applied sciences

MDPI

Article

Feature Identification, Solution Disassembly and Cost Comparison of Intelligent Driving under Different Technical Routes

Zongwei Liu [1,2], Wang Zhang [1,2], Hong Tan [1,2] and Fuquan Zhao [1,2,*]

[1] State Key Laboratory of Automobile Safety and Energy, Tsinghua University, Beijing 100084, China
[2] Tsinghua Automotive Strategy Research Institute, Tsinghua University, Beijing 100084, China
[*] Correspondence: zhaofuquan@tsinghua.edu.cn

Abstract: Technical route decision making of intelligent driving has always been the focus of attention of automotive enterprises and even the industry. Firstly, this study combs the main technical routes of intelligent driving at different levels from three dimensions: development strategy, intelligence allocation and sensor combination. Then, the methodology of technical component combination is designed to disassemble different technical routes into corresponding technical component combinations. Finally, an improved evaluation model of total cost of ownership of intelligent driving is developed and the total cost of ownership of intelligent driving system under different technical routes is compared. For the development strategy, even if the function superposition can follow some research and development achievements of low-level intelligent driving, scenario-driven is still the option with lower cost and better sustainability. For intelligence allocation, collaborative intelligence can effectively reduce the cost of the vehicle compared with single-vehicle intelligence by up to 46%, but the cost reduction depends on the original on-board hardware. For sensor combination, the multi-source fusion always has the cost advantage compared with vision-only, but the advantage is more obvious in the medium-level and high-level stage of single-vehicle intelligence.

Keywords: intelligent driving; technical routes; combination of technical components; total cost of ownership

check for updates

Citation: Liu, Z.; Zhang, W.; Tan, H.; Zhao, F. Feature Identification, Solution Disassembly and Cost Comparison of Intelligent Driving under Different Technical Routes. *Appl. Sci.* **2023**, *13*, 4361. https://doi.org/10.3390/app13074361

Academic Editors: Xiaojun Tan and Yi Han

Received: 26 February 2023
Revised: 18 March 2023
Accepted: 28 March 2023
Published: 29 March 2023

1. Introduction

Intelligent driving is gradually entering human society and becoming one of the standard functions of automobiles [1]. The first thing to be clearly defined is that intelligent driving and self-driving are not the same concept. Automation is only a main external feature of intelligent driving, and the external features of intelligent driving can also include networking, multi-agent collaboration, personalized driving experience and so on. In addition, intelligent driving also includes some internal features, such as digitalization of hardware and intelligence of software. At present, the industry usually uses the J3016 standard of the Society of Automotive Engineers (SAE) to divide intelligent driving into five levels [2]. L1 and L2 are assistant driving systems, which are driven by drivers. At this stage, machines assist human beings in perception, decision making and execution. L3 is a conditional automatic driving system, which is jointly controlled by the driver and machine. When the machine cannot handle the driving scenario, the driver needs to complete the takeover. L4 and L5 are advanced automatic driving systems driven by machines, which can achieve the minimum risk in most cases. Intelligent driving involves complex technological groups, not only of different levels, but also with different technical routes in different regions and different enterprises. Some technical routes are controversial. For example, whether the development of intelligent driving should skip L3 [3], whether intelligent driving above L3 must require lidar [4], whether intelligent driving should make vehicles, roadside infrastructure and cloud collaborate through vehicle-to-everything (V2X) [5], and so on.

The improvement of intelligence level is undoubtedly the main evolutionary direction of intelligent driving, but how to choose a technical route that can help products penetrate the market quickly is also a topic worthy of attention by the government and original equipment manufacturers (OEMs). According to the theory of technology diffusion, technological feasibility and legal permission can only help intelligent driving penetrate the market in the early stage [6]. Intelligent driving needs to be widely accepted by consumers if it is to be popularized. Some studies have investigated consumers' willingness to purchase various vehicle automation functions [7]. There are many factors that affect purchase decisions, but almost all studies have emphasized consumers' emphasis on economy. Shabanpour et al. [8] found that people are more sensitive to the purchase price of intelligent driving than other factors such as fuel efficiency, safety or environmental friendliness. According to a multinational survey, Chinese, German and American consumers are willing to pay USD 4600, USD 2900 and USD 3900, respectively, for autonomous driving [9]. If the cost exceeds consumers' willingness to pay, intelligent driving will be difficult to promote quickly. Although many technical routes have the possibility of achieving full self-driving, different technical routes determine the cost competitiveness of future intelligent driving products. For example, Tesla only uses cameras as sensors, which allows it to have stronger price adjustment ability in market competition. Therefore, OEMs must consider the cost characteristics of different technical routes when making technical strategic decisions. Moreover, because the government needs to formulate industrial policies to promote new technologies, it may also show some preference for low-cost technical routes [10]. For these reasons, it is necessary to evaluate the cost of intelligent driving systems under different technical routes.

Some scholars have studied the economy of intelligent driving [11–17]. All these studies adopt the total cost of ownership (TCO) analysis. TCO is the sum of all costs related to buying a car and driving it during the period of owning it. This technique is mainly used to compare the relative economic advantages of different competing technologies. Bösch et al. [11] introduced self-driving cars into the urban transportation system to calculate the total travel cost and TCO of self-driving cars in the future. There are many similar studies. Abe [12] discussed the influence of urban density and public transportation on the total travel cost and TCO. Turoń [13] used dynamic parameters such as the share of self-driving fleets and the demand for self-driving travel in the TCO analysis method. However, these studies all evaluate the cost from the perspective of consumer payment, so the intelligent driving system is packaged and there is no analysis of technical details. In addition, their research boundaries are also vague. These limitations lead to the distortion or idealization of the TCO of intelligent driving, which is seriously inconsistent with the real world. There is also more specific research on technical details. Bailo et al. [14] systematically analyzed the composition of TCO of intelligent driving from the perspectives of suppliers, OEMs and consumers, which were mainly divided into acquisition cost and use cost. They also discussed the importance and sensitivity of various costs under different research boundaries. On this basis, by building an intelligent driving system from bottom to top on a battery electric platform and evaluating its TCO, Ongel et al. [15] find that, although the acquisition cost of intelligent electric vehicles is higher than that of traditional electric vehicles, the TCO can be reduced by 75%. Their study shows a complete TCO analysis framework and process of intelligent driving, but it only evaluates the cost of a specific intelligent driving solution and compares it with traditional vehicles, rather than analyzing the cost differences within the intelligent driving technical group. Wadud [16] compared the TCO of autonomous passenger cars and autonomous commercial vehicles and found that full automation may reduce the TCO of passenger cars by about 30% and trucks by 20%. In his research, the technical solutions of intelligent driving are different due to the vehicle sizes. However, the difference in this technical solution only involves the number and layout of sensors, and it does not involve the dispute of the technical route, which is of little help to guide OEM development. Tan et al. [17] analyzed fourteen kinds of atomic sensing technologies on the vehicle and the roadside of intelligent driving, and obtained the optimal combination solution of atomic sensing technologies under safety constraints through the screening of full permutation combination algorithm. The granularity of this research is refined to the technical components of the vehicle and the roadside. However, the cost analysis in this study only focuses on the life cycle cost of the sensors, ignoring the software cost, use cost and hardware cost of computers, actuators and other components. Moreover, the discussion of different technical solutions in this study is limited to the combination of atomic sensing technologies on the vehicle and the roadside. There is no technical route dispute involving other dimensions. As can be understood from the above literature, previous studies have often paid more attention to the life cycle cost of hardware while ignoring the software and data. It should be emphasized that the value proportion of software in vehicles is increasing. Liu et al. [18] believe that in the future, software components will constitute a central general operating system, which may eventually account for 20–40% of the automobile value.

