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Research on the Social Values of Vehicle–Road Collaborative Intelligence Systems: A Case Study in Beijing

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Abstract: Intelligent vehicles are expected to yield significant benefits in traffic safety, traffic efficiency, energy conservation, and carbon emission reduction. As the collaborative intelligence technology route becomes an industry consensus, intelligent vehicles will generate greater social benefits under the empowerment of roadside intelligence infrastructure. At the same time, the introduction of roadside intelligence infrastructure also adds corresponding deployment costs and operation and maintenance costs. Currently, assessments of the comprehensive social benefits and cost inputs associated with the application of vehicle–road collaborative intelligence systems remain unclear, making it difficult to provide effective references for industry development. Therefore, it is necessary to conduct a comprehensive assessment of the multi-dimensional benefits generated by collaborative intelligence systems and the incremental costs. This study constructs a social value assessment model for vehicle–road collaborative intelligence systems, which includes three benefit sub-models for safety, efficiency, and carbon emission reduction, as well as two cost sub-models for vehicle-side networking and roadside intelligence infrastructure. Beijing is selected for case analysis. The social benefits and social incremental cost inputs of different intelligence deployment scenarios are scientifically evaluated and analyzed. The study indicates that by deploying roadside intelligence infrastructure and in-vehicle networking terminals as planned in Beijing, an accumulated safety benefit of 925.6 billion RMB, a traffic efficiency benefit of 628.9 billion RMB, and a carbon emission reduction benefit of 2.66 billion RMB are expected to be generated from 2024 to 2050. The cumulative cost investment of 28.8 billion RMB in roadside intelligence infrastructure and vehicle networking terminals is projected to yield approximately 20.8 times the increment in social comprehensive benefits. The deployment progress of roadside intelligence infrastructure and the loading progress of fleet networking terminals should be fully coordinated to maximize the social value of the system. The corresponding research findings can provide references for city managers in decision-making on intelligent road deployment, and for the coordination of vehicle manufacturers in equipping vehicle networking terminals.

Keywords: collaborative intelligence system; social benefit; safety; efficiency; carbon emission reduction; incremental cost

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1. Introduction

China has held the top position in global automobile production and sales for 15 consecutive years, with a record high of 30.16 million vehicles produced and 30.09 million vehicles sold in 2023 [1]. The sustained high operation of automobile sales led to a vehicle ownership of 336 million in China by 2023 [2], making it the country with the highest vehicle ownership in the world. With the continuous increase in the stock of vehicles, automotive social issues, such as traffic accidents, road congestion, and exhaust pollution, have become increasingly severe. According to data from the National Bureau of Statistics, traffic accidents in China resulted in 60,676 fatalities in 2022 [3]. Without policy and technological measures, traffic safety issues are expected to become even more concerning with increasing vehicle ownership. In terms of traffic efficiency, with an increase in vehicle ownership, 86% of the 100 major cities in China saw an increase in congestion indices during rush hours in 2023 compared to 2022, with an average increase of 7.17%, and some cities saw the highest increase reach 26.92%. Beijing ranks first among the most congested cities in China [4]. In terms of environmental impact, China's transportation sector emitted 930 million tons of carbon dioxide in 2020, accounting for 15% of the country's terminal carbon emissions, with road traffic carbon emissions accounting for 90% of transportation carbon emissions [5]. Traffic congestion leads to more idling and acceleration/deceleration operational conditions of vehicles, which will further increase energy consumption, carbon emissions, and pollutant emissions. The social issues of automobiles urgently need to be addressed through technological means and business innovation.

Intelligent vehicles, as a new generation of automobiles equipped with complex environmental perception, intelligent planning, and decision-making capabilities [6], are expected to yield significant benefits in various aspects, such as traffic safety [7,8], traffic efficiency [9–11], and energy conservation and carbon emission reduction [12,13]. Particularly as the collaborative intelligence approach gradually becomes an industry consensus [14], intelligent vehicles, along with external intelligent infrastructure, including roadside sensing devices, roadside computing, and cloud computing, integrated with latest communication and network technologies, will possess enhanced intelligent capabilities. They will not only substitute human driving actions more effectively but also generate greater social benefits. For instance, the "high-dimensional perspective" of roadside intelligence devices can address long-tail issues, such as occlusions and blind spots, from a purely vehicle-centric viewpoint [15]. They can also provide redundant perception and decision-making information to ensure safety redundancy in case of in-vehicle intelligent device failure, further reducing the probability of traffic accidents. Fewer traffic accidents also imply higher traffic efficiency. Through the collaboration of data from multiple terminals in a vehicle–road collaborative intelligence system, multi-vehicle cooperative planning and control at the road section and network levels can be achieved, enhancing overall traffic efficiency. At the same time, collaborative intellectualization will add to the deployment costs of roadside intelligence infrastructure and its ongoing operational and maintenance costs. City governments still have many concerns about the business models for intelligent infrastructure deployment and the actual social value it can generate. Currently, the deployment of roadside intelligence infrastructure is still fragmented, which is not conducive to supporting the large-scale application of intelligent driving technology, resulting in low participation from vehicle manufacturers. The collaborative intelligence technology route involves different vehicle-side and roadside intelligence schemes. It is necessary to scientifically evaluate and analyze the social comprehensive benefits and social incremental cost inputs generated by vehicle–road collaborative intelligence systems. This study is conducted against this backdrop.

Currently, most related research focuses on the benefit–cost assessment of specific technologies in intelligent vehicles, or the analysis of specific aspects of benefits. Schaudt developed a prototype vehicle to study the collision avoidance effectiveness of the Blind Spot Monitoring and Warning (BSD) function, conducting extensive real-world vehicle testing [16]. Samantha et al. used simulation methods to evaluate the collision avoidance effectiveness of Automatic Emergency Braking (AEB) for vehicle and pedestrian collisions in the United States [17]. The Australian Transport Council led the Safety Feature Assessment Project, with the core objective of identifying high-priority safety features among 15 functions, including forward collision warning, driver fatigue monitoring, and lane departure warning [18]. Guériau et al. established a multi-agent cooperative traffic model in the traffic simulator MovSim, studying the potential of different traffic control strategies to optimize traffic flow and alleviate congestion in various scenarios [19]. Song et al. applied traffic simulation methods to assess the impact of L2 assisted driving functions on traffic efficiency under different traffic flow rates [11]. Rommerskirchen et al. investigated the fuel-saving effects of anticipatory driving assistance functions, like visual cues for road information ahead, designing 18 road traffic scenarios and conducting experiments using a driving simulator [20]. Vahidi et al. reviewed a large number of eco-driving literature based on the first principles of motion and optimal control theory, and analyzed the potential of intelligent connected vehicles in energy conservation and carbon emission reduction [21]. At the same time, some scholars have conducted research on the overall benefit assessment of intelligent vehicles. Juan et al. reviewed previous assessments of the socio-economic impacts of Intelligent Transportation Systems (ITSs), applying cost–benefit analysis (CBA) and data envelopment analysis (DEA) to assess the socio-economic impacts of platooning systems, including factors such as travel time, emissions, traffic stability, and operational costs [22]. Farooq et al. also analyzed the economic impact of ITSs on other industries using the Regional Input–Output Modeling System (RIMS 2), in addition to considering the benefits of ITSs in terms of reduced time delays and fuel consumption [23]. Muller et al. conducted a literature review on the environmental and economic benefits of ITSs, with most studies indicating that ITSs can reduce carbon dioxide emissions by 5–20% and fuel consumption by up to 20% [24]. He et al. designed a comprehensive benefit evaluation system for urban ITSs from the point of view of three aspects: improving road capacity, saving labor costs, and reducing traffic accidents. They estimated the effects of using ITSs in Beijing from 2005 to 2008, concluding that the socio-economic benefits generated could reach 22 times the original investment, demonstrating a significant "leverage effect" [25]. Kuang assessed the social comprehensive benefits and costs of an intelligent fleet in China from a single-vehicle intelligence perspective [26]. Synthesizing existing research, there is significant divergence in methodologies, experimental conditions, and scenario assumptions across different studies, leading to a variety of focuses in benefit assessments, and making it challenging to standardize and compare the results. Moreover, few studies have quantitatively analyzed the comprehensive benefits and cost inputs of vehicle–road cooperative intelligence systems from a macro perspective.

As the connotations of cooperative intelligent transportation systems become richer, and the understanding of their multi-dimensional benefit mechanisms deepens, the existing assessment methods and results are no longer applicable to the current stage of development. There is an urgent need to construct a framework and methodology for the social comprehensive benefit–cost analysis of collaborative intelligence systems. The purpose of this study is to address the gap by providing a scientific evaluation and analysis of the social comprehensive benefits and incremental cost inputs generated by vehicle–road collaborative intelligence systems. The objective of this study is to address the gap by providing a scientific evaluation and analysis of the social comprehensive benefits and incremental cost inputs generated by vehicle–road collaborative intelligence systems. From the perspectives of in-vehicle networking terminal integration and roadside intelligence infrastructure deployment, the issue of how to achieve greater social comprehensive benefits with lower incremental cost investment is addressed. This study constructs a social value assessment model, which includes three benefit sub-models—safety, efficiency, and energy-saving and carbon emission reduction benefits—as well as two cost sub-models—incremental costs of roadside intelligence and incremental costs of vehicle networking. Beijing, with 7.589 million motor vehicles, ranks first among Chinese cities in terms of vehicle ownership [27]. The city's transportation is marked by prominent issues of safety, congestion, environment, and energy. There is urgent demand for the intelligent transformation of transportation infrastructure. This study selects Beijing as a case for analysis, and the research results can offer a reference for city managers, vehicle manufacturers, and other relevant parties to participate collaboratively in further industrial development.

2. Social Value Evaluation Model

2.1. Model Framework

This study constructs a comprehensive social value assessment model for a vehicle–road collaborative intelligence system, which includes three sub-models for benefits: safety, efficiency, and carbon emission reduction benefits, as well as two sub-models for costs: roadside intelligentization incremental cost and vehicle-side networking incremental cost. By integrating various intelligentization schemes for vehicles and roadside infrastructure, and considering diverse scenarios for the deployment of roadside intelligence infrastructure and the penetration rates of vehicle networking terminals (V2X T-Box), the model leverages traffic data, such as urban fleet driving patterns and the scale and usage intensity for different road types, to calculate the social comprehensive benefits and incremental societal costs under different scenarios, as illustrated in Figure 1. Further details of each sub-model will be presented subsequently.

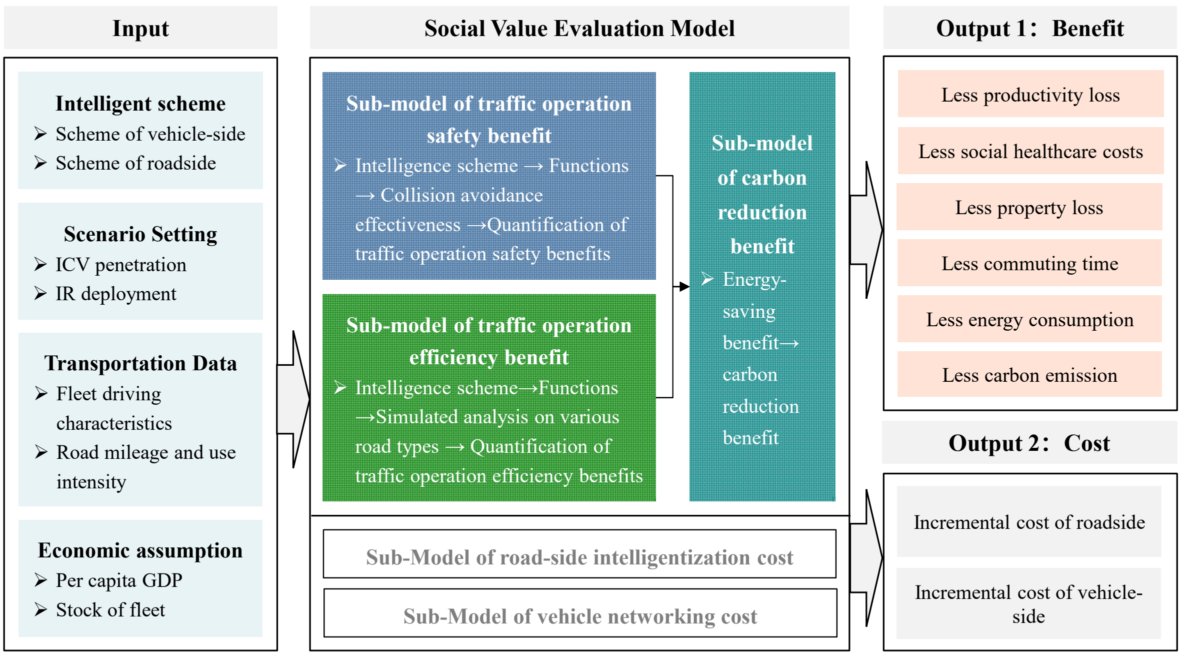


Figure 1. Social value evaluation model of vehicle–road collaborative intelligence system.

2.2. Typical Intelligence Scheme and Scenario Setting

2.2.1. Typical Vehicle-Side and Roadside Intelligence Scheme

As the level of autonomous driving advances, intelligent vehicles require a significant increase in the quantity and variety of sensors to enhance perception reliability in different complex environments. The industry's current standard for perception hardware configurations at the primary (mass production stage), intermediate (mass production stage), and advanced (testing stage) levels of autonomous driving are 5V3R, 5V5R2L, and 8V8R6L [28], respectively, as shown in Figure 2.

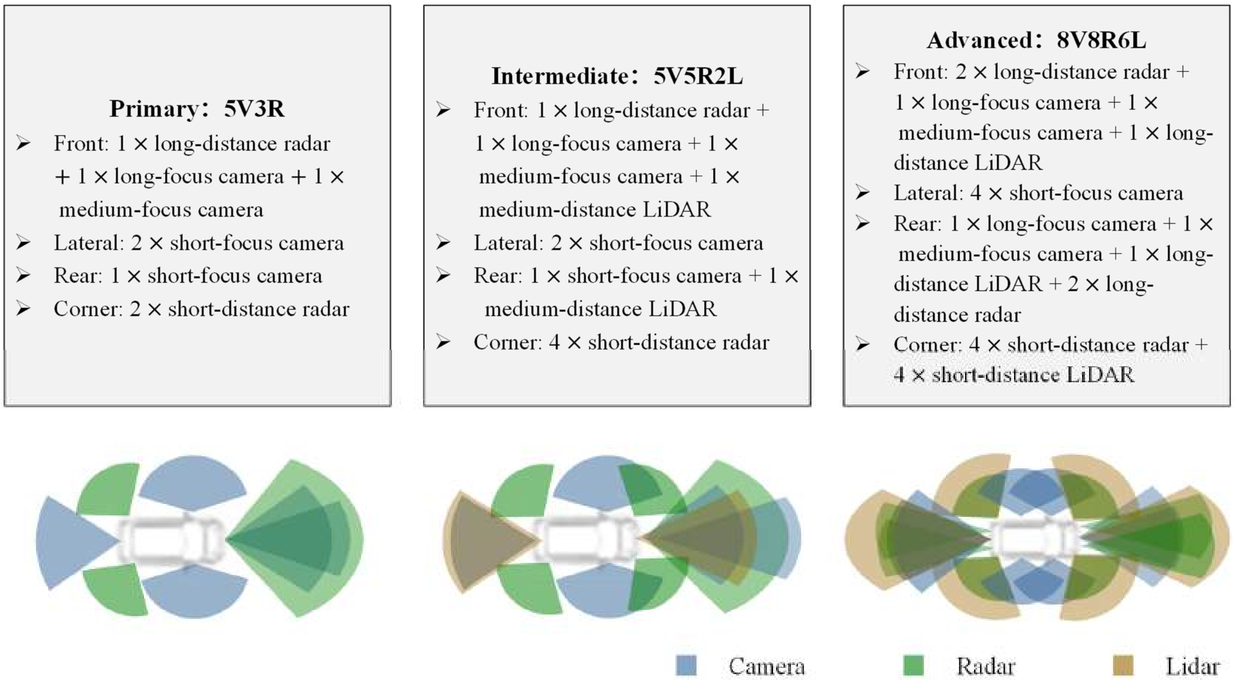


Figure 2. Typical perception schemes of ICVs [28].

Referring to the classification of roadside intelligent perception by industry groups [29], the schemes include primary perception with pure visual coverage, intermediate perception with visual and millimeter-wave data coverage, and advanced perception with simultaneous coverage of visual and millimeter-wave data and LiDAR point cloud data, as depicted in Figure 3. The roadside intelligent perception scheme selected in this study supports high-level intelligent driving with the advanced perception scheme. The computing power of the onboard computing platform and roadside MEC must match the corresponding perception schemes and software complexity of both the vehicle-side and roadside intelligence. An increase in perception-based hardware and more complex neural networks will mean greater computing power requirements for both the vehicle-side and roadside, jointly meeting the perception and computational decision-making needs of different levels of autonomous driving functions. Related results have been published in previous studies [28].

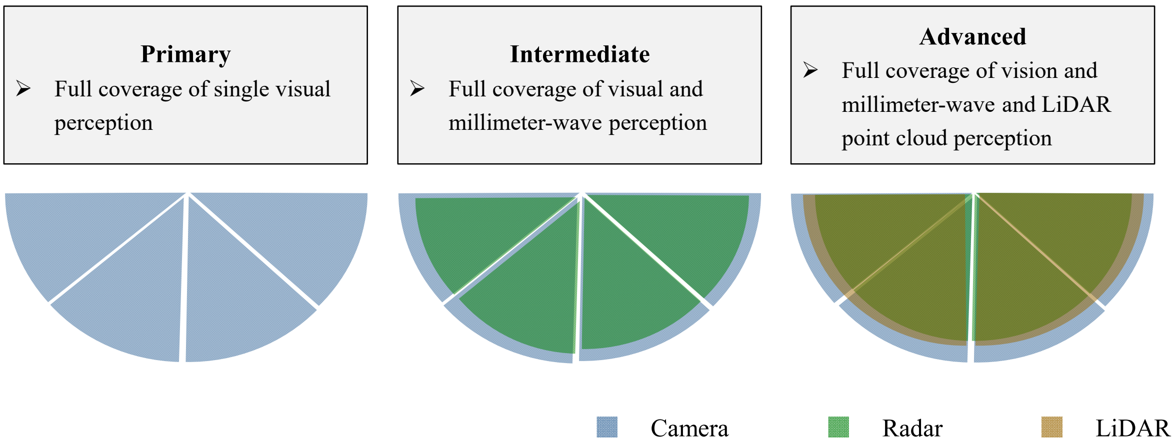


Figure 3. Perception schemes of roadside intelligence [29].

