and foster innovation. Third, safety and trust-building measures should be prioritized: mandatory incident reporting, certification protocols for cybersecurity, and structured public demonstration programs are recommended to enhance transparency and increase user confidence.

At the societal level, integration with sustainability and equity objectives is necessary to maximize positive externalities. Policymakers should encourage shared fleets through fiscal incentives, while carefully managing induced demand and potential increases in vehicle kilometres travelled. In parallel, labour market transitions in the transport sector must be anticipated, requiring proactive reskilling policies. Finally, multistakeholder governance frameworks are indispensable to align the perspectives of regulators, industry, urban planners, and civil society. Continuous monitoring, standardized impact evaluation, and transparent data-sharing practices will be crucial to ensure that these technologies evolve in line with both societal expectations and environmental goals. Furthermore, high-level management of automated vehicles is necessary to ensure their coordinated operation with traffic strategies, as the impact on increased mobility caused by technological opportunities can reduce the identified positive impacts.

On the other hand, if users do not accept automated and connected driving, the benefits derived from it cannot be obtained. However, acceptance may not be correlated with global interests, and users may not perceive the importance of some technological measures, which is reflected in individual and social motivational axes. In fact, when users assess the potential effects of automated and connected vehicles, even from an individual perspective, they do not usually associate these technologies with aspects that have a direct relationship with impacts on society (fuel consumption–polluting emissions, travel time–traffic efficiency), except safety. Therefore, it is important to have a deep understanding of the impacts to provide targeted information campaigns about the advantages from a more global perspective, not exclusively based on considerations of perceived risk. However, the study of the analyzed effects presents conclusions that are contradictory in some cases. Thus, this research line should seek to align the impacts of autonomous and connected vehicles with user expectations and needs, facilitating a more effective transition to this technology. It is considered essential to convey the message of the positive aspects that new technologies can bring so that users can perceive that certain individual objectives, previously overlooked, can be achieved and that these objectives have global repercussions. This greater awareness could not only increase the acceptance of autonomous vehicles but also their acceptance among other road users, thus facilitating their integration into mixed traffic.

In conclusion, while automated and connected mobility integration presents transformative opportunities, the successful deployment will require coordinated policy actions that combine technological development with robust regulatory, infrastructural, and societal frameworks. Only under such conditions can these systems deliver on their potential to contribute to a more sustainable, safe, and inclusive urban mobility future.

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