The purpose of this study is to compare the cost of intelligent driving systems under different technical routes from a more objective and accurate technical perspective to provide a quantitative reference for intelligent driving technical route decision making. The remainder of this study is organized as follows. Firstly, it combs the main technical routes of intelligent driving at different levels from different dimensions. Thereafter, the methodology of technical component combination is designed to disassemble different technical routes into corresponding technical component combinations. Next, this study develops the evaluation model of the TCO of intelligent driving systems and analyzes the TCO of different technical routes based on the technical component combinations. Finally, implications to OEMs and governments in choosing the intelligent driving technical route are drawn.

2. Feature Identification of Intelligent Driving Technical Routes

This study further integrates this classification according to the intelligence level of the system, with L1 and L2 as low-level intelligent driving, L3 as medium-level intelligent driving and L4 and L5 as high-level intelligent driving. The dividing line between the low- and medium-level lies in whether the driver is allowed to leave the steering wheel with both hands in the operational design domain (ODD) [19]. The dividing line between the medium- and high-level lies in whether the ODD can cover all daily travel scenarios and the system can automatically reach the minimum risk state, which will allow the steering wheel and brake in the cockpit to be cancelled [20]. The ODD of medium-level intelligent driving can be divided into simple scenarios and complex scenarios. Simple scenarios are characterized by no or few pedestrians, and usually include parking lots, closed parks, highways, etc. Complex scenarios are characterized by a large number of pedestrians and a complex traffic environment, usually including urban roads, congested road sections, etc. [21]. One of the performance goals of improving intelligent driving ability is that the system can handle more complex scenarios. However, the simpler the scenario, the more it can give full play to the function of intelligent driving by reducing human intervention [22].

In this section, based on the development logic of intelligent driving systems, the main controversial points in the development strategy, intelligence allocation and sensor combination are combed.

2.1. Development Strategy

The development of intelligent driving systems can be based on two strategies [23]. Following different development strategies, the same function will lead to different technical compositions and product forms.

The first strategy is called function superposition. Its development principle is to take the function of an advanced driving assistance system (ADAS) as the guide, develop different technical packages for different functions, pursue the realization of each function and achieve higher level intelligence through the combination and superposition of functions.

The product design under this strategy focuses on the marginal benefit and cost of a single new function and tends to pursue the function combination with the best cost performance.

The second strategy is called scenario-driven. Its development principle is to break up and reorganize the basic ADAS functions and to develop overall solutions for different scenarios by reshaping the electronic and electrical architecture. The product design under this strategy focuses on the application value in different scenarios and tends to pursue the best scenario experience and the lowest cost.

2.2. Intelligence Allocation

Intelligent driving requires enough hardware to provide perception and computational capacity, some of which can be mounted on vehicles, the roadside or the cloud [24].

The solution whereby all hardware is mounted on the car is called single-vehicle intelligence, and its advantages are a lower system complexity and more controllable network security. However, this solution may also have an upper limit on performance, such as for perception range. In addition, this solution will undoubtedly make consumers pay higher costs.

The solution of realizing intelligent driving through vehicle–road–cloud collaboration is called collaborative intelligence, which can not only transfer some hardware costs to public infrastructure, but also better integrate with other technical systems such as smart transportation and smart cities [25].

China has long decided on the technical roadmap for developing collaborative intelligence [1], and the European Union and the United States are also increasing their investment in intelligent road traffic infrastructure. However, from the perspective of products, single-vehicle intelligence still has great market potential and space to develop, especially against the background of long deployment periods, large investment and inconsistent standards of infrastructure.

2.3. Sensor Combination

Intelligent driving environment sensors mainly include cameras, millimeter wave (MMW) radars and lidar. Two technical routes have been developed around sensor combinations in the industry; one is "multi-source fusion", adopted by most automotive enterprises, and the other is "vision-only", represented by Tesla. Recently, Toyota also announced that it will adopt "vision-only" to develop high-level intelligent driving, which adds another uncertainty to the technical route dispute.

The multi-source fusion route is based on the combination of heterogeneous sensors to form a strong perception ability to handle complex scenarios. MMW radars provide stable ranging capability, the camera provides accurate recognition capability, and lidar provides rich 3D details. The combination of the three makes the system have better security redundancy. Some researchers believe that multi-source fusion is the best perception solution because it physically breaks through the limitations of human perception and gives the system the ability to perceive the environment from more dimensions [26].

The vision-only route is only equipped with cameras on the vehicle. Tesla researchers believe that the logic of visual perception fits the human eye and brain, and it is suitable for realizing high-level artificial intelligence through convolution neural networks and deep learning. The features of low cost, mature technology and uniform data format also make vision-only easier to realize productization. However, some researchers believe that cameras are easily interfered with by the environment, so their reliability is not ideal, and there are extreme cases that are difficult to handle [27].

2.4. Main Technical Routes of Intelligent Driving at Different Levels

As shown in Figure 1, the prominence of technical controversial points is different at different levels of intelligent driving systems, so the main technical routes of intelligent driving at different levels can be identified.