2.2.2. Forecast of Vehicle Ownership in Beijing

Beijing controls the growth of its vehicle ownership by regulating the number of new license plates issued. Since 2018, the number of new license plates issued has been basically stable, at around 100,000 per year. Therefore, the increase in vehicle ownership is determined by the number of new license plate indicators issued. The proportion of different levels of intelligent vehicles can be obtained through the "Intelligent Connected Vehicle Technology Roadmap 2.0", as shown in Figure 4.

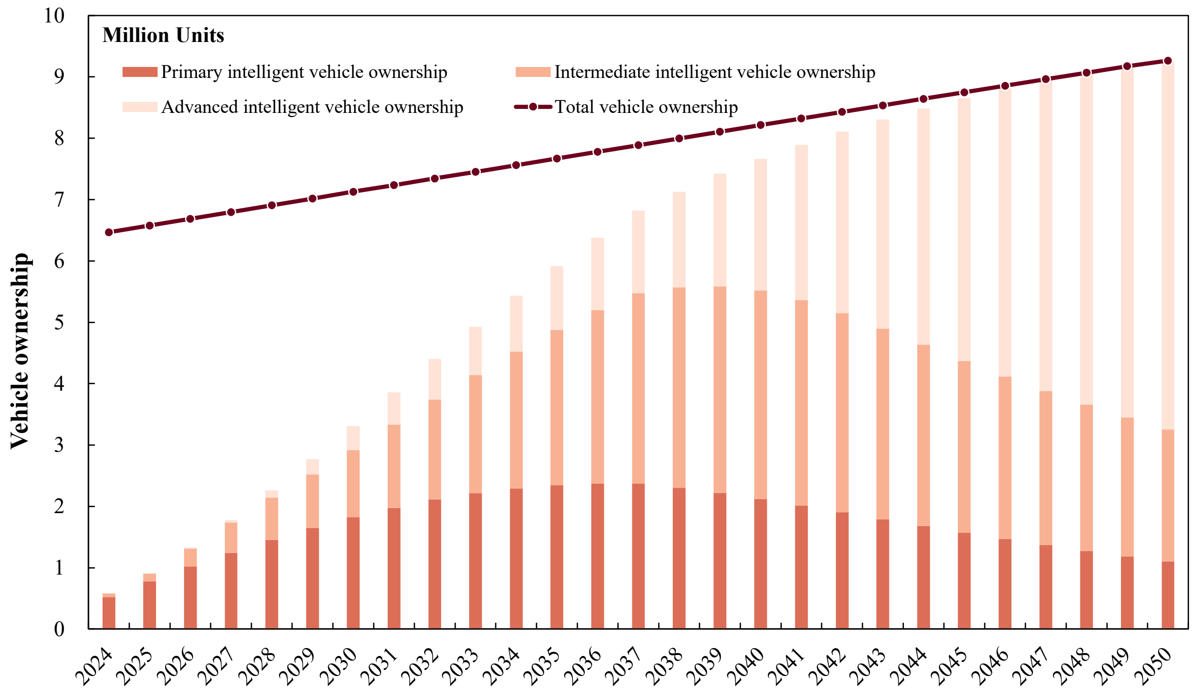


Figure 4. Forecast of vehicle ownership in Beijing.

2.2.3. Vehicle Networking Scenarios and Roadside Intelligence Deployment Scenarios

In the deployment of vehicle networking terminals, both the " Intelligent Connected Vehicle Technology Roadmap 2.0" and the "C-V2X Industrialization Path and Schedule Research White Book" indicate that by 2025, 50% of new vehicles will be equipped with a V2X T-Box to achieve connectivity, which is equivalent to all newly sold intelligent vehicles being equipped with a V2X T-Box [30,31]. Our study adopts this as the "As Planned Connected Vehicle Deployment Scenario (APCV)". However, in current industrial practice, the deployment progress is significantly lower than expected in China. The penetration rates of the V2X T-Box in new vehicles nationwide were only 0.14% in 2021, 0.76% in 2022, and 1.28% in 2023. Its penetration rate in the total vehicle ownership was less than one in a thousand. This study begins to collect historical statistics on vehicles equipped with a V2X T-Box from the year 2021. To better explore the impact of the V2X T-Box deployment progress on social value, on the basis of the "APCV", additional scenarios have been proposed, namely the "None Connected Vehicle Deployment scenario (NCV)" and the "Low Connected Vehicle Deployment scenario (LCV)", totaling three vehicle networking terminal deployment scenarios.

In the deployment of roadside intelligence infrastructure, our study sets the planning progress of "C-V2X Industrialization Path and Schedule Research White Book" as the "As Planned Intelligent Road Deployment Scenario (APIR)", which means focusing on the deployment of expressways and urban roads from 2022 to 2025, and gradually achieving full coverage of intelligent infrastructure for motorways, class-1 highways, class-2 highways, and urban roads after 2025. To explore the impact of the progress of intelligent infrastructure deployment on social value, on the basis of the APIR, additional scenarios have been proposed, namely the "None Intelligent Road Deployment Scenario (NIR)" and the "Aggressive Intelligent Road Deployment Scenario (RGIR)", totaling three scenarios for the progress of intelligent infrastructure deployment. The specific scenario settings for vehicle networking terminal deployment and intelligent infrastructure deployment are shown in Table 1.

Table 1. Intelligence scenario setting.

Classification	Scenarios	Notes
Vehicle networking	OBU equipment as planned (APCV)	➢ All intelligent vehicles will be equipped with OBU.
	OBU equipment less than expectations (LCV)	➢ By 2030, more than 50% of primary intelligent vehicles and more than 70% of intermediate and advanced intelligent vehicles will be equipped with OBU. ➢ By 2035, more than 80% of primary intelligent vehicles and more than 90% of intermediate and advanced intelligent vehicles will be equipped with OBU. ➢ By 2040, all intelligent vehicles will be equipped with OBU.
	None of vehicles deployed (NCV)	➢ No vehicles will be equipped with OBU.
Roadside intelligence deployment	Deployed faster (RGIR)	➢ The construction of intelligent roads for all highways is to be accelerated by 5 years compared with the APIR scenario. Expressways, class-1 highways, and class-2 highways will achieve 100% intelligent road coverage by 2025, 2030, and 2035, respectively. ➢ Urban expressways and other urban roads will be accelerated to achieve 100% intelligent road coverage by 2025.
	Deployed as planned (APIR)	➢ The intelligent road coverage rate of urban expressways is expected to reach 30% by 2025 and achieve 100% coverage by 2028. Other urban roads will begin in 2025 and achieve 100% coverage by 2035. ➢ The intelligent road coverage rate of expressways is projected to reach 20% in 2025 and achieve 100% coverage by 2030. Class-1 highways are expected to achieve an intelligent road coverage rate of 10% by 2030 and achieve 100% coverage by 2035. Class-2 highways will reach an intelligent road coverage rate of 10% by 2035 and achieve 100% coverage by 2040.
	None of roads deployed (NIR)	➢ None of the roads will be deployed as intelligent roads.

2.3. *Social Values Evaluation Model*

2.3.1. Quantified Assessment Sub-Model of Safety Benefit

Framework

The economic losses caused by traffic accidents mainly encompass five aspects: a loss of social productivity, an increase in societal medical costs, direct property damage, economic losses due to time delays caused by congestion, and energy consumption loss due to congestion delays. By employing a multivariable coupling model for safety effects, the comprehensive collision avoidance rates corresponding to different vehicle–road intelligence schemes are obtained. Combined with fleet size and usage characteristic data, statistical data of traffic accidents, and regional economic level data, the quantitative analysis of the economic benefits brought about by the reduction of road traffic accidents through collaborative intelligence systems in the aforementioned five aspects is conducted, as shown in Figure 5.

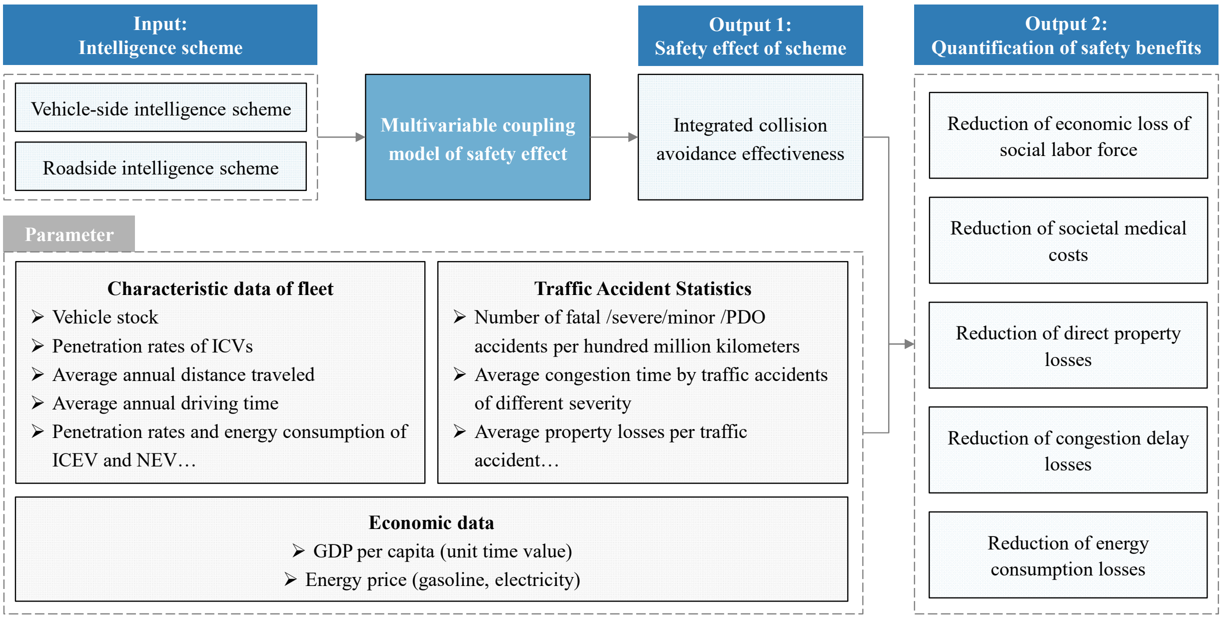


Figure 5. Analysis framework for traffic operation safety benefits.

Data

Based on the predictions for the number of fatal accidents per billion kilometers in China [32] and the forecasts for future car sales and vehicle ownership in Beijing [33], it is assumed that the number of fatal accidents per billion kilometers in Beijing will be consistent with the national forecast data. As the epidemic from 2020 to 2022 made it impossible to obtain the real travel demand of vehicle users, in order to better reflect the real travel demand, the impact of the epidemic is circumvented in the processing of the average annual distance traveled per vehicle. This study selects data from 2010 to 2019, over a period of 10 years, and calculates the average value. The relevant data, derived from the "Beijing transport annual report", have been compiled by the Beijing Transportation Research Institute over the years. They are assumed to remain unchanged in the future. Predictions for the number of fatal accidents, serious injury accidents, minor injury accidents, and property damage only (PDO) accidents in Beijing from 2025 to 2050 are made accordingly, as shown in Equation (1).

$$CN_{y,d,base} = \left(Stock_y \times AVKT \times FPT_{y,base} \times Degree_d\right)/10^9 \quad (1)$$

$CN_{y,d,base}$ represents the number of accidents with severity d in the year y under the baseline scenario; $Stock_y$ represents the vehicle stocks in Beijing in the year y; $AVKT$ is the average annual distance traveled per vehicle in Beijing; $FPT_{y,base}$ represents the number of fatal accidents per billion kilometers in the year y under the baseline scenario; and $Degree_d$ represents the coefficient for the number of accidents with severity d, where d = 0, 1, 2, 3 correspond to PDO (property damage only) accidents, minor injury accidents, serious injury accidents, and fatal accidents, respectively. By fitting the data from 2019, it was found that the number of serious injury accidents, minor injury accidents, and PDO accidents are 2.95 times, 47.06 times, and 147.7 times the number of fatal accidents, respectively [34]. Historical data also generally conform to this multiple relationship; hence, Degree0, Degree1, Degree2, and Degree3 are taken as 147.7, 47.1, 3.0, and 1, respectively. Predictions for the number of fatal accidents per hundred million kilometers $FPT_{y,base}$ in China from 2023 to 2050 have been given in previous studies by our research group [32].

The results indicate that under the baseline scenario, the number of traffic accidents in Beijing generally follows a trend of initial decline followed by an increase, and is expected to remain at a high level, as shown in Figure 6. The number of fatal traffic accidents in Beijing is projected to be 889 in 2025, 794 in 2035, and 800 in 2050. The forecasted traffic accident figures for Beijing can be viewed as a tug-of-war between the increasing trend in vehicle ownership and the decreasing trend in the number of fatal accidents per billion kilometers. Vehicle ownership in Beijing is primarily regulated by the government through policies controlling the issuance of new licenses, which means that the actual market demand is not fully realized, leading to a limited increase in vehicle ownership. The decline in traffic accidents from 2025 to 2040 is mainly attributed to the improvement in motorization rates, which leads to a decrease in the number of fatalities per billion kilometers. However, as the reduction in fatalities per billion kilometers slows down from 2040 to 2050, the number of traffic accidents rebounds and increases.

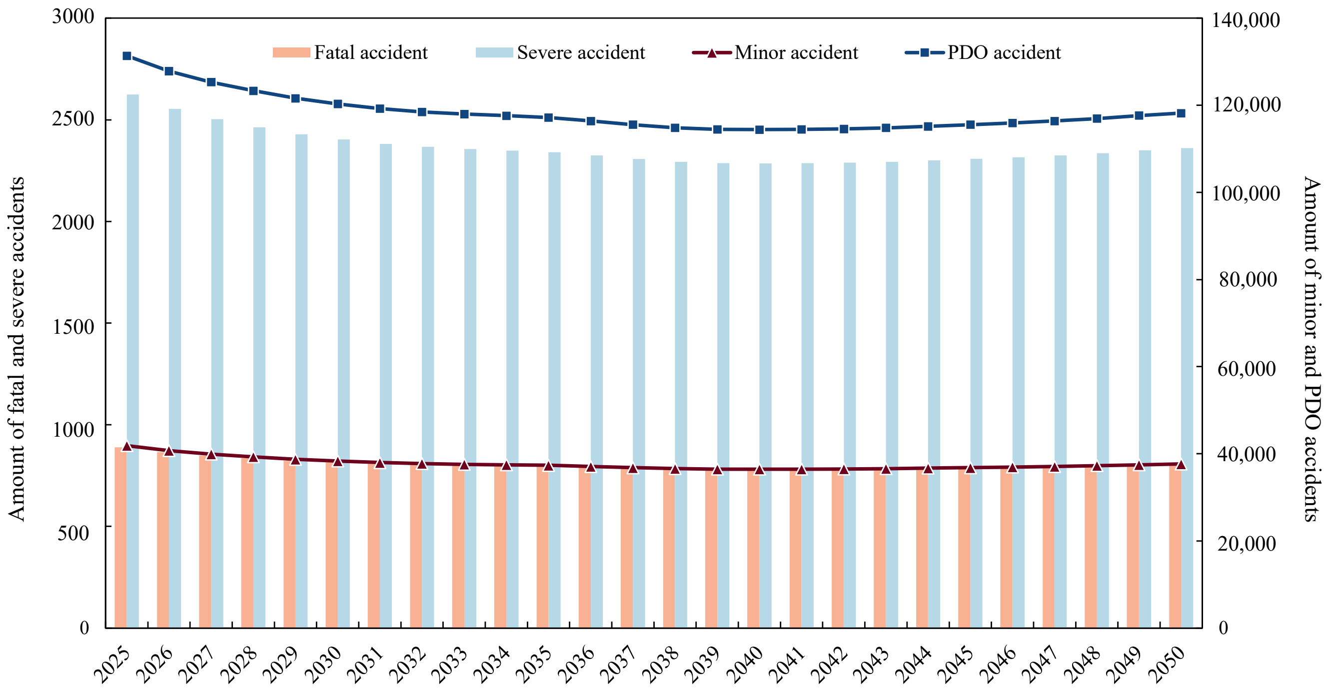


Figure 6. Forecast of amount of traffic accidents in 2025–2050 (baseline scenario).

Integrated collision avoidance effectiveness

Existing research by our research group has developed a multivariable coupling model for the safety effects of intelligent vehicles [7]. Based on the relationship between intelligent configuration combinations and safety functions, as well as the relationship between safety functions and accident types, the model utilizes basic hardware coupling sub-models, safety function coupling sub-models, and accident type coupling sub-models to quantify the comprehensive crash avoidance effectiveness corresponding to different hardware combinations, as illustrated in Figure 7.