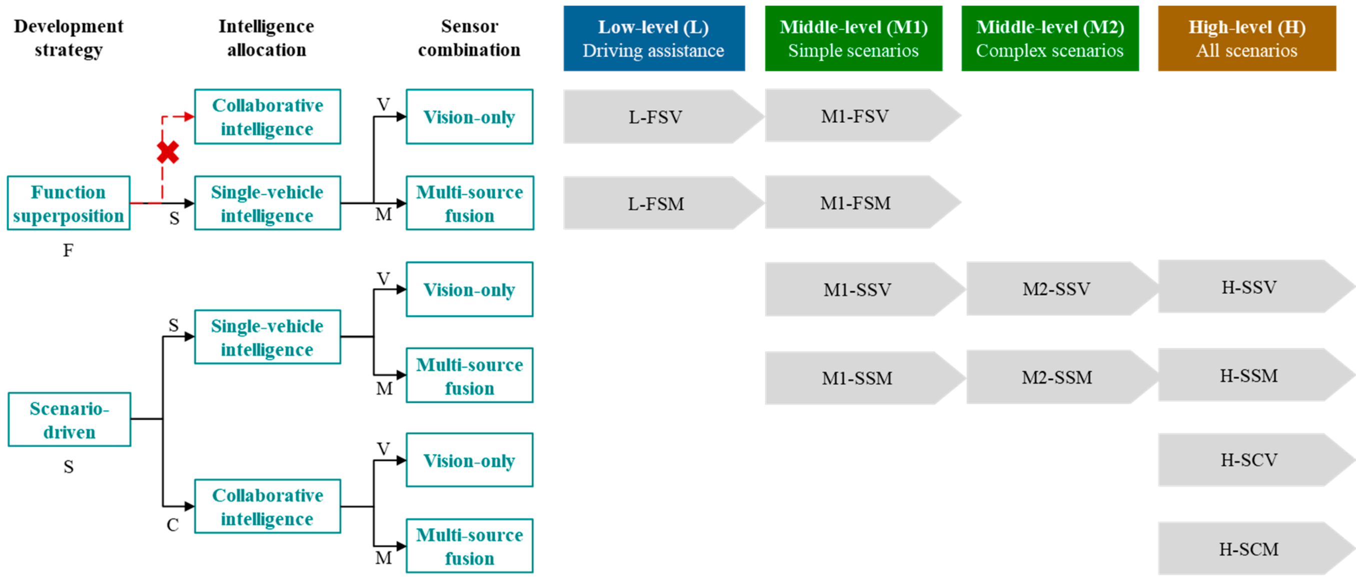

Figure 1. Main technical routes of intelligent driving at different levels.

For low-level intelligent driving, due to the ease of research and development, most products on the market develop the ADAS based on a function superposition strategy. In the intelligence allocation dimension, because collaborative intelligence technology is still immature, single-vehicle intelligence is still the only choice. Therefore, sensor combination has become the main technical dispute at this stage, and two technical routes of low-level intelligent driving, "L-FSV" and "L-FSM", are identified.

For medium-level intelligent driving, conditional automatic driving in simple scenarios, such as parking and closed road cruising, can be realized by adopting the function superposition strategy, but complex scenarios, such as urban road cruising, must be based on the scenario-driven strategy. In the intelligence allocation dimension, the scenario feature of medium-level intelligent driving means that the collaborative intelligence route will lead to frequent degradation of functions, which is extremely unfriendly to the user experience, so single-vehicle intelligence is still the best choice [28]. Similar to the low-level, medium-level intelligent driving is also faced with the choice of using vision-only and multi-source fusion. The difference is that the medium level can use lidar, while the low level usually does not. Therefore, six technical routes of medium-level intelligent driving are identified, including "M1-FSV", "M1-FSM", "M1-SSV", "M1-SSM", "M2-SSV" and "M2-SSM".

For high-level intelligent driving, the system complexity requires that it must be based on a scenario-driven strategy to solve the long tail problem of most extreme cases through continuous data accumulation [23]. At this stage, considering intelligence allocation has the real application value and there are still differences in sensor combinations between vision-only and multi-source fusion routes. Therefore, four technical routes of high-level intelligent driving are identified, including "H-SSV", "H-SSM", "H-SCV" and "H-SCM".

Behind every technical dispute lies the difference in the TCO of intelligent driving. In the development strategy dimension, each function in function superposition has its own hardware and software, while the scenario-driven option can effectively improve the integration of functions to reduce system redundancy and cost [29]. In the intelligent allocation dimension, collaborative intelligence allows some sensing and decision-making tasks to be transferred to the environment outside the vehicle, so the on-board hardware can be appropriately reduced, and the software may be more complex, which will change the cost. In the sensor combination dimension, the cost of lidar is more expensive than that of the camera, and the type and number of sensors will have a great impact on the cost. Therefore, in order to evaluate the cost difference between different technical routes more accurately, the specific technical solutions must be disassembled to the components for analysis.

3. Solution Disassembly of Intelligent Driving Technical Routes

The intelligent driving solution corresponding to each technical route consists of a series of technical components. The difference in the types and numbers of technical components is the main source of the cost difference between different technical routes. In this section, all the smallest functional units related to intelligent driving with separate costs are sorted out as a set of technical components. According to the requirements and characteristics of different technical routes, the necessary technical components in the set are selected and combined to form a complete intelligent driving system. In this way, the intelligent driving solutions of different technical routes are disassembled into multiple technical components.

3.1. Technical Components of Intelligent Driving

Table 1 shows the technical components of intelligent driving, including sensors, computers, actuators and communicators. This study mainly combed the incremental components from human driving to intelligent driving and fully considered the evolution trend of various technical components.

Table 1. Technical components of intelligent driving.

Category	Components
Sensors	• Camera (2 MP, 8 MP and 12 MP) • Millimeter-wave radar (short-range, long-range, 4D-imaging) • Lidar (mechanical, hybrid solid-state, solid-state) • Ultrasonic radar • High precision locator (meter, decimeter, centimeter) • Micro-electromechanical system
Computers	• Electronic control unit • Domain control unit • Central computer
Actuators	• Braking system (electric power-assisted, wire-controlled) • Steering system (electric power-assisted, wire-controlled)
Communicators	• Telematics BOX (4G-V2X, 5G-V2X)

The accuracy of sensors will continue to increase; for example, vehicles will be equipped with cameras with higher pixels and locators with smaller errors. In addition, sensors will have richer functions; for example, MMW radars will be able to achieve 4D imaging [30]. Considering the technology with lower cost, hybrid solid-state lidar and solid-state lidar will replace mechanical lidar in the future [31].

With the increase of sensors, the on-board computational capacity needs to be increased, which will further promote the centralization of the electronic and electrical architecture of the whole vehicle [32]. For the intelligent driving system developed based on the function superposition strategy, the control can be completed by the combination of several electronic control units (ECUs) with low computational capacity. For the intelligent driving system developed based on the scenario-driven strategy, all relevant data must be integrated, and a domain control unit (DCU) or even a central computer with higher computational capacity is needed to complete the data processing.

For actuators, electric power-assisted actuators have been widely used in ADAS, and the wire-controlled chassis with faster response speed and higher safety is considered the foundation of medium-level and high-level intelligent driving [33]. For communicators, a T-BOX based on 4G-V2X is sufficient to meet the common networking needs. However, to realize collaborative intelligence, vehicles need to communicate with roadside devices and the cloud, so 5G-V2X with higher broadband and more connections becomes a necessary choice. It should be noted that the cost of roadside and cloud equipment needed for collaborative intelligence should be borne by public finance, which will not directly affect the TCO of vehicles. Therefore, this study did not take these components into consideration. Liu et al. evaluated the cost of the intelligent upgrade of transportation infrastructure for intelligence-connected vehicles, which can be used as a supplement.

3.2. Methodology of Technical Component Combination

This study has designed a methodology of technical component combination from technical components to complete solutions. Table 2 shows the combination constraint principles, considering the compatibility, coherence, reusability and substitution of technical components.

Table 2. Combination constraints of technical components.

Attribute	Constraint Principle
Technical compatibility	• Sensors that collect different parameters are independent of each other. • Sensors, computers, actuators and communicators are not mutually exclusive.
Technical coherence	• The total perception ability is proportional to the total decision-making ability. • Communication ability meets the timeliness requirements of perception and decision coordination. • Some technical components have a fixed collocation relationship, such as related hardware in a high-precision locator.
Technical reusability	• Sensors can be reused by functions with the same parameter requirements. • The components related to high security or special use are not reusable.
Technical substitution	• For the sensors that collect the same parameters, the components with higher performance can replace the components with lower performance. • Redundant components do not change the normal realization effect of functions.

Based on the technical components and their combination constraints, the author and the invited technical experts in the automotive industry jointly screened and determined the combination solutions of intelligent driving technical components of different technical routes according to the process shown in Figure 2. The core idea of the process is to realize the full coverage and security redundancy of all functional requirements based on the first principle and the minimum change principle, taking the representative solution of industrial practice as the benchmark. Sensors and actuators are first determined, and the first technical constraint review focuses on the combination of sensors. According to the combination of sensors, the total computational capacity required by the system is evaluated, and then the on-board computers and communicator are matched according to the allocation of intelligence inside and outside the vehicle. Finally, the combination of all technical components goes through the second technical constraint review and expert review.

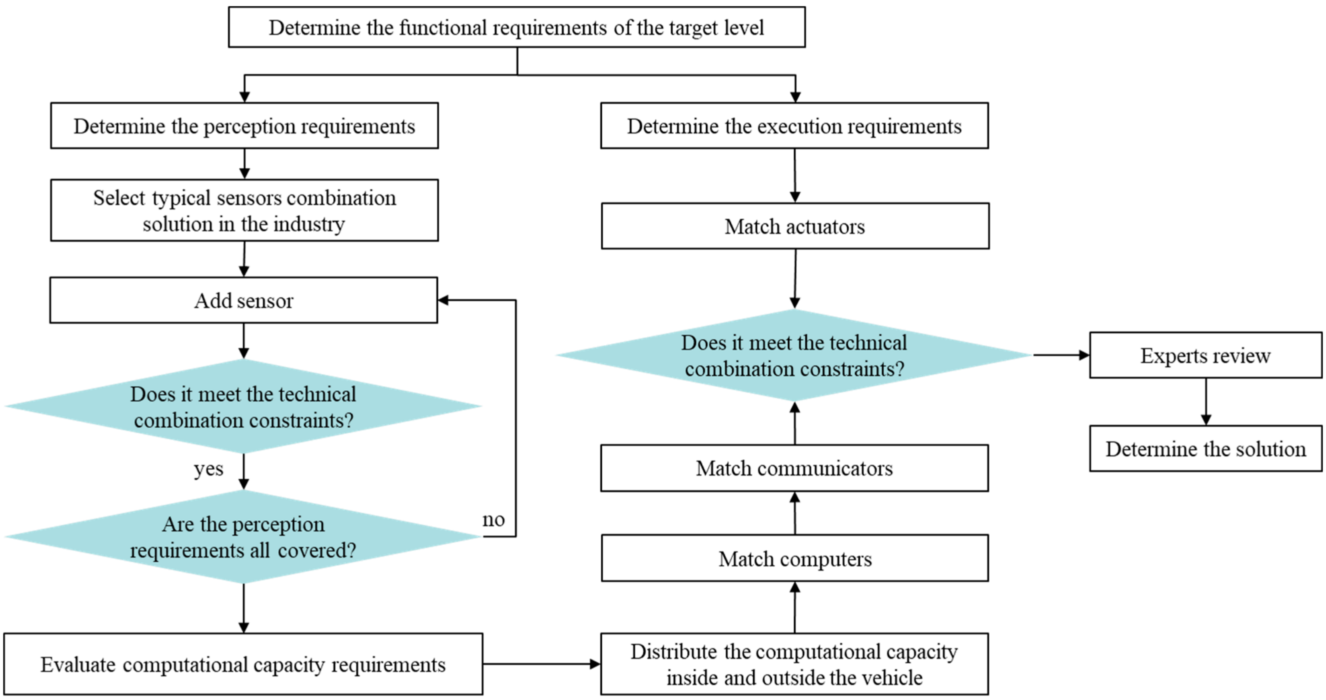

Figure 2. Combination process of the technical components of intelligent driving.

3.3. *Technical Component Combinations under Different Technical Routes*

Table 3 shows the combination solutions of technical components under different technical routes. The main difference between the two technical routes of low-level intelligent driving is the number of cameras and MMW radars. This study aims to compare it with the medium- and high-level systems, so as to provide a reference for OEMs. Compared with low-level systems, the actuators of medium-level systems need to be upgraded to the wire-controlled chassis. Among the different technical routes of medium-level intelligent driving, M1-FSV and M1-FSM with function superposition strategy will adopt the same distributed electronic and electrical architecture as the low-level system, and lidar will only adopt ordinary mechanical lidar. M1-SSV, M1-SSM, M2-SSV and M2-SSM with a scenario-driven strategy can be regarded as the phased achievements of the research and development (R&D) of high-level systems, so they will adopt more centralized domain architecture and higher performance hardware, such as 4D-imaging radar, hybrid-solid lidar, decimeter-level locator and DCU. The hardware of the high-level system needs further upgrades and redundant backup. In addition to the increase in the number of sensors, 12 MP cameras, centimeter-level locators, solid lidar and a central computer will be mounted on the bus. Horizontally, compared with single-vehicle intelligence, collaborative intelligence needs to adopt 5G technology in the communicator.

Table 3. Disassembly of technical components of intelligent driving under different technical routes.

Component	L-FSV	L-FSM	M1-FSV	M1-FSM	M1-SSV	M1-SSM	M2-SSV	M2-SSM	H-SSV	H-SSM	H-SCV	H-SCM
Camera	9*2 MP	5*2 MP	13*2 MP 3*8 MP	6*2 MP 3*8 MP	7*2 MP 3*8 MP	5*2 MP 2*8 MP	12*2 MP 3*8 MP	5*2 MP 2*8 MP	8*2 MP 4*8 MP 2*12 MP	4*2 MP 1*8 MP 2*12 MP	6*2 MP 3*8 MP 2*12 MP	4*2 MP 1*8 MP 2*12 MP
MMW radar	—	4*short-range	—	2*long-range 4*short-range	—	1*long-range 4*short-range	—	1*4D-imaging 1*long-range 4*short-range	—	1*4D-imaging 2*long-range 4*short-range	—	2*long-range 4*short-range
Lidar	—	—	—	1*mechanical	—	1*mechanical	—	1*mechanical 2*hybrid-solid	—	2*hybrid-solid 4*solid-state	—	2*solid-state
Ultrasonic radar	12	8	12	8	12	8	12	4	—	—	—	—
HD-Map	1*meter-level	1*meter-level	1*meter-level	1*meter-level	1*meter-level	1*meter-level	1*decimeter-level	1*decimeter-level	1*centimeter-level	1*centimeter-level	1*centimeter-level	1*centimeter-level
MEMS	2	2	3	3	3	3	3	3	4	4	4	4
Computer	3*ECU	3*ECU	3*ECU	3*ECU	2*DCU	2*DCU	2*DCU	2*DCU	1*central (256 TOPS)	1*central (1024 TOPS)	1*central (128 TOPS)	1*central (256 TOPS)
Actuators	1*electric power steering 1*electric power braking	1*electric power steering 1*electric power braking	1*wire-controlled steering 1*wire-controlled braking	1*wire-controlled steering 1*wire-controlled braking	1*wire-controlled steering 1*wire-controlled braking	1*wire-controlled steering 1*wire-controlled braking	1.5*wire-controlled steering 1.5*wire-controlled braking	1.5*wire-controlled steering 1.5*wire-controlled braking	2*wire-controlled steering 2*wire-controlled braking	2*wire-controlled steering 2*wire-controlled braking	2*wire-controlled steering 2*wire-controlled braking	2*wire-controlled steering 2*wire-controlled braking
Communicator	4G-V2X	4G-V2X	4G-V2X	4G-V2X	4G-V2X	4G-V2X	4G-V2X	4G-V2X	4G-V2X	4G-V2X	5G-V2X	5G-V2X