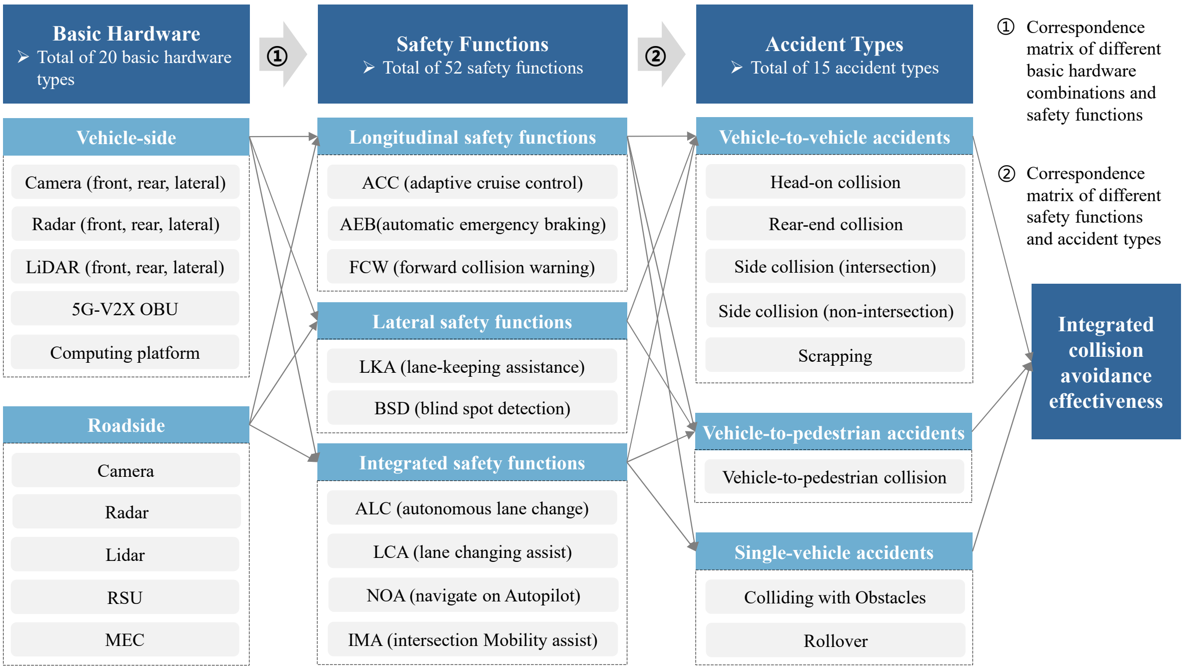


Figure 7. Multivariable coupling model of intelligent vehicle safety effects.

The basic hardware is categorized into two main groups: vehicle-side and roadside, comprising a total of 20 types of foundational hardware. Vehicle-side basic hardware includes cameras, millimeter-wave radars, LiDARs, onboard computing platforms, and onboard communication modules, as well as steering and braking systems. Roadside basic hardware includes cameras, millimeter-wave radars, LiDARs, roadside units (RSUs), and edge computing units. Safety functions are divided into lateral safety functions, longitudinal safety functions, and comprehensive safety functions, including automatic emergency braking (AEB), lane-keeping assistance (LKA), and navigate on autopilot (NOA), totaling 52 types of safety functions. Different safety functions are realized by invoking different basic hardware, constructing a correspondence matrix between basic hardware combinations and safety functions. Traffic accident types, based on the subjects involved in the collision, can be divided into vehicle-to-vehicle accidents, vehicle-to-pedestrian accidents, and single-vehicle accidents, including frontal collisions, rear-end collisions, pedestrian collisions, and rollovers, totaling 15 accident types. Different safety functions have varying degrees of collision avoidance effectiveness against different accident types, constructing a correspondence matrix between safety functions and accident types. Hundreds of papers published and indexed in mainstream databases, such as Web of Science, Taylor, Springer, and Elsevier, were reviewed to extract data on the collision avoidance effectiveness of safety functions. A meta-analysis model was used to obtain the collision avoidance effectiveness of different safety functions against various accident types. Combined with statistical data on the proportion of different accident types, the integrated collision avoidance effectiveness brought about by different vehicle–road intelligent basic hardware combinations could ultimately be obtained.

Based on the multivariable coupling model for the safety effects of intelligent vehicles, we obtained the comprehensive collision avoidance effectiveness of different vehicle-side intelligence schemes (Figure 2), as well as the comprehensive collision avoidance effectiveness of intelligent vehicles combined with vehicle-to-vehicle real-time communication (V2V) and advanced intelligent roads (IRA), as shown in Table 2. It is worth noting that a primary vehicle-side intelligence configuration combined with advanced intelligent infrastructure can achieve higher collision avoidance effectiveness than a single advanced vehicle-side intelligence scheme.

Table 2. Integrated collision avoidance effectiveness of various hardware combinations.

	Only Vehicle	Vehicle + V2V	Vehicle + IRA	Vehicle + IRA + V2V
Primary-5V3R	56.3%	75.1%	94.9%	97.1%
Intermediate-5V5R3L	77.8%	84.5%	96.2%	98.3%
Advanced-8V8R6L	89.2%	93.4%	98.3%	98.9%

The synergistic mechanism of intelligent configuration combinations can be understood as follows. Firstly, an increase in the number of sensors leads to a broader coverage angle and cross-validation of perception results, which enhances the comprehensive collision avoidance effectiveness. Secondly, the integration of heterogeneous sensors such as cameras, millimeter-wave radars, and LiDARs extends the range of perception and increases the types and dimensions of perception information, thereby enhancing the comprehensive collision avoidance effectiveness. Thirdly, information exchange between V2V (vehicle-to-vehicle), V2I (vehicle-to-infrastructure), and V2N (vehicle-to-network) expands the coverage range and adds to the types and dimensions of perception information, further enhancing the comprehensive collision avoidance effectiveness.

The number of traffic accidents in various vehicle–road intelligence deployment scenarios

Different vehicle–road intelligence deployment scenarios correspond to varying penetration rates of vehicle networking terminals and mileage coverages of intelligent road schemes. By integrating the stock and average annual distance traveled of intelligent vehicles, the number of traffic accidents per billion kilometers under the baseline scenario, and the comprehensive collision avoidance effectiveness of different levels of intelligent vehicles operating in different driving environments, we calculated the reduction in fatal accidents, serious injury accidents, minor injury accidents, and PDO accidents under different intelligence deployment scenarios, as shown in Equation (2).

$$RCN_{y,d} = \sum_{v=1}^{3} (VS_{v,y} \times AVKT \times FPT_{y,base} \times \sum_{r=1}^{2} (RTS_{r,y} \times (PVN_y^2 \times (1 - ICAE_{v,r,1}) + (1 - PVN_y^2) \times (1 - ICAE_{v,r,0})))) \times Degree_d - CN_{y,d,base} \quad (2)$$

$RCN_{y,d}$ represents the reduction in the number of accidents with severity d in the year y under various vehicle–road intelligence deployment scenarios. $VS_{v,y}$ denotes the number of vehicles of the level v in the year y, where v = 1, 2, 3 correspond to primary, intermediate, and advanced intelligent vehicles, respectively. $RTS_{r,y}$ the proportion of total mileage traveled on conventional and intelligent roads in the year y, where r = 1, 2 represent conventional and intelligent roads, respectively. PVN_y indicates the penetration rate of vehicle networking terminals in the fleet in the year y. $ICAE_{v,r,1}$ denotes the comprehensive collision avoidance effectiveness of the level v intelligent vehicles traveling on conventional or intelligent roads, where both the vehicle itself and the other vehicle are equipped with a V2X T-Box. $ICAE_{v,r,0}$ denotes the comprehensive collision avoidance effectiveness of level v intelligent vehicles traveling on conventional or intelligent roads.

The number of fatalities reduced in road traffic accidents in Beijing from 2024 to 2050 under various intelligence deployment scenarios was obtained, as shown in Figure 8. All seven vehicle–road intelligence deployment scenarios can significantly reduce the number of traffic accidents. The large-scale deployment of intelligent vehicles is the foundation for the decline in the number of traffic accidents. As the penetration rate of intelligent vehicles increases, the reduction in traffic accidents also becomes more significant. Under the NIR-NCV scenario, which relies solely on vehicle intelligence, it is expected that the number of fatal traffic accidents will be reduced by 9.78% (87 cases), 34.97% (285 cases), 74.90% (580 cases), and 86.07% (689 cases) in 2025, 2030, 2040, and 2050, respectively. In the NIR-APCV scenario, where the deployment of vehicle networking terminals initially has a modest effect on reducing traffic accidents, the impact becomes more noticeable in the middle-to-late stages as the penetration rate of vehicle networking terminals increases. Compared to the NIR-NCV scenario, it is anticipated that there will be an additional reduction of 0.11% (1 cases), 1.18% (10 cases), 4.14% (32 cases), and 2.99% (24 cases) in fatal traffic accidents in 2025, 2030, 2040, and 2050, respectively. The reduction in traffic accidents under the RGIR-LCV and APIR-LCV scenarios is basically equal. Accelerating the deployment of roadside intelligence infrastructure in the LCV scenario has a negligible impact on reducing the number of accidents, while the APIR-APCV scenario shows a relatively significant reduction in traffic accidents compared to the RGIR-LCV scenario. Therefore, the effectiveness of intelligent road deployment in reducing traffic accidents is contingent upon the widespread adoption of in-vehicle networking terminals, which determines the pace of the decline in accident numbers. In the RGIR-APCV scenario, it is projected that by 2025, 2030, 2040, and 2050, the reduction in fatal traffic accidents will be 13.06% (116 cases), 45.26% (369 cases), 92.24% (715 cases), and 99.17% (794 cases), respectively.

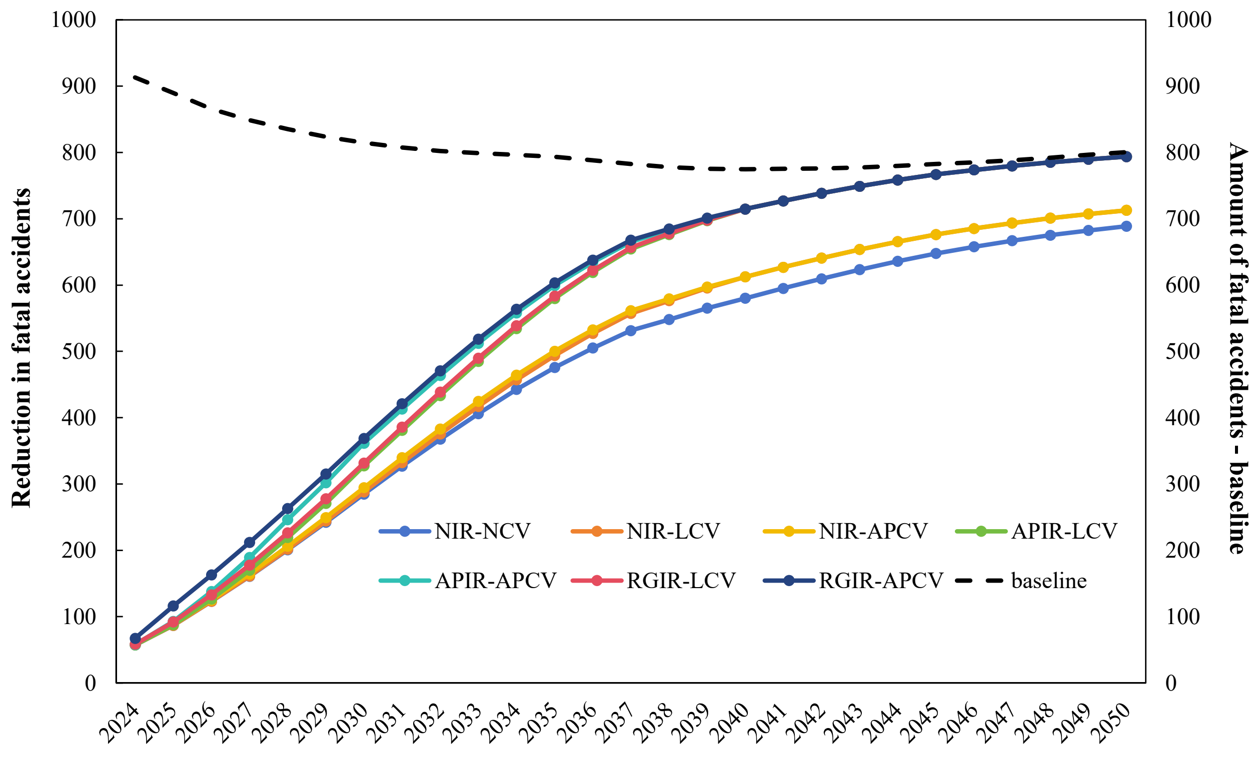


Figure 8. Reduction in fatal accidents in various vehicle–road intelligence deployment scenarios.

Quantitative Analysis of Safety Benefit

The social and economic losses caused by traffic accidents primarily encompass five aspects: a loss of social productivity, direct property damage, an increase in societal medical costs, economic losses due to time delays caused by congestion, and energy consumption losses caused by congestion [32]. These five aspects basically comprehensively cover all the economic losses caused by road traffic accidents, as illustrated in Equation (3).

$$EC = PL + PD + MC + TDC + SE \quad (3)$$

EC stands for the comprehensive economic loss due to traffic accidents, *PL* represents the loss of productivity, *PD* denotes the direct property damage, *MC* refers to the increased societal medical costs, *TDC* signifies the economic loss due to time delay, and *SE* indicates the energy consumption loss due to traffic congestion.

The productivity loss caused by traffic accidents represents the disappearance of the victims' social productivity due to premature death, while severe or minor injuries may result in a discount or even loss of the victims' ability to work. The quantification of productivity loss caused by traffic accidents in the year y is shown in Equation (4).

$$PL_y = \sum_{d=1}^{3} \left(VSL_y \times CAS_d \times VSI_d \right) \tag{4}$$

VSL_y represents the statistical value of life in the year y, following the conclusions of the International Road Assessment Program, which is set to 70 times the per capita GDP of that year [35]. CAS_d represents the number of casualties caused by accidents with severity d, assuming that each fatal accident results in one death, each serious injury accident results in one serious injury, and each minor injury accident results in one minor injury, with PDO accidents causing no casualties. VSI_d is the coefficient of the statistical value of injury relative to the statistical value of life, with minor injuries set to a coefficient of 0.003 and serious injuries set to a coefficient of 0.25 [36].

Traffic accidents and casualties also lead to an increase in societal medical costs, with varying degrees of severity in traffic accidents resulting in different medical costs. The increase in societal medical costs due to traffic accidents in the year y is as shown in Equation (5).

$$MC_y = \sum_{d=1}^{3} \left(CN_{y,d,base} \times mc_d \right) \tag{5}$$

mc_d represents the medical economic loss due to traffic accidents with severity d. Referring to the "China Health Statistics Yearbook 2022", published by the National Health Commission [37], the societal medical economic losses resulting from traffic accidents of different severity levels were obtained, as shown in Table 3.

Table 3. Medical–economic losses from traffic accident injuries and deaths.

Severity	Medical Cost (RMB)	Notes
Slight injury	340.7	➢ Medical costs are mainly for outpatient charge.
Serious injury	11,398.4	➢ Medical costs include hospitalization, treatment, surgery, outpatient, etc.
Death	56,648.9	➢ Compared to serious injury, funeral expenses are added.

Direct property loss includes the damage to vehicles, cargo, and other related facilities, as well as the costs associated with on-site handling. The average direct property loss per accident is based on the data disclosed in "People's Republic of China road traffic accident statistics Annual report", and equals 11,274 RMB. The direct property loss caused by traffic accidents in the year y is calculated as shown in Equation (6).

$$PD_y = \sum_{d=0}^{3} CN_{y,d,base} \times DC_{base} \tag{6}$$

DC_{base} denotes the average direct property loss per accident.

The economic losses due to time delays caused by congestion are related to the accident handling time, traffic volume, and unit time cost, with the severity of the accident affecting the handling time. On average, it takes about 1.07 h to handle each accident in China [34]. It is assumed that for PDO and minor injury accidents, the average congestion time loss per vehicle at the scene is one-eighth of the accident handling time, approximately 0.13 h, with the road capacity dropping to three-fourths of its original level after the accident. For serious injury accidents, the average congestion time loss per vehicle is one-fourth of the accident handling time, about 0.27 h, with the road capacity dropping to half of its original level after the accident. For fatal accidents, the average congestion time loss per vehicle is half of the accident handling time, around 0.54 h, with the road capacity dropping to zero after the accident. It is further assumed that, on average, each vehicle is occupied by one driver accompanied by 0.5 passengers. The average time loss per vehicle is shown in Equation (7). The economic loss due to time delay is shown in Equation (8).

$$ART_d = \frac{1}{2} \times PT \times \left(1 - \frac{CAP_d}{F}\right) \tag{7}$$

$$TDC_y = AW_y \times \sum_{r=1}^{9} \sum_{d=0}^{3} (AAHT_{rt} \times NC_{rt,d} \times ART_d) \tag{8}$$

ART_d represents the average congestion time loss per vehicle in accidents with severity d. PT denotes the processing time at the scene of the accident. CAP_d refers to the proportion of traffic capacity change after accidents with severity d. F stands for the traffic flow at the scene of the accident. TDC_y is the economic loss due to traffic congestion and delay caused by traffic accidents in the year y. AW_y is the average unit time value in the year y, which is the average hourly wage. $AAHT_r$ is the average hourly traffic flow on the road type rt, where rt = 1, 2, 3, . . ., 9, respectively, represent urban expressways, urban main roads, urban secondary roads, urban local roads, highways, class-1 highways, class-2 highways, class-3 highways, and class-4 highways. $NC_{rt,d}$ is the number of accidents with severity d on the road type rt each year.

When a traffic accident occurs ahead, the vehicles in the trailing convoy are generally idling during the congestion period to ensure the operation of in-vehicle equipment such as air conditioning. Given the significant differences in energy consumption losses among vehicles of different power types, it is necessary to calculate the energy consumption losses for new energy vehicles (*NEV*s) and internal combustion engine vehicles (*ICEV*s) separately. The energy consumption loss due to traffic congestion caused by road traffic accidents is illustrated in Equation (9).

$$\begin{aligned} SE_y = \sum_{r=1}^{9} \sum_{d=0}^{3} (&AAHT_r \times NC_{r,d} \times ART_d \times Prop\_NEV_y \times EC\_idle_{NEV} \times Price_{elec} \\ &+ AAHT_r \times NC_{r,d} \times ART_d \times Prop\_ICEV_y \times EC\_idle_{ICEV} \\ &\times Price_{gas}) \end{aligned} \tag{9}$$

SE_y represents the energy consumption loss of the fleet due to traffic accidents in the year y. $Prop\_NEV_y$ denotes the penetration rate of *NEV*s in the year y. $Prop\_ICEV_y$ signifies the penetration rate of *ICEV*s in the year y. $Price_{elec}$ is the price per kilowatt-hour of electricity. $Price_{gas}$ is the price per liter of gasoline. EC_idle_{NEV} refers to the idling energy consumption of *NEV*s. EC_idle_{ICEV} indicates the idling power consumption of *ICEV*s.