4. TCO Evaluation Model of Intelligent Driving

The TCO of intelligent driving can be divided into purchase cost and use cost. The purchase cost mainly refers to the on-board hardware and software. For the use cost, this study considers the cost of electricity consumption, data traffic and maintenance over the life cycle of the vehicle. In some other studies, some scholars have also considered the change of use cost indirectly caused by tax changes and the reduction of insurance coverage [34]. However, this part of the cost change is still controversial in the industry, and not the key factor for the technical route decision, so it does not be considered in this study. In addition, because the intelligent driving technology is developing faster under the impetus of electrification, the electric vehicle is considered the best platform for intelligent driving systems in the future [15], so the related cost evaluation is based on the battery electric vehicle platform.

The commercial application of intelligent driving at different levels is at different time nodes. According to the planning of the Chinese Intelligent Connected Vehicle Technology Roadmap, medium-level intelligent driving will achieve mass production in 2025 and high-level intelligent driving will achieve mass production in 2030 [2]. Therefore, this study sets the cost evaluation time nodes of intelligent driving at three levels, i.e., in 2021, 2025 and 2030, respectively.

4.1. Hardware Cost

With the expansion of the production scale and the iteration of technology (such as the optimization of integration and structure), the hardware cost gradually decreases. The change of hardware cost is assumed to follow the law of learning curve [35]. The total hardware cost of intelligent driving can be expressed as (1):

$$C_H = \sum [\, C_{i,single,base} \times (1-\alpha)^{(T-2021)} \times N_i \,]. \quad (1)$$

The average market price of component i in 2021 is selected as the benchmark $C_{i,single,base}$, and the original data comes from 3 OEMs cooperating with the research team. The cost reduction rate α is revised by taking the change rate of market price in previous years as a reference and integrating the current technical development trend and production characteristics of technical components. The parameter T, corresponding to the three levels of low, medium and high, are 2021, 2025 and 2030, respectively. N_i is the number of components i in the technical solution. Table 4 shows the unit cost of each technical component in different years.

Table 4. Cost and power consumption of various technical components. All costs are shown in USD.

Components	2021	2025	2030
Camera (2 MP)	$33, 10 W	$31, 8 W	$30, 6 W
Camera (8 MP)	$93, 15 W	$86, 12 W	$78, 10 W
Camera (12 MP)	$148, 20 W	$120, 16 W	$93, 12 W
MMW (short-range)	$76, 5 W	$73, 4 W	$69, 3 W
MMW (long-range)	$140, 12 W	$130, 10 W	$117, 8 W
MMW (4D-imaging)	$312, 20 W	$204, 18 W	$121, 16 W
Lidar (mechanical)	$2836, 45 W	$1866, 40 W	$1104, 36 W
Lidar (hybrid-solid)	$933, 40 W	$760, 35 W	$588, 32 W
Lidar (solid-state)	$560, 35 W	$367, 32 W	$216, 30 W
MEMS	$3, 1 W	$2.8, 1 W	$2.7, 1 W
Ultrasonic radar	$24, 12 W	$23, 11 W	$22, 10 W
HD map (m)	$343, 1 W	$279, 1 W	$216, 1 W
HD map (dm)	$1104, 2 W	$957, 2 W	$740, 2 W
HD map (cm)	$2015, 4 W	$1858, 4 W	$1433, 3 W
T-Box (4G-V2X)	$21, 4 W	$17, 4 W	$13, 4 W
T-Box (5G-V2X)	$93, 8 W	$61, 8 W	$36, 8 W

Table 4. *Cont.*

Components	2021	2025	2030
Electric power steering	$224, 40 W	$215, 40 W	$204, 40 W
Electric power braking	$179, 50 W	$172, 50 W	$164, 50 W
Wire-controlled steering	$522, 70 W	$482, 70 W	$436, 70 W
Wire-controlled braking	$373, 80 W	$343, 80 W	$310, 80 W
Computer (<100 TOPS)	$7.5, 1 W/TOPS	$6, 0.4 W/TOPS	$4.5, 0.17 W/TOPS
Computer (100–500 TOPS)	$2.8, 1 W/TOPS	$2.2, 0.4 W/TOPS	$1.8, 0.17 W/TOPS
Computer (>500 TOPS)	$1.5, 1 W/TOPS	$1.2, 0.4 W/TOPS	$0.9, 0.17 W/TOPS

4.2. Software Cost

Unlike hardware, software only has R&D costs, which mainly depends on the complexity and abundance of software [36]. Complexity is related to the system architecture, sensor type and decision algorithm. Abundance is related to the level of intelligent driving and the number of technical components. According to the current business model of the industry, OEMs usually charge according to the hardware cost in proportion to amortize the R&D expenses of the software. The value range of software cost proportion is based on the practical experience of OEMs.

The parameter factors in COCOMO II, a software constructive cost model, are used to distinguish the software complexity between different technical routes [37]. Centralized architecture helps to improve software reusability and make software development easier. Therefore, the low-level system with distributed architecture, the medium-level system with domain architecture and the high-level system with central architecture are given complexity factors of 1, 0.8 and 0.6, respectively. The more kinds of sensors, the more complex the fusion algorithm of heterogeneous data is. Therefore, vision, vision plus MMW radar and vision plus lidar are given complexity factors of 1, 1.2 and 1.5, respectively. The decision algorithm of collaborative intelligence needs to coordinate the data and software inside and outside the vehicle, which is more complicated than that of single-vehicle intelligence. Therefore, single-vehicle intelligence and collaborative intelligence are given complexity factors of 1 and 1.2, respectively.

The higher the level of intelligent driving, the more basic the software and functional applications needed. In addition, each technical component needs the corresponding driver and control applications. In this study, an evaluation model of software cost proportion as shown in Figure 3 is built, which introduces the software cost proportion required by three levels: underlying hardware, functional subsystems and electronic/electrical architecture. The research results of VSI Labs on the share of software cost in the total cost is helpful to determine the software abundance factor [38]. Underlying hardware such as sensors needs drivers, hardware abstract middleware and information security software to ensure its running. The abundance factors $F_{abun,sensor}$ of low-, medium- and high-level systems are assigned as 3%, 5% and 8%, respectively. The underlying hardware and computer can form a functional subsystem, which needs software such as an operating system, basic software platform, and perception-decision algorithms to realize data processing. The abundance factors $F_{abun,subsys}$ of low-, medium- and high-level systems are assigned as 8%, 12% and 15%, respectively. A number of functional subsystems cooperate with actuators and communicators to form the electronic and electrical architecture of the whole vehicle, which needs OTA software, functional safety software, control algorithm and scenario application to complete the control of intelligent driving functions. The abundance factors $F_{abun,arch}$ of low-, medium- and high-level systems are assigned as 12%, 18% and 25%, respectively.

Combining the hardware cost and the complexity and abundance of software, the total software cost of intelligent driving can be expressed as (2):

$$C_S = \Big(\sum C_{i,sensor} \times F_{abun,sensor} \times F_{abun,subsys} \times F_{abun,arch} + \sum C_{j,computer} \times F_{abun,subsys} \times F_{abun,arch} + \sum C_{i,actuator\&communicator} \times F_{abun,arch}\Big) \times F_{complexity} \quad (2)$$

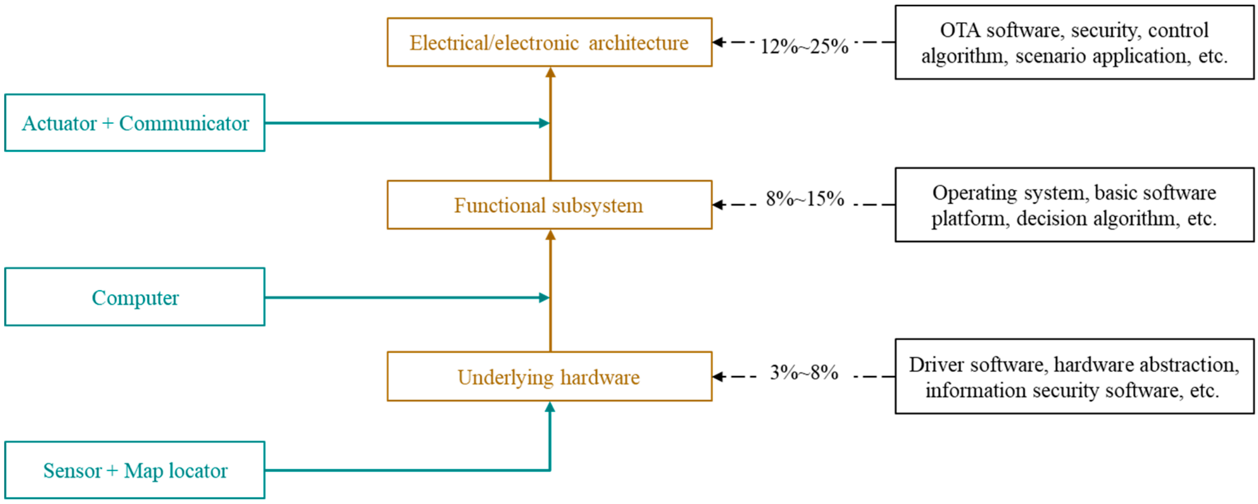

Figure 3. Evaluation model of software cost proportion.

4.3. Power Consumption Cost

Intelligent driving systems will generate additional power consumption, and this part of the cost needs to be borne by consumers during the use period, which can be expressed as (3):

$$C_E = \sum(P_i \times N_i) \times Life \times UT \times UR \times EF \quad (3)$$

The parameter P_i is the typical rated power of technical component i, which can be found in Table 4. $Life$ is the average service life of battery electric vehicles in China, with a value of 10 years. UT is the average annual service time of electric vehicles in China, with a value of 950 h/year. UR is the average function utilization proportion of intelligent driving in China, which is related to the subjective psychology of consumers and the deployment of infrastructure [39]. According to an industry survey, the function opening proportion of ADAS is around 20% [40]. With the progress of technology, the value of UR will gradually increase and become more stable. This study assumes that the UR of medium-level intelligent driving is 60% in 2025, and that of high-level intelligent driving is 95% in 2030. EF is the average charging cost in China, with a value of 0.15 USD/kwh.

4.4. Data Traffic Cost

When the intelligent driving system is in use, some information services such as map navigation, V2X, over-the-air upgrade, remote monitoring, etc. will generate a large amount of data traffic, for which consumers have to pay. The data traffic cost can be expressed as (4):

$$C_D = Life \times C_{t,year} \quad (4)$$

where $C_{t,year}$ is the average annual data traffic cost calculated based on the scale of data in vehicles, and the values of the low-, medium- and high-level systems are USD 3, USD 15 and USD 75, respectively.

4.5. Maintenance Cost

To ensure the safety of intelligent driving, it is necessary to carry out regular inspection, sensor cleaning and re-calibration, etc., which leads to new maintenance costs. The maintenance cost is proportional to the hardware and software cost of the system and can be expressed as (5):

$$C_M = (C_H + C_S) \times \beta_M \quad (5)$$

The maintenance factor β_M is as cited by McKinsey's research, and the values of low-, medium- and high-level systems are 10%, 15% and 20%, respectively [41].

5. Results and Discussion

Figure 4 shows the total cost of ownership of intelligent driving under different technical routes. The arrows of different colors in Figure 4 show the cost comparison of different dimensions.

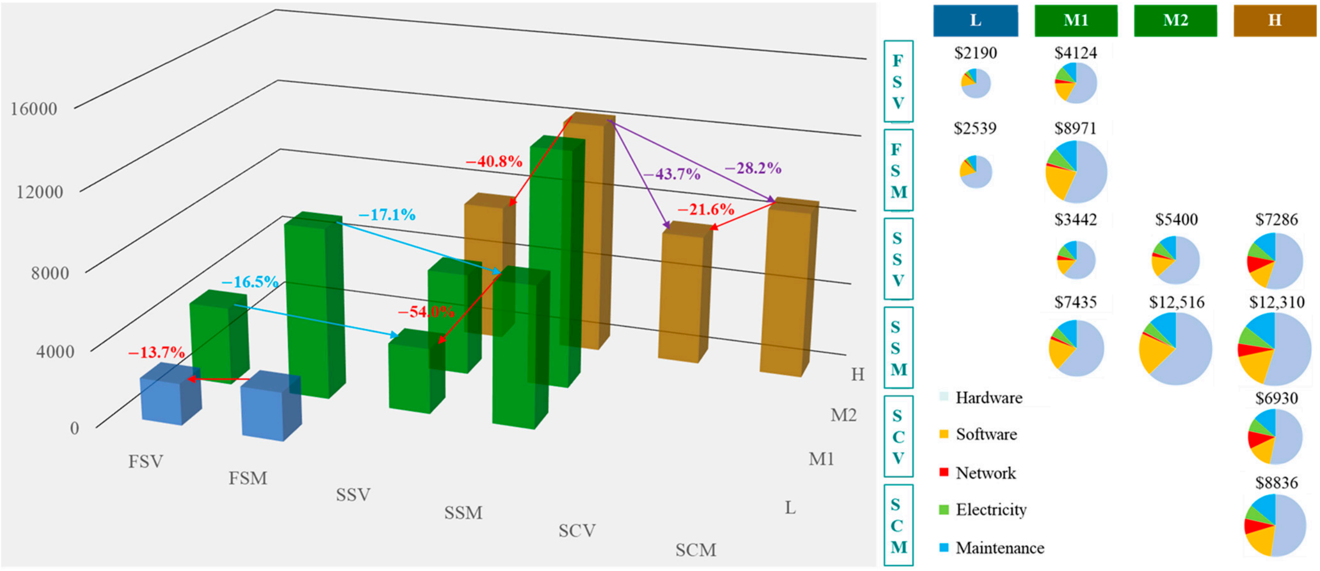

Figure 4. Cost comparison of intelligent driving under different technical routes. Costs are expressed in USD.