Based on various vehicle–road intelligence deployment scenarios and their impact on the number of traffic accidents in Beijing (Figure 8), as well as the quantification of economic losses caused by fatalities, serious injuries, minor injuries, and PDO accidents, a comprehensive safety benefit for different scales of vehicle–road intelligence deployment scenarios can be obtained, as shown in Equation (10).

$$ECB_y = \sum_{d=0}^{3} \frac{RCN_{y,d}}{CN_{y,d,base}} \times (PL_y + MC_y + PD_y + TDC_y + SE_y) \quad (10)$$

2.3.2. Quantified Assessment Sub-Model of Traffic Efficiency Benefit

Different vehicle–road collaborative intelligence deployment scenarios, and the penetration rate of intelligent vehicles at different development stages, will have varying levels of impact on traffic efficiency. Additionally, different types of roads have distinct structural characteristics and designed service capabilities, and the enhancement of traffic efficiency on different road types due to intelligence technologies is also different. By constructing a traffic efficiency impact assessment sub-model, we obtained the changes in percentage reduction in travel time per mile and percentage reduction in energy consumption per mile under different road types, different input traffic flow rates, different penetration rates of intelligent vehicles, and different vehicle–road intelligence deployment scenarios, relative to the baseline scenario of fully manual driving fleets. Combining the duration proportion of different road types in Beijing's road network under different traffic flow rate ranges, as well as data on the scale of road mileage, energy (electricity, fuel) prices, and the unit time value, we can quantify the economic benefits produced by vehicle–road collaborative intelligence deployment in terms of traffic efficiency. The analytical framework for traffic efficiency benefits in this study is shown in Figure 9.

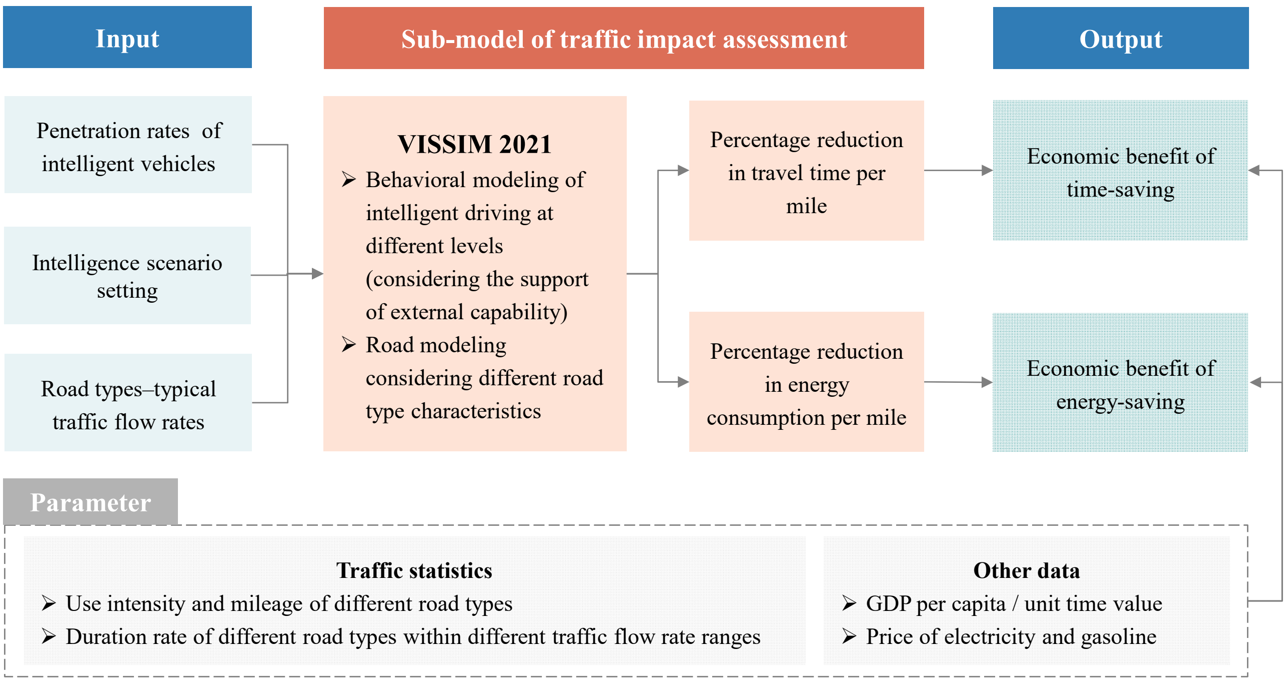


Figure 9. Analysis framework for traffic efficiency benefit.

Based on existing studies within our group and on relevant research from the literature [11,21,38], the traffic efficiency benefits generated by the vehicle–road collaborative intelligence system primarily encompass the economic benefits of travel time resulting from improved traffic efficiency and the energy-saving economic benefits derived from reduced traffic congestion. These two aspects basically cover the full range of economic benefits from improved transportation efficiency, as shown in Equation (11).

$$TB_y = TSEB_y + EEB_y \quad (11)$$

$TSEB_y$ denotes the economic benefits of travel time savings in the year y. EEB_y signifies the energy-saving economic benefits in the year y.

Sub-model of traffic efficiency impact assessment

Within the traffic efficiency sub-model, we have taken into account a range of schemes and functional combinations for varying levels of intelligent driving, from primary to advanced, and have modeled the intelligent driving behaviors across these levels, with human-driven vehicles (HVs) modeled using the Wiedemann 99 model. Enhancements such as roadside perception and computing devices extend vehicles' capabilities, enabling "high-dimensional perspective" perception and cooperative optimization decision-making. Functions including cooperative lane changing, intelligent merging, and green wave passage further influence the intelligent driving behaviors of vehicles. We have chosen three representative types of roads—urban expressways, urban main roads, and urban secondary roads—and have modeled them in accordance with the "Urban Comprehensive Traffic System Planning Standard GB/T 51328-2018 [39]". Urban expressways are characterized as semi-closed, while urban main and secondary roads are open, capturing a variety of road scenario characteristics. These road types, with their distinct design service capabilities, are assigned corresponding traffic flow rate combinations. Utilizing VISSIM and traffic flow theory, we performed traffic flow simulations to determine the average travel time per kilometer for each vehicle under various road types, traffic flow rates, and penetration rates of intelligent vehicles, thereby assessing the impact of vehicle–road collaborative intelligence. By integrating traffic flow data with vehicle dynamics theory, we calculated the average energy consumption per kilometer for each vehicle under the same variables. To more accurately reflect the impact of vehicle–road intelligence deployment, we established a baseline using the average travel time per kilometer and energy consumption per vehicle for human-driven fleets, against which we measured the percentage reduction in travel time per mile and the percentage reduction in energy consumption per mile for different intelligence deployment scenarios. The traffic efficiency impact assessment sub-model is depicted in Figure 10.

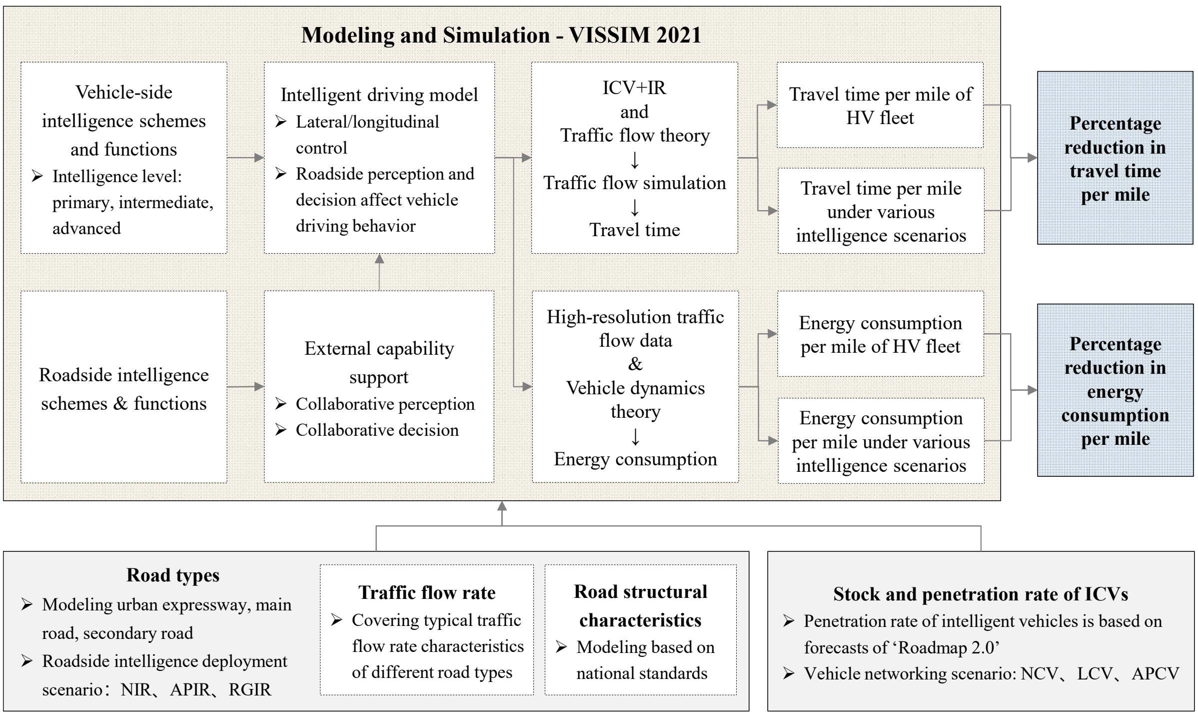


Figure 10. Sub-model of traffic efficiency impact assessment.

Due to varying travel demands among the public at different times of the day, there is a significant disparity in road traffic volumes across various time periods. Obtaining real-time traffic flow data for different road types within an urban network is challenging. Additionally, it is difficult to perform high-resolution analysis and calculations for all traffic flow conditions across all road types in practical simulations. This study combines the average operating speeds of vehicles on various types of roads in Beijing over a 24 h period [40] with the relationship between average speed and average traffic volume for each road type [41]. We were able to determine the duration proportion of different traffic volume intervals for various road types in Beijing, and, consequently, derive the average daily traffic volume for different road types across different traffic flow rate intervals. The average values within typical traffic volume intervals for different road types were selected for simulation, thereby allowing us to obtain the percentage reduction in travel time per mile and the percentage reduction in energy consumption per mile across different traffic flow intervals. The simulation results for urban expressways and urban main roads can be found in the Appendix A.

Quantitative analysis of traffic operation efficiency benefit

Based on the traffic flow simulation results, combined with the duration proportion of different traffic flow rate ranges for various road types in Beijing, as well as data on the scale of road mileage and the unit time value, this study quantitatively assesses the economic benefits of enhancing traffic efficiency. The economic benefits of travel time saved by the vehicle–road collaborative intelligence system in the year y are illustrated in Equation (12).

$$TSEB_y = \sum_{r=1}^{9} \sum_{q} \frac{1}{v_{r,q}} \times \Delta t_{r,q,p} \times flow_{r,q} \times mileage_r \times AW_y \times 365 \tag{12}$$

$v_{r,q}$ represents the average speed of fully human-driven vehicle fleets on road type r under traffic flow rate q. $\Delta t_{r,q,p}$ denotes the percentage reduction in travel time per mile on road type r with a traffic flow rate of q and a penetration rate of intelligent vehicles p. $flow_{r,q}$ signifies the average daily traffic volume on road type r under traffic flow rate q. AW_y is the unit time value in the year y.

The energy-saving economic benefits brought about by the vehicle–road collaborative intelligence system primarily consist of two parts: the energy-saving benefits for the *ICEV* fleet and the energy-saving benefits for the *NEV* fleet, as shown in Equation (13).

$$\begin{aligned} EEB_y = &\sum_{r=1}^{9} \sum_{q=1}^{4} EC_{NEV} \times \Delta EC_{r,q,p} \times flow_{r,q} \times Prop\_NEV_y \times mileage_r \\ &\times Price_{elec} \times 365 \\ &+ \sum_{r=1}^{9} \sum_{q=1}^{4} EC_{ICEV} \times \Delta EC_{r,q,p} \times flow_{r,q} \times Prop\_ICEV_y \\ &\times mileage_r \times Price_{gas} \times 365 \end{aligned} \tag{13}$$

EC_{NEV} represents the average energy consumption per mile for *NEV*s, while EC_{ICEV} denotes the average energy consumption per mile for *ICEV*s. $\Delta EC_{r,q,p}$ is the percentage reduction in energy consumption per mile on road type r with a traffic flow rate of q and a penetration rate of intelligent vehicles p. It is assumed that the percentage reduction in energy consumption for both *ICEV*s and *NEV*s is the same. In recent years, the proportion of diesel vehicles in China's passenger car market has been declining, and currently, diesel vehicles account for less than 1% of the total vehicle ownership. It is assumed that the *ICEV* fleet in Beijing is composed entirely of gasoline vehicles. The relevant data and parameters are shown in Table 4, where the price of gasoline used in this study is the average of the lowest (7.44 RMB/L) and highest (8.43 RMB/L) prices of 92-octane gasoline in 2023.

Table 4. Data and parameters related to traffic benefit assessment.

	Value	Unit	Source	Notes
EC_idle_{NEV}	1.5	L/h	[42]	➢ Assuming the idling energy consumption levels of *NEV*s and *ICEV*s remain unchanged.
EC_idle_{ICEV}	1	kW		
EC_{NEV}	0.13	kWh/km		➢ Assuming the energy consumption of *NEV*s and *ICEV*s remain unchanged in the future.
EC_{ICEV}	0.062	L/km		
$Price_{elec}$	0.722	RMB/kWh	[38]	➢ Assuming the price of electricity and gasoline remain unchanged in the future.
$Price_{gas}$	7.93	RMB/L	[43]	

2.3.3. Quantified Assessment Sub-Model of Carbon Emission Reduction Benefit

Vehicle–road collaborative intelligence systems will enhance road traffic safety, reduce the number of traffic accidents, and consequently decrease the energy consumption losses caused by traffic congestion and delays. Additionally, the improved traffic efficiency brought about by collaborative intelligence systems will also affect the energy consumption levels of fleets. Based on the reduction in road traffic accidents and the changes in per-vehicle energy consumption due to changes in traffic efficiency, and combining the future changes in the penetration rates of vehicles with different power types in the fleet, the comprehensive change in energy consumption (including fuel and electricity) brought about by vehicle-to-road collaborative intelligence can be obtained. By integrating the changes in fleet energy consumption with the future carbon emission factors corresponding to different energy types, the carbon emission reduction benefits brought about by vehicle-to-road collaborative intelligence can be quantified. The sub-model of carbon emission reduction benefit in this study is shown in Figure 11.

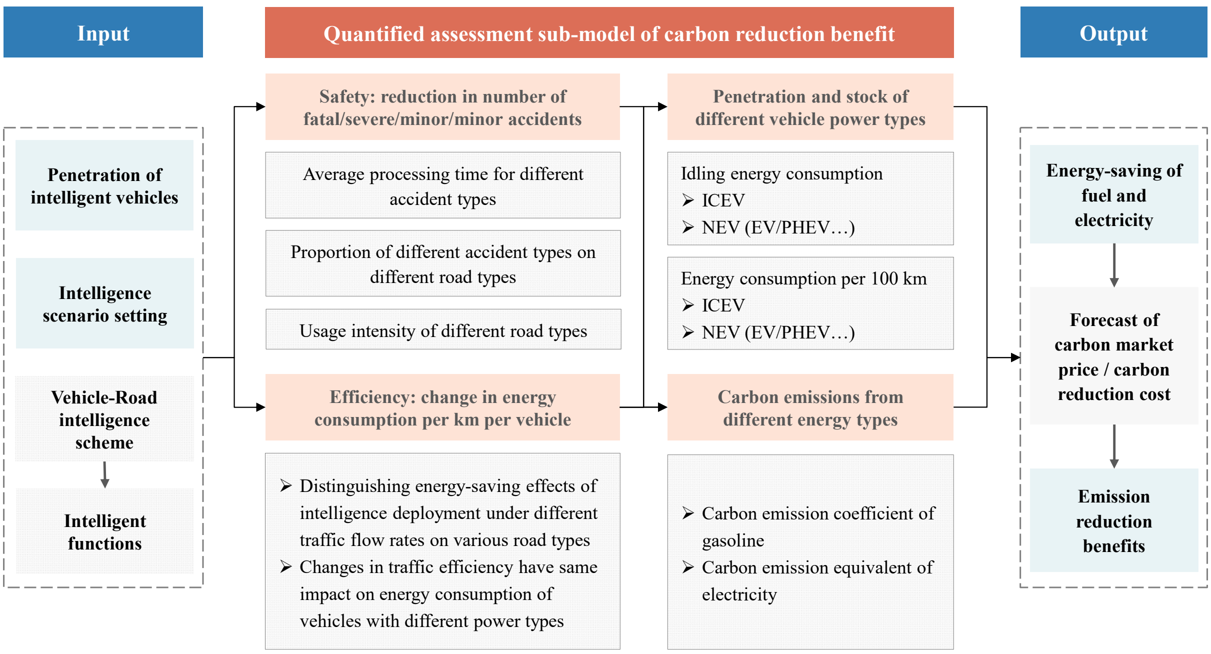


Figure 11. Sub-model of carbon emission reduction benefit.

The energy-saving amount of the NEV fleets and ICEV fleets, respectively, under different intelligence deployment scenarios are shown in Equations (14) and (15). The energy-saving amount of both power types of fleets consist of two parts: one part is the reduction in congestion energy loss due to the improvement of traffic safety, and the other part is the change in the average energy consumption level of the fleet due to the improvement of traffic efficiency.

$$\begin{aligned} ES\_elec_y = & \sum_{r=1}^{9}\sum_{d=0}^{3}\frac{RCN_{y,d}}{CN_{y,d,base}} \times AAHT_r \times NC_{r,d} \times ART_d \times Prop\_NEV_y \\ & \times EC\_idle_{NEV} \\ & + \sum_{r=1}^{9}\sum_{q=1}^{4} EC_{NEV} \times \Delta EC_{r,q,p} \times flow_{r,q} \times Prop\_NEV_y \\ & \times mileage_r \times 365 \end{aligned} \tag{14}$$

$$\begin{aligned} ES\_gas_y = & \sum_{r=1}^{9}\sum_{d=0}^{3}\frac{RCN_{y,d}}{CN_{y,d,base}} \times AAHT_r \times NC_{r,d} \times ART_d \times Prop\_ICEV_y \\ & \times EC\_idle_{ICEV} \\ & + \sum_{r=1}^{9}\sum_{q=1}^{4} EC_{ICEV} \times \Delta EC_{r,q,p} \times flow_{r,q} \times Prop\_ICEV_y \\ & \times mileage_r \times 365 \end{aligned} \tag{15}$$

ES_gas_y is the energy-saving amount of NEV fleets in the year y. ES_elec_y is the energy-saving amount of ICEV fleets in the year y.