5.1. Cost Comparison of Different Levels

According to Figure 4, with the improvement of intelligent driving levels, the TCO of the same technical route is on the rise due to the increase in the number of sensors and the improvement of hardware performance. The only exception is that the TCO of M2-SSM is higher than that of H-SSM. The reason is that M2-SSM is the conditional automatic driving in the complex scenario realized in 2025, which belongs to a relatively advanced solution. The cost of the lidar and computer used by M2-SSM is still high. According to Table 5, from the perspective of cost composition, with the improvement of the intelligent driving level, the power consumption cost increases significantly with the increase in the system utilization rate, the data traffic cost increases significantly with the increase in the demand for networking, and the maintenance cost increases with the increase in system maintenance demand [42], which leads to the continuous decline of the proportion of hardware cost; from about 70% in the low-level system to about 50% in the high-level one. The software cost share is maintained within a stable range, which means that the absolute increase of software cost is positively related to the intelligence level. Therefore, increasing software investment is a necessary condition to promote intelligence improvement.

Table 5. TCO composition share at different levels of intelligent driving.

TCO Composition	Low-Level	Medium-Level	High-Level
Hardware	70.1–71.7%	56.9–63.3%	52.3–55.3%
Software	14.1–16.9%	13.6–21.3%	12.9–18.0%
Data Traffic	1.1–1.3%	1.2–4.2%	5.9–10.5%
Power Consumption	3.2–4.4%	4.9–10.7%	7.4–8.3%
Maintenance	8.6–8.7%	11.2–12.2%	13.6–14.3%

5.2. Cost Comparison of Different Development Strategies

Because the low-level intelligent driving system is generally developed based on the less difficult function superposition strategy in the industry, and the high-level intelligent driving system cannot be developed based on the function superposition, the technical route dispute of the development strategy mainly exists at the medium-level system. The cost comparison of different development strategies is shown by the cerulean arrow in Figure 4. Table 6 shows the TCO composition of related technical routes. For medium-level intelligent driving, the scenario-driven option can reduce the cost by 13% compared with function superposition because it optimizes the integration of functions to reduce the redundancy of sensors and the scale of computational capacity. Considering that the R&D of medium-level systems adopting the function superposition strategy is often based on the already developed low-level system, this means that some functions can be directly inherited. In this study, by subtracting the software R&D cost of L-FSV and L-FSM from M1-FSV and M1-FSM, it is found that M1-SSV and M1-SSM still have about a 10% cost advantage. It should be pointed out that under the scenario-driven development strategy, the medium-level intelligent driving system in simple scenarios can make the ODD of the system cover complex scenarios by upgrading the hardware and software. From M1-SSV to M2-SSV, the TCO needs to be increased by USD 1958, and from M1-SSM to M2-SSM, the TCO needs to be increased by USD 5085.

Table 6. Cost comparison of different development strategies. All costs are shown in USD.

TCO Composition	M1-FSV	M1-SSV	M2-SSV	M1-FSM	M1-SSM	M2-SSM
Hardware	$2361	$2083	$3371	$5027	$4530	$7737
Software	$670	$462	$765	$1884	$1353	$2337
Data Traffic	$143	$143	$143	$143	$143	$143
Power Consumption	$437	$323	$423	$752	$420	$609
Maintenance	$455	$382	$620	$1037	$883	$1511

5.3. Cost Comparison of Different Intelligence Allocations

Because the application scenarios of low- and medium-level intelligent driving are limited, which means that the economy of large-scale infrastructure deployment is low, the technical route dispute of intelligent allocation mainly exists at the high level. Table 7 shows the cost composition of four high-level technical routes. The cost comparison of different intelligent allocations is shown by the purple arrow in Figure 4. Although collaborative intelligence can reduce the on-board hardware of high-level intelligent driving, to ensure basic safety, the vehicle still needs to retain the necessary sensors and computational capacity. Therefore, in the case of vision-only routes, single-vehicle intelligence uses low-cost hardware, and the cost reduction brought by collaborative intelligence is very limited. In the case of multi-source fusion routes, collaborative intelligence can reduce the cost by about 30%. In the case where the cost decreases even more, by transferring expensive sensors to the roadside, the system changes from the original single-vehicle intelligence with multi-source fusion to the collaborative intelligence with vision-only, and the cost can be reduced by 41.7%.

Table 7. Cost comparison of different intelligence allocations. All costs are listed in USD.

TCO Composition	H-SSV	H-SCV	H-SSM	H-SCM
Hardware	$3970	$3642	$6679	$4559
Software	$923	$1004	$2017	$1570
Data Traffic	$714	$714	$714	$714
Power Consumption	$596	$541	$985	$641
Maintenance	$979	$929	$1739	$1226

5.4. Cost Comparison of Different Sensor Combinations

The technical route dispute of sensor combination runs through all levels of intelligent driving. The cost comparison of different sensor combinations at different levels under single-vehicle intelligence is shown by the red arrow in Figure 4. Table 8 shows the TCO composition of related technical routes. Regardless of level, the vision-only route has a lower cost than the multi-source fusion route because of its simple hardware design and software complexity. However, the cost advantage of the vision-only route is most obvious at the medium- and high-level stages of single-vehicle intelligence. At the low-level stage, the cost advantage of vision-only is 11.2% because only a low-cost MMW radar is used in the multi-source fusion route. At the medium-level stage, the cost advantage of the vision-only route is expanded to 51.6% due to the use of high-cost hardware such as lidar in multi-source fusion. At the high-level stage, on the one hand, it is expected that the cost of the lidar and 4D-imaging MMW radar will be greatly reduced; on the other hand, the use cost will increase, resulting in a reduction in the proportion of hardware cost. Therefore, the absolute difference between the vision-only route and the multi-source fusion route is widened, but the relative difference is slightly reduced to 38.8%. An important finding is that when collaborative intelligence is adopted, the relative cost difference between the vision-only and multi-source fusion routes is further reduced to 17.7%, and the absolute difference is no more than USD 2000, which means that for some cost-insensitive vehicle models, the cost difference between vision-only and multi-source fusion options can already be accepted by OEMs and consumers [43].

Table 8. Cost comparison of different sensor combinations. All costs are shown in USD.