The carbon emission coefficient for gasoline throughout its lifecycle remains essentially constant. As renewable energy generation becomes more widespread, the lifecycle carbon emission factor for electricity will decrease year by year. By combining the energy-saving amount of gasoline and electricity under different scenarios, the corresponding reduction in carbon emissions can be obtained, as shown in Equation (16).

$$RA\_GHG_y = CE\_Coef_{gas} \times ES\_gas_y + CE\_Coef_{elec,y} \times ES\_elec_{s,y} \tag{16}$$

RA_GHG_y represents the carbon emission reduction in the year y under different vehicle–road intelligence deployment scenarios. CE_Coef_{gas} is the lifecycle carbon emission factor corresponding to gasoline. $CE\_Coef_{elec,y}$ denotes the lifecycle carbon emission factor corresponding to electricity in the year y.

The carbon market price represents the marginal cost of carbon abatement. Based on predictions of future carbon market prices, the carbon emission reduction benefits under different intelligence deployment scenarios can be quantified, as illustrated in Equation (17).

$$EB_y = RA\_GHG_y \times Price\_GHG_y \tag{17}$$

$Price\_GHG_y$ is the carbon market price in the year y.

The relevant literature has forecasted the lifecycle carbon emission factors for electricity and carbon market prices for every five years from 2025 to 2050 [44,45]. The intermediate year values can be obtained through linear interpolation. The lifecycle carbon emission coefficient for gasoline is 91g-CO_2eq/MJ, with the combustion phase contributing 76% to the carbon emissions [46,47]. The fixed chemical reactions in the combustion phase determine that the carbon emissions are relatively stable, and the production phase, where oil refining and catalyst technologies are already mature, has limited potential for future emission reductions. Therefore, it is assumed that the carbon emission factor per liter of gasoline remains constant. The relevant parameters are shown in Table 5.

Table 5. Carbon emission coefficient of gasoline and electricity.

Year	2025	2030	2035	2040	2045	2050	Unit	Source
CE_Coef_{elec}	463.1	418.7	352.7	286.7	246.0	205.2	g/kWh	[44]
CE_Coef_{gas}	2872.6						g/L	[46,47]
$Price\_GHG$	68	104	178	287	435	751	RMB/ton	[45]

2.4. Social Incremental Cost Evaluation Model

The social incremental costs of vehicle–road collaborative intelligence systems mainly include vehicle-side costs and roadside costs. The vehicle-side costs encompass the costs of intelligent configuration and power consumption, while the roadside costs include the deployment costs of intelligent infrastructure and corresponding power consumption costs. Our study primarily explores the incremental social benefits generated by the deployment of roadside intelligent infrastructure, considering the impact of different deployment scenarios for roadside intelligent infrastructure and in-vehicle networking terminals on incremental social benefits. In reality, the deployment of roadside intelligent infrastructure under different schemes will also affect the vehicle-side intelligence schemes, thereby influencing the costs of vehicle-side intelligence. This aspect has been thoroughly discussed in our previous studies [28,33], and will not be reiterated here. The deployment of roadside intelligent infrastructure requires the installation of in-vehicle networking terminals to fully realize its value. Hence, the related costs of networking terminals in the fleet are also within the scope of cost calculations in this study.

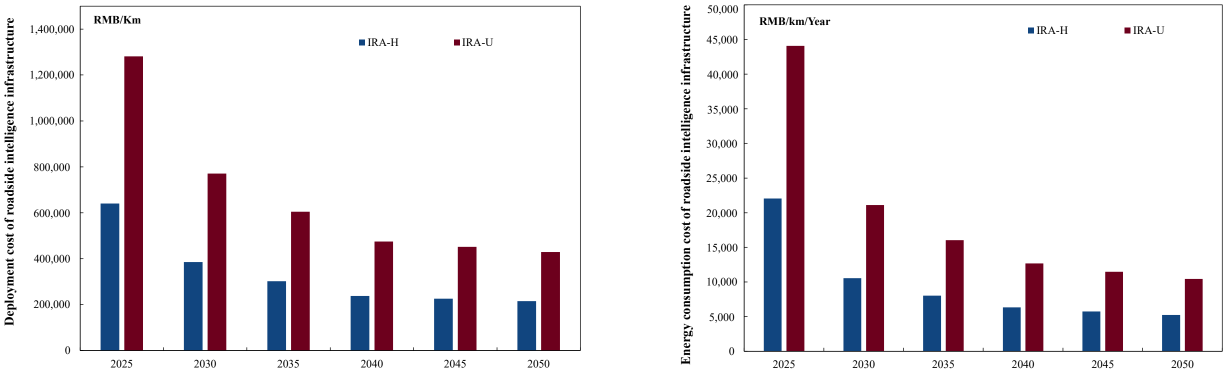
The annual deployment costs and power consumption costs of the fleet for in-vehicle networking terminals are illustrated in Equations (18) and (19), respectively.

$$Cost_{deploy-networking,y} = \sum_{v=1}^{v=3} Sales_{v,y} \times PR_{v,y} \times cost_{T-box,y} \tag{18}$$

$$Cost_{usage-networking,y} = \sum_{i=2024}^{y} \sum_{v=1}^{v=3} Sales_{v,i} \times PR_{v,i} \times ecr_{T-box,i} \times (1 - OMR_{i,y}) \tag{19}$$

$Sales_{v,y}$ represents the sales volume of intelligent vehicles of grade v in the year y. $PR_{v,y}$ denotes the penetration rate of in-vehicle networking terminals in intelligent vehicles of level v in the year y. $cost_{T-box,y}$ is the deployment cost of one in-vehicle networking terminal in the year y. $ecr_{T-box,i}$ is the annual energy consumption cost generated by the in-vehicle networking terminals deployed in the year i. $OMR_{i,y}$ is the y year's turnover rate of vehicles purchased in the year i.

Incorporating the roadside intelligence deployment schemes tailored for urban roads and highways, as well as the hardware costs and power consumption of intelligent configurations in different years [33], the deployment costs and power consumption costs per kilometer for advanced roadside intelligence schemes from 2025 to 2050 are illustrated in Figure 12a,b, respectively. "IRA-H" represents the intelligence deployment scheme for highways, and "IRA-U" represents the intelligence deployment scheme for urban roads. With the advancement of technology, both the deployment costs and power consumption costs per kilometer of intelligent roads trend downward. It is projected that the deployment costs for advanced intelligence schemes on urban roads will be 1.28 million RMB/Km in 2025, 0.6 million RMB/Km 2035, and 0.43 million RMB/Km in 2050. The power consumption costs will be 44,000 RMB/Km/Year in 2025, 16,000 RMB/Km/Year in 2035, and 10,000 RMB/Km/Year in 2050. The highway scheme differs from urban roads in the deployment density of intelligent configurations, with the corresponding deployment costs and power consumption costs being half of those for urban roads.



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

Figure 12. Deployment cost and energy consumption cost of roadside intellectualization. (**a**) Deployment cost, (**b**) energy consumption cost.

3. Results and Discussion

3.1. Social Benefit Under Various Intelligence Scenarios

3.1.1. Traffic Safety Benefit

Based on the ability of different vehicle–road intelligence deployment scenarios to reduce the number of traffic accidents in Beijing (Figure 8), a quantitative assessment of the safety benefits generated in five dimensions—reducing the loss of social productivity, lowering societal medical costs related to traffic accidents, reducing direct property damage, decreasing economic losses due to time delays, and reducing energy consumption losses—was conducted. A comparison of the cumulative comprehensive safety benefits from 2024 to 2050 under five scenarios is illustrated in Figure 13.

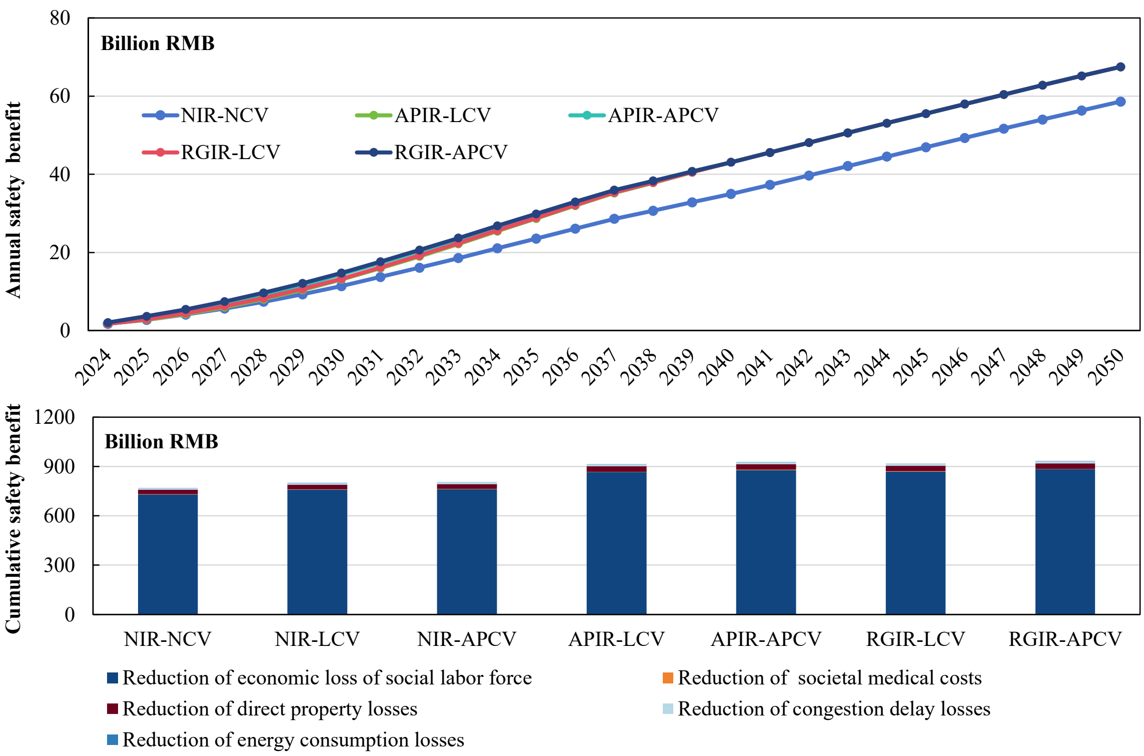


Figure 13. Safety benefits under various intelligence scenarios from 2025 to 2050.

It can be observed that under the NIR-NCV scenario, where neither networking terminals are installed in vehicles, nor is roadside intelligence infrastructure deployed, a cumulative safety benefit of 769.8 billion RMB is projected to be achieved with single-vehicle intelligence for the period from 2024 to 2050. Building on the planned deployment of in-vehicle networking terminals, if combined with the planned deployment of roadside intelligence infrastructure (APIR-APCV), the cumulative safety benefit will increase to 925.6 billion RMB. Comparing the APIR-LCV and APIR-APCV scenarios, where the deployment of roadside intelligence infrastructure is the same, the coverage of in-vehicle networking terminals will better enhance safety benefits. Comparing the APIR-APCV, RGIR-APCV, APIR-LCV, and RGIR-LCV scenarios, it can be seen that under the LCV scenario, accelerating the deployment process of roadside intelligence infrastructure results in a limited increase in cumulative safety benefits, generating only an additional safety benefit of 2.8 billion RMB (compared to APIR-LCV), at which point the penetration rate of in-vehicle networking terminals becomes the key factor constraining further enhancement of safety benefits.

Among all the intelligence deployment scenarios, the reduction in the loss of social productivity accounts for approximately 95% of the comprehensive safety benefits. The other dimensions of benefits, ranked from largest to smallest by proportion, are the reduction in direct property loss, reduction in economic losses due to congestion and delay, reduction in societal medical costs, and reduction in energy consumption loss, with respective proportions of about 3.59%, 1.30%, 0.17%, and 0.01%.

3.1.2. Traffic Efficiency Benefit

Due to the high concentration of traffic volume on urban roads in the central urban areas of Beijing, these roads bear the highest usage intensity among all types of roads in the city, and are also the most congested. In contrast, highways of various grades are primarily located in the surrounding jurisdictions of the central urban area. Although these highways have a large scale in terms of mileage, they are essentially in a state of free traffic flow because the population and economic activities in the surrounding jurisdictions are relatively sparse, meaning the actual usage intensity of these roads is far from reaching their designed service capacity. Therefore, this study only considers the traffic efficiency benefits generated by urban expressways, main roads, and secondary roads. Based on the results of traffic flow simulation, combined with the proportion of time spent in different traffic flow rate ranges for different types of roads in Beijing, as well as data on the scale of road mileage and the value of time per capita, the vehicle–road collaborative intelligence system brings about travel time-saving economic benefits and energy-saving economic benefits through improving traffic efficiency, as shown in Figure 14.

It is evident that the development of vehicle–road collaborative intelligence will significantly enhance traffic efficiency benefits. Comparing the APIR-APCV and RGIR-LCV scenarios, the former will cause an earlier climb in annual traffic efficiency benefits, even though the coverage rate of road intelligence in the former is not as high as in the latter. The timely deployment of in-vehicle networking terminals is key to leveraging the traffic efficiency benefits of vehicle–road collaborative intelligence systems. The traffic efficiency benefits produced annually by the APIR-LCV and RGIR-LCV scenarios are essentially overlapping, further illustrating that if the development of vehicle networking does not meet expectations, the significance of accelerating the deployment of roadside intelligence infrastructure is limited. After 2040, the penetration rate of vehicle networking is basically 100%, and the annual traffic efficiency benefits of the four scenarios—APIR-LCV, APIR-APCV, RGIR-LCV, and RGIR-APCV—are essentially the same, with the annual traffic efficiency benefits further increasing alongside economic development and the rise in per capita

GDP. Under the NIR-NCV scenario, it is projected that from 2024 to 2050, a cumulative traffic efficiency benefit of 186.6 billion RMB will be generated, including 161.1 billion RMB in travel time-saving benefits and 25.5 billion RMB in energy-saving benefits. Under the APIR-APCV scenario, the cumulative traffic efficiency benefit will increase to 628.9 billion RMB, with travel time saving benefits further magnified to 604.5 billion RMB, while the increase in the average speed of the fleet implies an increase in average energy consumption, reducing energy-saving benefits to 24.4 billion RMB. The RGIR-APCV scenario will yield the greatest traffic efficiency benefit of 634.6 billion RMB.

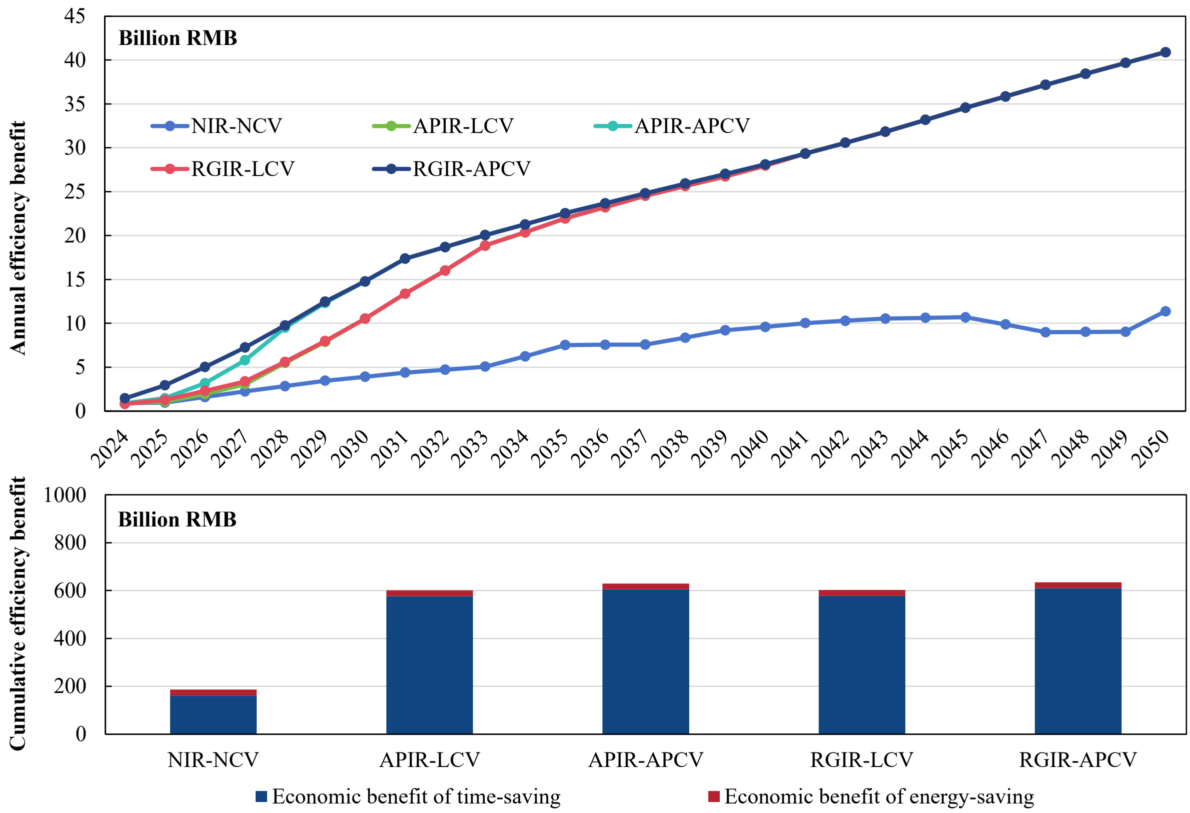


Figure 14. Traffic efficiency benefits under various intelligence scenarios from 2025 to 2050.

3.1.3. Carbon Emission Reduction Benefit

Distinct vehicle–road intelligence deployment scenarios are associated with different reductions in congestion-related energy losses attributable to traffic safety enhancements, as well as variations in per-vehicle energy consumption due to improvements in traffic efficiency. By taking into account the projected changes in the ownership and penetration rates of vehicles with diverse powertrains within the future fleet [44], we can determine the alterations in fuel and electric energy consumption for the fleet under various intelligence deployment scenarios. Factoring in the carbon emission coefficients for fuel from Table 5, the future carbon emission factors associated with electricity, and anticipated carbon market prices, Figure 15 illustrates the reductions in carbon dioxide emissions and the economic benefits of these reductions across different intelligence deployment scenarios.

As the penetration of NEVs in the fleet increases and ICEVs are phased out year by year, and given that the carbon emissions of NEVs in use are significantly lower than those of ICEVs, the electrification of the fleet also implies that the baseline for emission reductions corresponding to safety and traffic efficiency achieved by intelligence is reduced. It can be observed that the carbon emission reductions under different intelligence scenarios will peak around 2030 and then decrease year by year. However, as the difficulty of future emission reductions increases annually, the carbon market price also rises accordingly. The increase in societal carbon reduction costs exceeds the reduction in fleet emissions brought about by electrification and intelligentization deployment, resulting in an upward trend in the carbon reduction economic benefits for the five scenarios from 2024 to 2050. Overall, the differences in carbon reduction economic benefits among the five scenarios—NIR-NCV, APIR-LCV, APIR-APCV, RGIR-LCV, and RGIR-APCV—are relatively small, with cumulative carbon reduction economic benefits from 2024 to 2050 amounting to 2.82 billion RMB, 2.63 billion RMB, 2.66 billion RMB, 2.63 billion RMB, and 2.66 billion RMB, respectively.

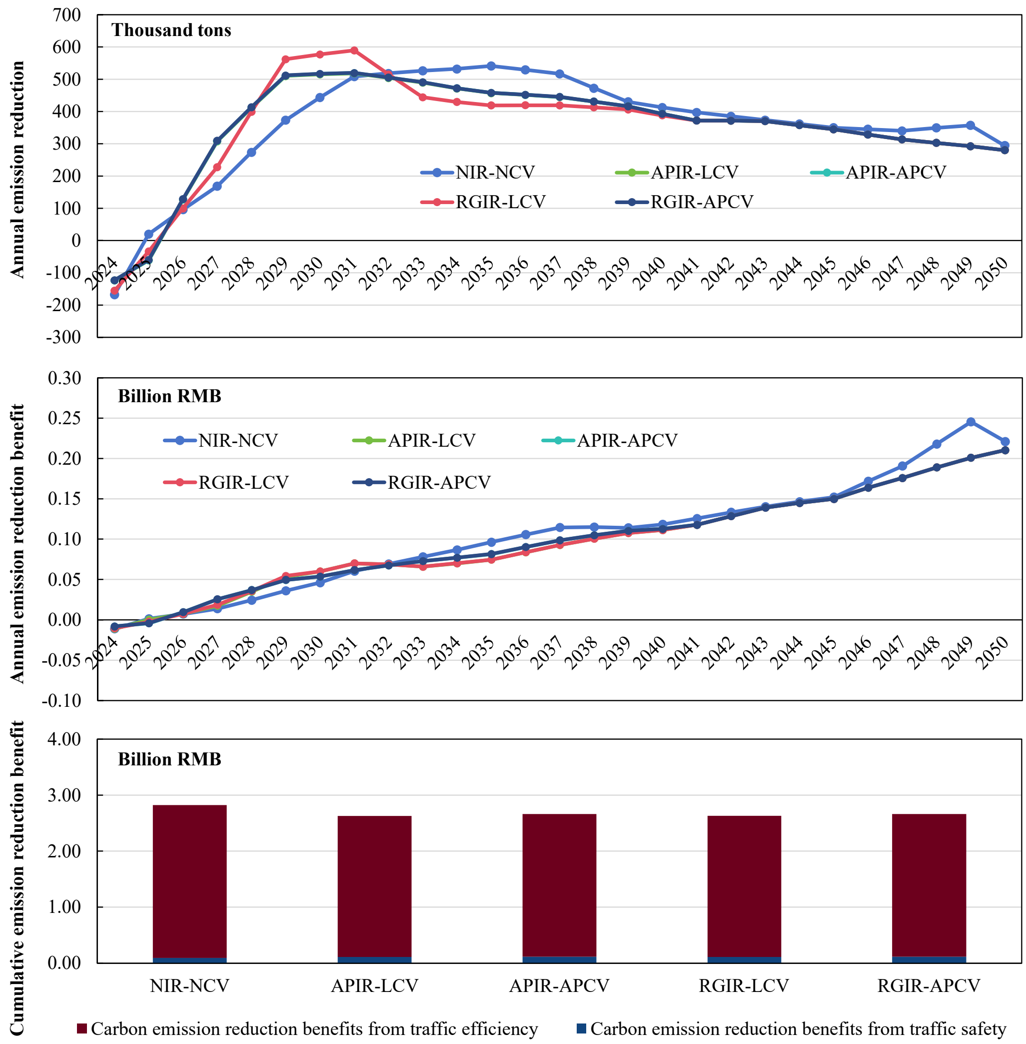


Figure 15. Carbon emission reduction benefits under various intelligence scenarios from 2025 to 2050.

3.2. Social Cost Under Various Intelligence Scenarios

3.2.1. Incremental Cost of Roadside Intelligence Infrastructure

Based on the deployment costs and power consumption costs of roadside intelligence infrastructure at different periods (Figure 12), combined with the mileage of different road types and roadside intelligence infrastructure deployment scenarios (Table 1), the annual incremental costs of intelligence infrastructure for the APIR and RPIR deployment scenarios from 2024 to 2050 were obtained, as shown in Figure 16. It can be observed that the annual incremental costs fluctuate periodically in line with the lifespan of intelligence configurations, which is 7 years. Under both scenarios, since the scale of road mileage eventually covered by intelligent infrastructure is exactly the same, the annual incremental costs will gradually converge as intelligent devices are replaced later on. However, different deployment schedules in the early stages will lead to significant differences in deployment costs. The RGIR scenario implies that the Beijing municipal government needs to concentrate nearly 4.5 billion RMB in the two years from 2024 to 2025, focusing on deploying roadside intelligence infrastructure. Subsequently, as the costs and power consumption of intelligence configurations, such as perception, communication, and computing, decline, the annual costs for roadside intelligence infrastructure also decrease year by year.

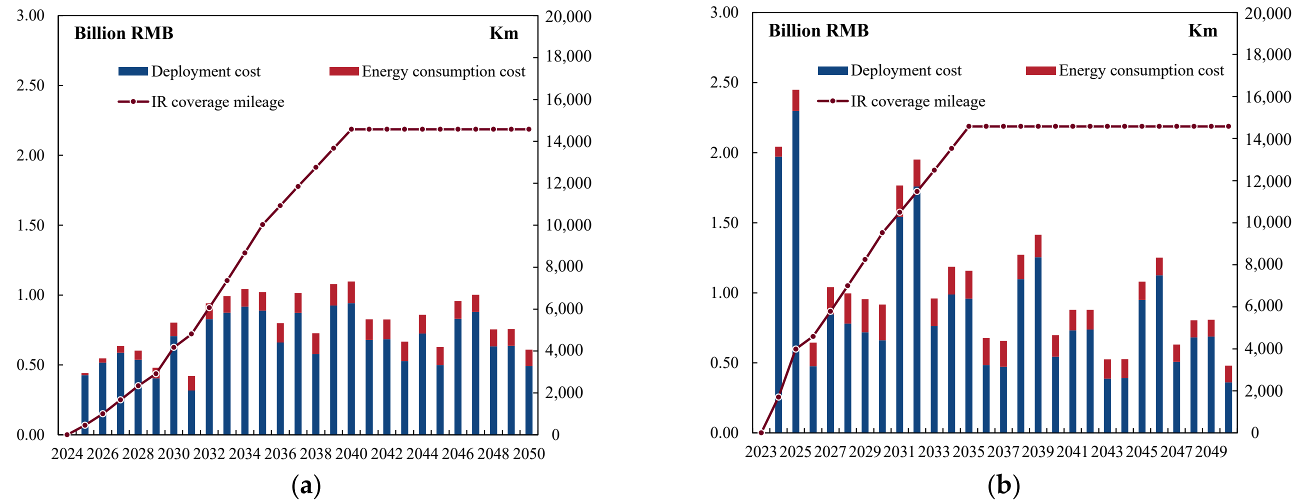


Figure 16. Annual incremental cost of roadside intelligence infrastructure. (**a**) APIR, (**b**) RPIR.

The total incremental roadside intelligence infrastructure costs for the APIR and RPIR scenarios from 2024 to 2050 are shown in Figure 17. Under the APIR scenario, the cumulative total cost (including deployment and power consumption costs) for roadside intelligence in Beijing is 20.54 billion RMB, and the deployment costs account for 85.57% of the total cost. Meanwhile, under the RPIR scenario, the cumulative total cost is 28.64 billion RMB, and the deployment costs account for 84.41% of the total cost. It is noteworthy that the costs for urban expressways only account for 6.4% and 5.2% of the total costs for seven types of roads, yet urban expressways represent 32% of the usage intensity in the entire urban road network. In contrast, urban local roads account for 32.9% and 35.6% of the total costs in the two scenarios, with their usage intensity only representing 1.7% of the urban road network.

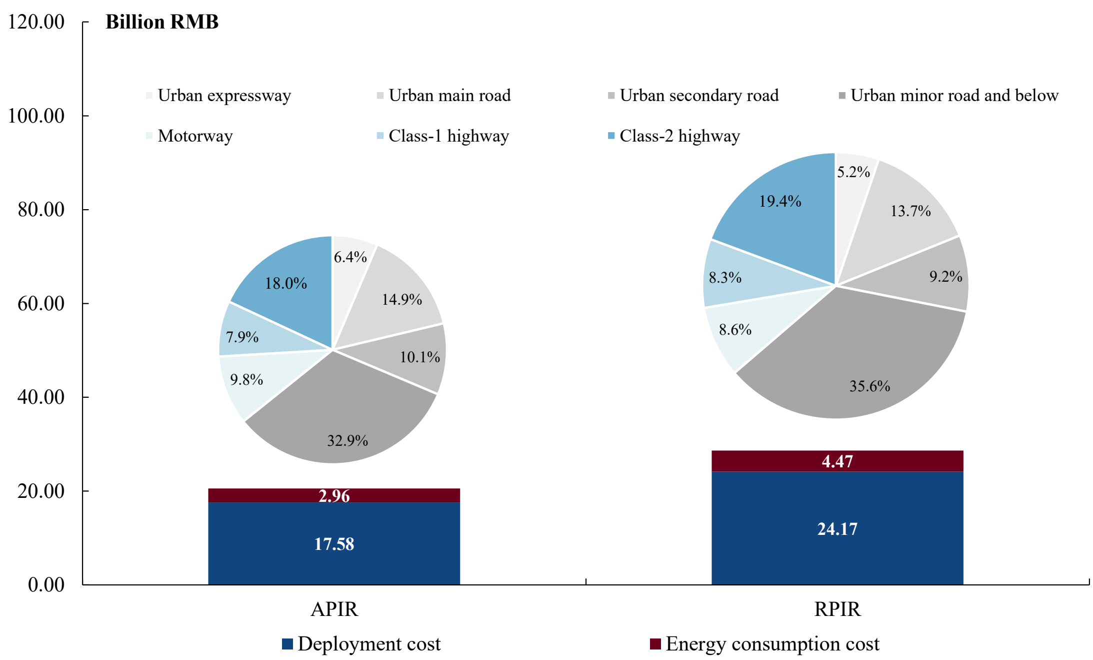


Figure 17. Cumulative cost of roadside intelligence infrastructure (2024–2050).

3.2.2. Incremental Cost of Vehicle-Side Networking

Based on the deployment costs and power consumption costs of in-vehicle networking terminals at different periods, and considering the penetration rates under various scenarios, the annual incremental costs of vehicle networking for the LCV and APCV scenarios from 2024 to 2050 were obtained, as shown in Figure 18. The differences between the scenarios are mainly reflected in the varying penetration rates and costs in the early stages. After 2040, all intelligent vehicles are fully connected, and the annual vehicle networking costs under both scenarios also tend to be roughly equal. Under the LCV scenario, it is expected that the cumulative incremental cost of vehicle networking for the fleet from 2024 to 2050 will be 7.453 billion RMB, including 7.109 billion RMB for deployment costs and 344 million RMB for power consumption costs. Under the APCV scenario, it is expected that the cumulative incremental cost of vehicle networking for the fleet from 2024 to 2050 will be 8.264 billion RMB, including 7.874 billion RMB for deployment costs and 390 million RMB for power consumption costs.

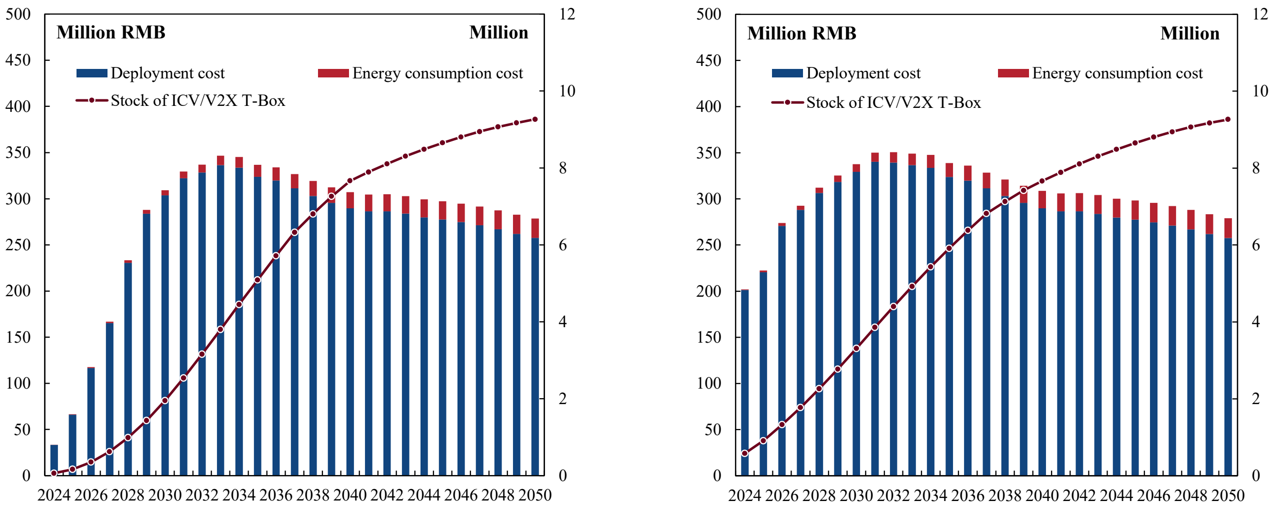


Figure 18. Annual incremental cost of vehicle-side networking. (**a**) LCV, (**b**) APCV.

3.3. Social Value Under Various Intelligence Scenarios

Based on the comprehensive social benefits generated by existing vehicle–road collaborative intelligence systems in the dimensions of safety, efficiency, and carbon emission reductions, as well as on research findings on the incremental costs of fleet networking and roadside intelligence infrastructure, the social value is defined as the ratio of the incremental comprehensive social benefits produced by the vehicle–road collaborative intelligence system compared to single-vehicle intelligence, to the incremental social costs. This ratio is used to measure the cost-effectiveness of deploying roadside intelligence infrastructure and vehicle networking terminals. As shown in Figure 19, under the NIR-NCV scenario, which relies solely on vehicle-side intelligence development, Beijing can generate an accumulated social benefit of 958.3 billion RMB. Under the APIR-APCV scenario, by accumulating an incremental social cost of 28.8 billion RMB from 2024 to 2050 (with vehicle-side incremental costs accounting for 28.7% and roadside incremental costs accounting for 71.3%), a cumulative social benefit increment of 598.8 billion RMB is generated compared to the NIR-NCV scenario. This means that the investment in roadside intelligence infrastructure and in-vehicle networking terminals can generate a social value of approximately 20.8 times the cost. Comparing the APIR-APCV and RGIR-APCV scenarios, accelerating the deployment of intelligence infrastructure introduces more roadside cost investment (an increment of 8.1 billion RMB), but the resulting social benefit increment is limited (11.6 billion RMB), reducing the social value to 16.5. Overall, the social value of constructing a vehicle–road collaborative intelligence system is enormous, but it is still necessary to fully match the deployment pace of roadside intelligence infrastructure with the installation progress of in-vehicle networking terminals.

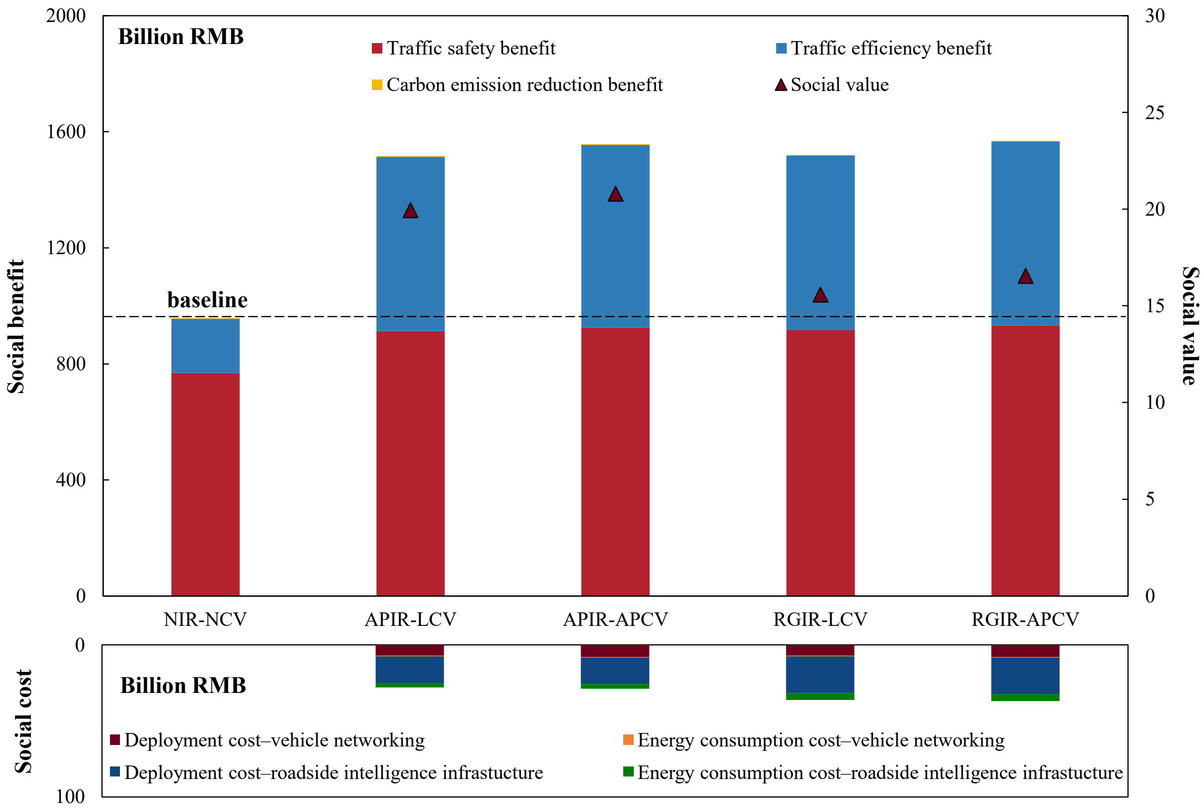


Figure 19. Social values of various intelligence scenarios.

4. Conclusions and Policy Suggestions

Contribution: This study constructs a social value assessment model for collaborative intelligence systems, which includes three benefit sub-models—safety benefits, traffic efficiency benefits, and carbon emission reduction benefits—as well as two cost sub-models—incremental costs of roadside intelligence and incremental costs of vehicle networking. In terms of benefit sub-models, by organizing different combinations of vehicle–road intelligence schemes and the intelligent functions they can achieve, the safety effects (comprehensive collision avoidance effectiveness) and traffic efficiency effects (percentage reduction in travel time per mile, percentage reduction in energy consumption per mile) are analyzed. Furthermore, the carbon emission reduction benefit sub-model quantifies the indirect energy conservation and carbon emission reduction levels resulting from improvements in traffic safety and efficiency. Taking Beijing as a case study, the model integrates urban fleet driving characteristics, the mileage scales and usage intensity of different road types, and economic data such as the average unit time value and carbon market prices, as well as cost and power consumption data of vehicle-side and roadside intelligence configurations. It assesses the social cost of upgrading roadside intelligence infrastructure and deploying vehicle networking, as well as the social benefits generated by vehicle–road collaborative intelligence in terms of safety, efficiency, energy-saving, and carbon emission reductions. Our study compares these benefits and costs with the single-vehicle intelligence scenario to analyze the incremental social value of deploying roadside intelligence infrastructure and popularizing in-vehicle networking terminals.

Research findings: From the perspective of the social benefits of vehicle–road collaborative intelligence systems, the introduction of roadside intelligence infrastructure expands the perception range of vehicles, reduces vehicle perception blind spots, and the mutual verification of heterogeneous sensors between the vehicle-side and roadside greatly enhances the reliability and stability of perception. This effectively reduces the number of traffic accidents of varying severity. If roadside intelligence infrastructure and in-vehicle networking terminals are deployed as planned (APIR-APCV), a safety benefit of 925.6 billion RMB is expected to be accumulated from 2024 to 2050, significantly higher than the 768.9 billion RMB in the single-vehicle intelligence scenario (NIR-NCV). Concurrently, roadside perception and computing capabilities empower vehicles with beyond-line-of-sight perception and cooperative optimization decision-making. Functions such as cooperative lane changing, intelligent merging, and green wave passage optimize intelligent driving behaviors and enhance overall urban traffic efficiency. Under the APIR-APCV scenario, it is expected that a traffic efficiency benefit of 628.9 billion RMB will be accumulated from 2024 to 2050, which includes 604.5 billion RMB in travel time-saving benefits and 24.4 billion RMB in energy-saving benefits. This is higher than the 186.6 billion RMB cumulative traffic efficiency benefit in the NIR-NCV scenario, which includes 161.1 billion RMB in travel time-saving benefits and 25.5 billion RMB in energy-saving benefits. Fewer traffic accidents and more efficient traffic flow also imply different levels of fleet energy consumption and carbon emissions. In the APIR-APCV scenario, it is projected that a carbon emission reduction benefit of 2.66 billion RMB will be accumulated from 2024 to 2050, lower than the 2.82 billion RMB in the NIR-NCV scenario. This is primarily due to the increase in average vehicle speed as a result of improved traffic efficiency, leading to higher energy consumption per mile (especially as the penetration rate of NEVs increases, this energy consumption characteristic will be more pronounced). From the perspective of the incremental social cost of vehicle–road collaborative intelligence systems, it is estimated that the cumulative total cost for Beijing to deploy roadside intelligence infrastructure as planned from 2024 to 2050 (APIR) is 20.54 billion RMB, including 17.58 billion RMB in deployment costs and 2.96 billion RMB in energy consumption costs. It is expected that the cumulative incremental cost for Beijing to deploy in-vehicle networking terminals as planned (APCV) from 2024 to 2050 is 8.26 billion RMB, including 7.87 billion RMB in deployment costs and 390 million RMB in energy consumption costs. From the perspective of the social value of vehicle–road collaborative intelligence systems, the cost of deploying roadside intelligence infrastructure and in-vehicle networking terminals will generate approximately 20.8 times the incremental social comprehensive benefits. The social value of constructing vehicle–road collaborative intelligence systems is enormous. However, it is still necessary to fully match the deployment progress of roadside intelligence infrastructure with the loading progress of fleet networking terminals. If these two do not move in the same direction, the deployment penetration rate of in-vehicle networking terminals that do not meet expectations and the overly rapid deployment of intelligence infrastructure will both lead to varying degrees of waste of public resources, reducing their social value.

Policy suggestions and industry participant recommendations: Currently, the construction of the "Vehicle–road-Cloud Integration System" in China is still in its infancy, and the "fragmentation" of roadside intelligence infrastructure construction cannot support the large-scale application of autonomous driving technology and connected functions. This has resulted in a weak willingness of vehicle manufacturers to equip their products with in-vehicle networking terminals, with a predominant focus on single-vehicle intelligence technology routes. The government should lead industrial development from the perspective of enhancing social values such as traffic safety, efficiency, and carbon emission reductions. It should strengthen the construction of standard systems, accelerate the deployment of the C-V2X network environment, and prepare for the standardization and subsequent large-scale deployment of intelligence infrastructure. Considering the current low penetration rate of in-vehicle networking terminals, the government could prioritize intelligence infrastructure deployment and technological iteration in road scenarios with high usage intensity, such as urban expressways in Beijing, to avoid wasting of public resources. With the assistance of large-scale roadside intelligence infrastructure, vehicle manufacturers, in the development and design of intelligent vehicles, should fully integrate roadside perception, computing, and other external intelligence capabilities, actively deploy in-vehicle networking terminals, and provide the market with ICVs that have lower costs and superior performance, thereby accelerating their large-scale popularization and application. Technology companies with rich experience in big data and software algorithms need to develop cooperative perception algorithms and cooperative decision-making and planning algorithms that are oriented towards the vehicle–road collaborative technology route, providing technical support for vehicle manufacturers and government transportation departments.

This study has the following limitations. The penetration rates of intelligent vehicles in this study are based on the forecasts in the "Intelligent Connected Vehicle Technology Roadmap 2.0". These forecasts implicitly assume that the penetration rates of new intelligent vehicles of different levels remain constant across different vehicle–road intelligence deployment scenarios. In the actual industrial development and popularization of intelligent vehicles, the deployment of roadside intelligence infrastructure will enable users to achieve higher safety, efficiency, and energy-saving benefits from intelligent connected vehicles at a lower cost of vehicle intelligence, significantly enhancing the user value. This implies that users will have a higher willingness to purchase intelligent vehicles, and ultimately increase the penetration rate. In subsequent research, we plan to quantify the correlation between user value and the market penetration rate of intelligent vehicles, taking into full consideration the different penetration rates of intelligent vehicles corresponding to different intelligence deployment scenarios, thereby enabling a more accurate and systematic analysis of the social value generated by vehicle–road collaborative intelligence systems. Besides this, the service life of the roadside intelligence device is set at 7 years, with corresponding deployment costs and energy consumption costs taken into account in this study. The roadside device is replaced at the end of its lifecycle. Other potential cost factors, such as corresponding maintenance costs and technology upgrade costs, are not considered in this study.

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Appendix A

The average travel time per mile on urban expressways under different intelligence scenarios and various traffic flow rates (Q = 4486 pcu/h, Q = 5607 pcu/h, Q = 6728 pcu/h) is presented in Table A1, Table A2, and Table A3, respectively.

Table A1. Travel time per mile on urban expressways (Q = 4486 pcu/h).

	HV—Human-Driven	Single-Vehicle Intelligence	APCV—Collaborative Perception and Decision	LCV—Collaborative Perception and Decision
2024	63.88	57.84	49.54	57.67
2025	63.88	57.61	47.15	54.82
2026	63.88	55.78	45.91	52.11
2027	63.88	53.94	44.67	49.41
2028	63.88	52.10	44.05	47.48
2029	63.88	50.25	43.42	45.54
2030	63.88	49.83	43.24	44.79
2031	63.88	49.41	43.06	44.04
2032	63.88	48.79	42.79	43.55
2033	63.88	48.17	42.52	43.06
2034	63.88	48.02	42.30	42.78
2035	63.88	47.87	42.07	42.49
2036	63.88	47.49	41.84	42.13
2037	63.88	47.10	41.61	41.76
2038	63.88	47.07	41.49	41.65
2039	63.88	47.04	41.37	41.53
2040	63.88	46.89	41.30	41.38
2041	63.88	46.74	41.22	41.22
2042	63.88	46.50	41.15	41.15
2043	63.88	46.26	41.08	41.08
2044	63.88	46.05	41.02	41.02
2045	63.88	45.84	40.96	40.96
2046	63.88	45.70	40.91	40.91
2047	63.88	45.57	40.87	40.87
2048	63.88	45.54	40.86	40.86
2049	63.88	45.51	40.86	40.86
2050	63.88	45.36	40.86	40.86

Table A2. Travel time per mile on urban expressways (Q = 5607 pcu/h).

	HV—Human-Driven	Single-Vehicle Intelligence	APCV—Collaborative Perception and Decision	LCV—Collaborative Perception and Decision
2024	110.07	98.95	93.98	100.78
2025	110.07	100.77	90.23	99.19
2026	110.07	98.72	78.05	96.10
2027	110.07	96.66	65.87	93.02
2028	110.07	95.37	56.89	81.27
2029	110.07	94.07	47.92	69.53

Table A2. *Cont.*

	HV—Human-Driven	Single-Vehicle Intelligence	APCV—Collaborative Perception and Decision	LCV—Collaborative Perception and Decision
2030	110.07	93.43	46.78	59.51
2031	110.07	92.78	45.64	49.49
2032	110.07	90.66	44.93	47.61
2033	110.07	88.55	44.23	45.74
2034	110.07	82.94	43.72	45.02
2035	110.07	77.34	43.22	44.30
2036	110.07	77.39	43.13	43.71
2037	110.07	77.44	43.03	43.13
2038	110.07	73.26	42.77	42.91
2039	110.07	69.09	42.50	42.70
2040	110.07	67.15	42.37	42.47
2041	110.07	65.22	42.24	42.24
2042	110.07	64.23	42.04	42.04
2043	110.07	63.24	41.84	41.84
2044	110.07	59.81	41.60	41.60
2045	110.07	56.38	41.37	41.37
2046	110.07	58.19	41.19	41.19
2047	110.07	60.01	41.01	41.01
2048	110.07	57.34	41.01	41.01
2049	110.07	54.66	41.01	41.01
2050	110.07	56.15	41.01	41.01

Table A3. Travel time per mile on urban expressways (Q = 6728 pcu/h).

	HV—Human-Driven	Single-Vehicle Intelligence	APCV—Collaborative Perception and Decision	LCV—Collaborative Perception and Decision
2024	106.75	103.93	101.45	105.29
2025	106.75	107.95	99.54	105.16
2026	106.75	107.12	96.99	103.83
2027	106.75	106.29	94.45	102.49
2028	106.75	106.33	85.67	99.59
2029	106.75	106.37	76.89	96.70
2030	106.75	106.37	64.65	88.40
2031	106.75	106.37	52.42	80.11
2032	106.75	107.50	50.35	66.17
2033	106.75	108.63	48.27	52.23
2034	106.75	107.07	47.25	49.70
2035	106.75	105.50	46.22	47.18
2036	106.75	107.17	45.86	46.56
2037	106.75	108.84	45.51	45.95
2038	106.75	108.90	45.45	45.96
2039	106.75	108.96	45.38	45.97

Table A3. *Cont.*

	HV—Human-Driven	Single-Vehicle Intelligence	APCV—Collaborative Perception and Decision	LCV—Collaborative Perception and Decision
2040	106.75	110.43	44.62	44.91
2041	106.75	111.89	43.85	43.85
2042	106.75	113.71	43.91	43.91
2043	106.75	115.53	43.97	43.97
2044	106.75	119.22	43.16	43.16
2045	106.75	122.90	42.36	42.36
2046	106.75	126.58	42.38	42.38
2047	106.75	130.25	42.40	42.40
2048	106.75	133.72	42.14	42.14
2049	106.75	137.18	41.88	41.88
2050	106.75	127.87	41.88	41.88

The average power consumption per mile on urban expressways under different intelligence scenarios and various traffic flow rates (Q = 4486 pcu/h, Q = 5607 pcu/h, Q = 6728 pcu/h) is presented in Table A4, Table A5, and Table A6, respectively.

Table A4. Power consumption per mile on urban expressways (Q = 4486 pcu/h).

	HV—Human-Driven	Single-Vehicle Intelligence	APCV—Collaborative Perception and Decision	LCV—Collaborative Perception and Decision
2024	0.1380	0.1390	0.1402	0.1391
2025	0.1380	0.1352	0.1400	0.1383
2026	0.1380	0.1352	0.1392	0.1386
2027	0.1380	0.1352	0.1384	0.1390
2028	0.1380	0.1364	0.1377	0.1392
2029	0.1380	0.1376	0.1370	0.1395
2030	0.1380	0.1383	0.1373	0.1389
2031	0.1380	0.1389	0.1376	0.1382
2032	0.1380	0.1388	0.1376	0.1384
2033	0.1380	0.1387	0.1376	0.1385
2034	0.1380	0.1387	0.1376	0.1385
2035	0.1380	0.1386	0.1376	0.1385
2036	0.1380	0.1386	0.1379	0.1385
2037	0.1380	0.1385	0.1381	0.1385
2038	0.1380	0.1386	0.1382	0.1384
2039	0.1380	0.1387	0.1383	0.1384
2040	0.1380	0.1386	0.1385	0.1385
2041	0.1380	0.1385	0.1387	0.1387
2042	0.1380	0.1390	0.1386	0.1386
2043	0.1380	0.1395	0.1386	0.1386
2044	0.1380	0.1398	0.1385	0.1385
2045	0.1380	0.1400	0.1384	0.1384
2046	0.1380	0.1402	0.1384	0.1384

Table A4. *Cont.*

	HV—Human-Driven	Single-Vehicle Intelligence	APCV—Collaborative Perception and Decision	LCV—Collaborative Perception and Decision
2047	0.1380	0.1405	0.1384	0.1384
2048	0.1380	0.1405	0.1384	0.1384
2049	0.1380	0.1405	0.1384	0.1384
2050	0.1380	0.1403	0.1384	0.1384

Table A5. Power consumption per mile on urban expressways (Q = 5607 pcu/h).

	HV—Human-Driven	Single-Vehicle Intelligence	APCV—Collaborative Perception and Decision	LCV—Collaborative Perception and Decision
2024	0.1493	0.1632	0.1621	0.1628
2025	0.1493	0.1577	0.1582	0.1587
2026	0.1493	0.1541	0.1486	0.1507
2027	0.1493	0.1505	0.1391	0.1428
2028	0.1493	0.1431	0.1403	0.1355
2029	0.1493	0.1357	0.1415	0.1281
2030	0.1493	0.1298	0.1409	0.1345
2031	0.1493	0.1240	0.1403	0.1408
2032	0.1493	0.1231	0.1402	0.1411
2033	0.1493	0.1222	0.1401	0.1413
2034	0.1493	0.1227	0.1397	0.1410
2035	0.1493	0.1232	0.1393	0.1408
2036	0.1493	0.1240	0.1397	0.1406
2037	0.1493	0.1249	0.1401	0.1405
2038	0.1493	0.1273	0.1399	0.1401
2039	0.1493	0.1297	0.1397	0.1398
2040	0.1493	0.1307	0.1398	0.1399
2041	0.1493	0.1318	0.1400	0.1400
2042	0.1493	0.1327	0.1397	0.1397
2043	0.1493	0.1337	0.1394	0.1394
2044	0.1493	0.1356	0.1394	0.1394
2045	0.1493	0.1375	0.1393	0.1393
2046	0.1493	0.1378	0.1392	0.1392
2047	0.1493	0.1382	0.1390	0.1390
2048	0.1493	0.1384	0.1390	0.1390
2049	0.1493	0.1386	0.1390	0.1390
2050	0.1493	0.1394	0.1390	0.1390

Table A6. Power consumption per mile on urban expressways (Q = 6728 pcu/h).

	HV—Human Driven	Single-Vehicle Intelligence	APCV—Collaborative Perception and Decision	LCV—Collaborative Perception and Decision
2024	0.1740	0.1733	0.1734	0.1714
2025	0.1740	0.1652	0.1730	0.1674
2026	0.1740	0.1620	0.1685	0.1635

Table A6. *Cont.*

	HV—Human Driven	Single-Vehicle Intelligence	APCV—Collaborative Perception and Decision	LCV—Collaborative Perception and Decision
2027	0.1740	0.1588	0.1639	0.1597
2028	0.1740	0.1557	0.1536	0.1531
2029	0.1740	0.1527	0.1433	0.1465
2030	0.1740	0.1516	0.1431	0.1393
2031	0.1740	0.1506	0.1428	0.1322
2032	0.1740	0.1485	0.1428	0.1378
2033	0.1740	0.1464	0.1427	0.1433
2034	0.1740	0.1444	0.1427	0.1432
2035	0.1740	0.1425	0.1427	0.1431
2036	0.1740	0.1403	0.1428	0.1431
2037	0.1740	0.1382	0.1428	0.1432
2038	0.1740	0.1386	0.1423	0.1428
2039	0.1740	0.1389	0.1418	0.1425
2040	0.1740	0.1377	0.1417	0.1420
2041	0.1740	0.1364	0.1415	0.1415
2042	0.1740	0.1361	0.1410	0.1410
2043	0.1740	0.1358	0.1404	0.1404
2044	0.1740	0.1323	0.1403	0.1403
2045	0.1740	0.1288	0.1402	0.1402
2046	0.1740	0.1273	0.1402	0.1402
2047	0.1740	0.1257	0.1401	0.1401
2048	0.1740	0.1214	0.1401	0.1401
2049	0.1740	0.1171	0.1400	0.1400
2050	0.1740	0.1267	0.1400	0.1400

The average travel time per mile on urban main roads under different intelligence scenarios and various traffic flow rates (Q = 1650 pcu/h, Q = 2100 pcu/h) is presented in Tables A7 and A8, respectively.

Table A7. Travel time per mile on urban main roads (Q = 1650 pcu/h).

	HV—Human-Driven	Single-Vehicle Intelligence	APCV—Collaborative Perception and Decision	LCV—Collaborative Perception and Decision
2024	90.66	90.50	89.99	90.62
2025	90.66	90.70	89.79	90.46
2026	90.66	90.48	89.54	90.14
2027	90.66	90.25	89.29	89.83
2028	90.66	90.02	88.96	89.42
2029	90.66	89.80	88.64	89.01
2030	90.66	89.71	88.20	88.66
2031	90.66	89.63	87.77	88.30
2032	90.66	89.57	87.34	88.04
2033	90.66	89.52	86.91	87.77

Table A7. *Cont.*

	HV—Human-Driven	Single-Vehicle Intelligence	APCV—Collaborative Perception and Decision	LCV—Collaborative Perception and Decision
2034	90.66	89.52	86.79	87.22
2035	90.66	89.52	86.67	86.68
2036	90.66	89.32	86.24	86.38
2037	90.66	89.12	85.81	86.08
2038	90.66	89.21	85.82	85.99
2039	90.66	89.30	85.83	85.91
2040	90.66	89.11	85.75	85.79
2041	90.66	88.92	85.66	85.66
2042	90.66	88.77	85.66	85.66
2043	90.66	88.62	85.66	85.66
2044	90.66	88.90	85.45	85.45
2045	90.66	89.19	85.25	85.25
2046	90.66	89.10	85.13	85.13
2047	90.66	89.00	85.00	85.00
2048	90.66	89.03	85.03	85.03
2049	90.66	89.05	85.06	85.06
2050	90.66	88.76	85.06	85.06

Table A8. Travel time per mile on urban main roads (Q = 2100 pcu/h).

	HV—Human-Driven	Single-Vehicle Intelligence	APCV—Collaborative Perception and Decision	LCV—Collaborative Perception and Decision
2024	97.55	96.88	95.90	96.65
2025	97.55	96.66	95.32	97.06
2026	97.55	96.40	94.71	96.37
2027	97.55	96.14	94.10	95.67
2028	97.55	96.01	93.76	94.97
2029	97.55	95.88	93.43	94.27
2030	97.55	95.53	92.77	93.63
2031	97.55	95.19	92.11	92.98
2032	97.55	95.09	91.67	92.64
2033	97.55	94.99	91.22	92.30
2034	97.55	94.82	90.68	91.71
2035	97.55	94.65	90.14	91.11
2036	97.55	94.61	90.07	90.72
2037	97.55	94.57	90.01	90.34
2038	97.55	94.42	89.65	90.01
2039	97.55	94.26	89.29	89.69
2040	97.55	94.18	89.53	89.73
2041	97.55	94.11	89.77	89.77
2042	97.55	93.81	89.52	89.52
2043	97.55	93.51	89.27	89.27

Table A8. *Cont.*

	HV—Human-Driven	Single-Vehicle Intelligence	APCV—Collaborative Perception and Decision	LCV—Collaborative Perception and Decision
2044	97.55	93.66	89.44	89.44
2045	97.55	93.82	89.61	89.61
2046	97.55	93.68	89.42	89.42
2047	97.55	93.53	89.23	89.23
2048	97.55	93.47	89.27	89.27
2049	97.55	93.40	89.31	89.31
2050	97.55	93.46	89.31	89.31

The average power consumption per mile on urban main roads under different intelligence scenarios and various traffic flow rates (Q = 1650 pcu/h, Q = 2100 pcu/h) is presented in Tables A9 and A10, respectively.

Table A9. Power consumption per mile on urban main roads (Q = 1650 pcu/h).

	HV—Human-Driven	Single-Vehicle Intelligence	APCV—Collaborative Perception and Decision	LCV—Collaborative Perception and Decision
2024	0.2091	0.2100	0.2079	0.2101
2025	0.2091	0.2098	0.2081	0.2104
2026	0.2091	0.2098	0.2076	0.2104
2027	0.2091	0.2098	0.2071	0.2104
2028	0.2091	0.2102	0.2067	0.2094
2029	0.2091	0.2105	0.2063	0.2084
2030	0.2091	0.2103	0.2059	0.2078
2031	0.2091	0.2100	0.2055	0.2072
2032	0.2091	0.2103	0.2058	0.2072
2033	0.2091	0.2106	0.2062	0.2073
2034	0.2091	0.2107	0.2069	0.2076
2035	0.2091	0.2108	0.2076	0.2079
2036	0.2091	0.2111	0.2071	0.2076
2037	0.2091	0.2114	0.2065	0.2072
2038	0.2091	0.2115	0.2069	0.2070
2039	0.2091	0.2116	0.2073	0.2069
2040	0.2091	0.2118	0.2075	0.2073
2041	0.2091	0.2120	0.2077	0.2077
2042	0.2091	0.2116	0.2072	0.2072
2043	0.2091	0.2111	0.2068	0.2068
2044	0.2091	0.2119	0.2068	0.2068
2045	0.2091	0.2127	0.2068	0.2068
2046	0.2091	0.2125	0.2068	0.2068
2047	0.2091	0.2124	0.2068	0.2068
2048	0.2091	0.2129	0.2070	0.2070
2049	0.2091	0.2134	0.2071	0.2071
2050	0.2091	0.2113	0.2071	0.2071

Table A10. Power consumption per mile on urban main roads (Q = 2100 pcu/h).

	HV—Human-Driven	Single-Vehicle Intelligence	APCV—Collaborative Perception and Decision	LCV—Collaborative Perception and Decision
2024	0.2139	0.2139	0.2125	0.2141
2025	0.2139	0.2138	0.2117	0.2133
2026	0.2139	0.2141	0.2106	0.2136
2027	0.2139	0.2144	0.2094	0.2138
2028	0.2139	0.2143	0.2094	0.2127
2029	0.2139	0.2142	0.2094	0.2116
2030	0.2139	0.2136	0.2091	0.2110
2031	0.2139	0.2129	0.2088	0.2103
2032	0.2139	0.2134	0.2088	0.2103
2033	0.2139	0.2139	0.2089	0.2103
2034	0.2139	0.2130	0.2091	0.2106
2035	0.2139	0.2122	0.2092	0.2109
2036	0.2139	0.2131	0.2087	0.2102
2037	0.2139	0.2140	0.2082	0.2096
2038	0.2139	0.2143	0.2085	0.2096
2039	0.2139	0.2147	0.2088	0.2095
2040	0.2139	0.2150	0.2095	0.2099
2041	0.2139	0.2154	0.2102	0.2102
2042	0.2139	0.2147	0.2098	0.2098
2043	0.2139	0.2141	0.2094	0.2094
2044	0.2139	0.2146	0.2094	0.2094
2045	0.2139	0.2151	0.2095	0.2095
2046	0.2139	0.2150	0.2100	0.2100
2047	0.2139	0.2149	0.2105	0.2105
2048	0.2139	0.2146	0.2101	0.2101
2049	0.2139	0.2143	0.2097	0.2097
2050	0.2139	0.2147	0.2097	0.2097

References

1. The Central People's Government of the People's Republic of China. China's Automobile Production and Sales Volume Exceeded 30 Million Units for the First Time in 2023. Available online: https://www.gov.cn/yaowen/liebiao/202401/content_6925448.htm (accessed on 11 January 2024).
2. Ministry of Public Security of the People's Republic of China. The Total Number of Motor Vehicles in China Reached 435 Million in 2023. Available online: https://www.mps.gov.cn/n2254098/n4904352/c9384864/content.html (accessed on 11 January 2024).
3. National Bureau of Statistics of China. *China Statistical Yearbook 2023*; National Bureau of Statistics of China: Beijing, China, 2023.
4. Baidu Map. *China Urban Transportation Report 2023*; Baidu Map: Beijing, China, 2023.
5. China EV100. *Research on the Goal, Path and Policy of Achieving Carbon Peak and Carbon Neutrality in Collaboration with Automobiles, Transportation and Energy*; China EV100: Beijing, China, 2022.
6. China Industry Innovation Alliance for the Intelligent and Connected Vehicles. *Technology Roadmap for Intelligent & Connected Vehicles 2.0*; China Industry Innovation Alliance for the Intelligent and Connected Vehicles: Beijing, China, 2021.
7. Tan, H.; Zhao, F.; Zhang, W.; Liu, Z. An Evaluation of the Safety Effectiveness and Cost of Autonomous Vehicles Based on Multivariable Coupling. *Sensors* **2023**, *23*, 1321. [CrossRef] [PubMed]
8. Li, Y.; Li, Z.; Wang, H.; Wang, W.; Xing, L. Evaluating the safety impact of adaptive cruise control in traffic oscillations on freeways. *Accid. Anal. Prev.* **2017**, *104*, 137–145. [CrossRef] [PubMed]

9. Olia, A.; Razavi, S.; Abdulhai, B.; Abdelgawad, H. Traffic capacity implications of automated vehicles mixed with regular vehicles. *J. Intell. Transp. Syst.* **2018**, *22*, 244–262. [CrossRef]
10. Stogios, C.; Kasraian, D.; Roorda, M.J.; Hatzopoulou, M. Simulating impacts of automated driving behavior and traffic conditions on vehicle emissions. *Transp. Res. Part D Transp. Environ.* **2019**, *76*, 176–192. [CrossRef]
11. Song, H.; Zhao, F.; Zhu, G.; Liu, Z. Impacts of connected and autonomous vehicles with level 2 automation on traffic efficiency and energy consumption. *J. Adv. Transp.* **2023**, *2023*, 6348778. [CrossRef]
12. Milakis, D.; Van Arem, B.; Van Wee, B. Policy and society related implications of automated driving: A review of literature and directions for future research. *J. Intell. Transp. Syst.* **2017**, *21*, 324–348. [CrossRef]
13. Qiu, L.; Qian, L.; Abdollahi, Z.; Kong, Z.; Pisu, P. Engine-map-based predictive fuel-efficient control strategies for a group of connected vehicles. *Automot. Innov.* **2018**, *1*, 311–319. [CrossRef]
14. Li, K.; Dai, Y.; Li, S.; Bian, M. State-of-the-art and technical trends of intelligent and connected vehicles. *J. Automot. Saf. Energy* **2017**, *8*, 1–14.
15. Institute for AI Industry Research of Tsinghua University. *Key Technologies and Developing Prospect of Vehicle Infrastructure Cooperated Driving (VICAD)2.0*; Institute for AI Industry Research of Tsinghua University: Beijing, China, 2022.
16. Schaudt, W.A.; Bowman, D.S.; Hanowski, R.J.; Olson, R.L.; Marinik, A.; Soccolich, S.; Joslin, S.; Toole, L.; Rice, J.C. *Federal Motor Carrier Safety Administration's Advanced System Testing Utilizing a Data Acquisition System on the Highways (FAST DASH): Safety Technology Evaluation Project #1 Blindspot Warning, Field Studies*; Federal Motor Carrier Safety Administration: Washington, DC, USA, 2014.
17. Haus, S.H.; Sherony, R.; Gabler, H.C. Estimated benefit of automated emergency braking systems for vehicle–pedestrian crashes in the United States. *Traffic Inj. Prev.* **2019**, *20* (Suppl. 1), S171–S176. [CrossRef] [PubMed]
18. Anderson, R.; Hutchinson, T.; Linke, B.; Ponte, G. *Analysis of Crash Data to Estimate the Benefits of Emerging Vehicle Technology*; Centre for Automotive safety Research, The University of Adelaide: Adelaide, Australia, 2010.
19. Guériau, M.; Billot, R.; El Faouzi, N.-E.; Monteil, J.; Armetta, F.; Hassas, S. How to assess the benefits of connected vehicles? A simulation framework for the design of cooperative traffic management strategies. *Transp. Res. Part C Emerg. Technol.* **2016**, *67*, 266–279. [CrossRef]
20. Rommerskirchen, C.; Helmbrecht, M.; Bengler, K. Increasing complexity of driving situations and its impact on an ADAS for anticipatory assistance for the reduction of fuel consumption. In Proceedings of the 2013 IEEE Intelligent Vehicles Symposium (IV), Gold Coast, Australia, 23–26 June 2013; IEEE: New York, NY, USA, 2013; pp. 573–578.
21. Vahidi, A.; Sciarretta, A. Energy saving potentials of connected and automated vehicles. *Transp. Res. Part C Emerg. Technol.* **2018**, *95*, 822–843. [CrossRef]
22. Juan, Z.; Wu, J.; Mike, M. Socio-economic impact assessment of intelligent transport systems. *Tsinghua Sci. Technol.* **2006**, *11*, 339–350. [CrossRef]
23. Farooq, U.; Hardy, J.L.; Gao, L.; Siddiqui, M.A. Economic Impact/Forecast Model of Intelligent Transportation Systems in Michigan: An Input Output Analysis. *J. Intell. Transp. Syst.* **2008**, *12*, 86–95. [CrossRef]
24. Grant-Muller, S.; Usher, M. Intelligent Transport Systems: The propensity for environmental and economic benefits. *Technol. Forecast. Soc. Change* **2014**, *82*, 149–166. [CrossRef]
25. He, J.; Zeng, Z.; Li, Z. Benefit Evaluation Framework of Intelligent Transportation Systems. *J. Transp. Syst. Eng. Inf. Technol.* **2010**, *10*, 81–87. [CrossRef]
26. Kuang, X. *Research on the Benefits and Business Models of Intelligent Connected Vehicles*; Tsinghua University: Beijing, China, 2019.
27. The People's Government of Beijing Municipality. Beijing Statistical Bulletin of National Economic and Social Development in 2023. The People's Government of Beijing Municipality. Available online: https://www.beijing.gov.cn/zhengce/zhengcefagui/202403/t20240321_3596451.html (accessed on 21 March 2024).
28. Zhu, G.; Zhao, F.; Song, H.; Zhang, W.; Liu, Z. Research on Vehicle-Road Intelligent Capacity Redistribution and Cost Sharing in the Context of Collaborative Intelligence. *Appl. Sci.* **2024**, *14*, 7286. [CrossRef]
29. China EV100. *Smart City Infrastructure and Intelligent Connected Vehicle Collaborative Development Annual Research Report*; China EV100: Beijing, China, 2022.
30. China Industry Innovation Alliance for the intelligent and Connected Vehicles. *C-V2X Industrialization Path and Schedule Research White Book*; China Industry Innovation Alliance for the intelligent and Connected Vehicles: Beijing, China, 2019.
31. Ministry of Industry and Information Technology of the People's Republic of China. *Intelligent Connected Vehicle Technology Roadmap 2.0*; Ministry of Industry and Information Technology of the People's Republic of China: Beijing, China, 2020.
32. Tan, H. *Research on the Safety Benefits and Cost of Autonomous Vehicles Based on Miltivariable Coupling*; Tsinghua University: Beijing, China, 2023.
33. Zhu, G.; Zhao, F.; Song, H.; Liu, Z. Cost Analysis of Vehicle-Road Cooperative Intelligence Solutions for High-Level Autonomous Driving: A Beijing Case Study. *J. Adv. Transp.* **2024**, *2024*, 6170743. [CrossRef]

34. Ministry of Public Security of the People's Republic of China. *The Road Accident Statistical Annual Report of China (2019)*; Ministry of Public Security of the People's Republic of China: Beijing, China, 2020.
35. McMahon, K.; Dahdah, S. *The True Cost of Road Crashes: Valuing Life and the Cost of A Serious Injury*; iRAP: London, UK, 2008.
36. U.S. Department of Transportation. *Treatment of the Value of Preventing Fatalities and Injuries in Preparing Economic Analyses*; U.S. Department of Transportation: Washington, DC, USA, 2015.
37. China Population and Development Research Center. *China Health Yearbook in 2022*; China Population and Development Research Center: Beijing, China, 2023.
38. Song, H.; Zhao, F.; Zhu, G.; Zhang, H.; Liu, Z.; Li, M.E. Evaluation of Traffic Efficiency and Energy-Saving Benefits of L3 Smart Vehicles under the Urban Expressway Scenario. *Sustainability* **2024**, *16*, 4125. [CrossRef]
39. *GB/T 51328-2018*; Urban Comprehensive Transportation System Planning Standard. The Standardization Administration of the People's Republic of China: Beijing, China, 2018.
40. Yu, L.; Song, G. *Urban Traffic Flow Theory*; Beijing Jiaotong University Press: Beijing, China, 2016.
41. Dai, S.; Liu, J.; Zhao, L. *Research Report on Metropolis's Road Traffic Development in China*; China Communication Press: Beijing, China, 2020.
42. Liu, X. *Research on Evaluation Methods and Eelection Strategies of Vehicle Multi-Power Source Coupling Technology Solutions*; Tsinghua University: Beijing, China, 2024.
43. Global Petrol Prices. Gasoline Price in China. Available online: https://www.globalpetrolprices.com/gasoline_prices/ (accessed on 25 November 2024).
44. Zhang, H. *Life Cycle Carbon Emission Analysis of Intelligence Electric Passenger Vehicles in China*; Tsinghua University: Beijing, China, 2024.
45. Zhang, X.; Huang, X.; Zhang, D. Research on the Pathway and Policies for China's Energy and Economy Transformation toward Carbon Neutrality. *Manag. World* **2022**, *38*, 35–66.
46. Intergovernmental Panel on Climate Change. *IPCC Guidelines for National Greenhouse Gas Inventories*; IPCC: Geneva, Switzerland, 2006.
47. Burnham, A. *Updated Vehicle Specifications in the GREET Vehicle-Cycle Model*; Argonne National Laboratory: Lemont, IL, USA, 2012.