TCO Composition	L-FSV	L-FSM	M1-SSV	M1-SSM	H-SSV	H-SSM
Hardware	$1547	$1756	$2083	$4530	$3970	$6679
Software	$304	$422	$462	$1353	$923	$2017
Data Traffic	$29	$29	$143	$143	$714	$714
Power Consumption	$94	$79	$323	$420	$596	$985
Maintenance	$185	$218	$382	$883	$979	$1739

5.5. Uncertainty Analysis

There are two possible uncertainties in the above cost evaluation. One is the cost reduction rate of some technical components. 4D-imaging MMW radars, lidars and high-precision locators are widely believed to achieve technological breakthrough and mass production in the next few years, so their cost reduction is set at a high rate. Once the progress of technological breakthrough is not as fast as expected, the cost may be higher. For this assumption, the result caused by this uncertainty does not affect the cost ranking among technical routes, but further enlarges the cost difference between the vision-only route and multi-source fusion route. Another uncertainty is the function utilization proportion of intelligent driving. The assumption of the function utilization proportion of intelligent driving in this study is also optimistic. However, if the public opinion about intelligent driving is not good or the infrastructure deployment speed is slow, it may lead to a reduction in the function utilization proportion of intelligent driving at the medium and high levels [44]. According to the scenario forecast, the result caused by this uncertainty also does not affect the cost ranking between technical routes and has little influence on the conclusion.

6. Conclusions

This study systematically combed the main technical route alternatives of intelligent driving at different levels. Based on the unique perspective of the disassembly and combination of technical components, the TCO of different technical routes is evaluated. It is found that there are obvious cost differences among different technical routes:

- At the low-level, the vision-only route has an 11% cost advantage compared with the multi-source fusion route.
- At the medium-level with simple scenarios, the scenario-driven strategy saves about 13% TCO compared with the function superposition strategy. Even considering the inheritance of R&D cost of low-level systems under the function superposition strategy, the scenario-driven strategy still has a cost advantage of 10%.

- At the medium-level with complex scenarios, the hardware cost of the sensor combination solution with a multi-source fusion route reaches USD 7737, far exceeding the current willingness of consumers in China to pay USD 4600, while the TCO of the vision-only route can be controlled at USD 5400.
- At the high-level, collaborative intelligence can save up to 46% of the TCO compared with single-vehicle intelligence, and the reduction of costs depends on the type and quantity of the original on-board hardware. In addition, with the help of collaborative intelligence, the cost difference between vision-only and multi-source fusion routes will be controlled within USD 2000.

Based on these findings, this study provides the following suggestions for OEMs to formulate technical strategies and the government to formulate industrial policies:

- In the choice of development strategy, a scenario-driven strategy not only has cost advantages, but also can continuously evolve to a higher level of intelligence. OEMs should shift their development strategy to scenario-driven options as soon as possible and put products on the market to build a data closed loop. At the same time, due to the high cost of medium-level intelligent driving in complex scenarios, whether OEMs should commercialize it in 2025 is a topic worthy of further discussion.
- In the choice of intelligence allocation, collaborative intelligence can effectively reduce the TCO compared with single-vehicle intelligence. On the premise that China has announced that it will develop collaborative intelligence, the government should speed up the deployment of infrastructure, the construction of pilot demonstration areas and the improvement of relevant standards and regulations. OEMs should actively seek cross-border cooperation and jointly explore the new value that collaborative intelligence can create, such as traffic safety and travel efficiency, so as to further enhance the economy of collaborative intelligence [45].
- In the choice of sensor combinations, the vision-only route has an obvious cost advantage, but at present, only a few OEMs, such as Tesla, have made some breakthroughs in technology. Therefore, OEMs which lack previous relevant technical experience should avoid blindly switching technical routes. In addition, because collaborative intelligence can effectively narrow the cost gap between vision-only and multi-source fusion routes, OEMs need not worry too much that choosing multi-source fusion will make the product lose its market competitiveness.
- Compared with the TCO of medium- and high-level intelligent driving, China consumers' willingness to pay is relatively low at present. OEMs and the government should consciously increase consumers' willingness to pay for intelligent driving through advertising, popular science and other methods, and may also need to provide appropriate subsidies at the initial stage of market penetration of innovation.

There are still some points worthy of optimization in this study. Firstly, although each technical component combination solution is determined according to a certain process under given constraints, it still depends on expert experience. It is doubtful whether these solutions will retain a high degree of consistency with real solutions in the future. For example, this study believes that the multi-source fusion route of medium- and high-level intelligent driving will be equipped with lidar, but the progress of 4D MMW radars makes some people in the industry think that lidar can be replaced. Even the latest Tesla autopilot computing platform has reserved the interface for the 4D MMW radar, which suggests it may abandon the vision-only route in the future [46]. Therefore, research on the TCO of each technical route and industrial practice may be a mutually promoting relationship. The calculation results can provide guidance for the future development direction of the industry, and the latest industrial practice can influence the research objects and results. Secondly, some indirect derivative costs, such as financial cost, market opportunity cost, travel cost and infrastructure use cost, are not included in the TCO evaluation model. Further expansion of the model can be considered. However, in fact, not all costs will affect consumers' purchase decisions. Some studies believe that the cost perceived by consumers can be reduced through the change of business models [47,48]. For example, it is more acceptable for consumers to convert the one-time purchase cost of software into the form of pay-per-use subscription [47]. Combining business model innovation with TCO analysis is a direction that can be expanded in the future. Finally, this study assumes that the deployment of infrastructure can meet the ideal needs of collaborative intelligence in all scenarios. However, the deployment of infrastructure may be a long and gradual process, and the system is facing the degradation from collaborative intelligence to single-vehicle intelligence. Therefore, more technical component combination solutions of collaborative intelligence may be designed in the future, which is an issue that can be further explored.

Author Contributions: Conceptualization, Z.L. and W.Z.; methodology, W.Z. and H.T.; validation, Z.L. and F.Z.; formal analysis, Z.L. and W.Z.; investigation, W.Z. and H.T.; resources, W.Z. and H.T.; data curation, H.T.; writing—original draft preparation, Z.L. and W.Z.; writing—review and editing, Z.L. and W.Z.; visualization, W.Z.; supervision, Z.L.; project administration, F.Z.; funding acquisition, Z.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the National Natural Science Foundation of China with funding account number 52272371 and Tsinghua-Toyota Joint Research Fund with funding account number 20213930030.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data generated or used during the current study are available from the corresponding author upon request.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Kuang, X.; Zhao, F.; Hao, H.; Liu, Z. Intelligent connected vehicles: The industrial practices and impacts on automotive value-chains in China. *Asia Pac. Bus. Rev.* **2018**, *24*, 1–21. [CrossRef]
2. Xu, Q.; Li, K.; Wang, J.; Yuan, Q.; Yang, Y.; Chu, W. The status, challenges, and trends: An interpretation of technology roadmap of intelligent and connected vehicles in China (2020). *J. Intell. Connect. Veh.* **2022**, *5*, 1–7. [CrossRef]
3. Tang, T.Q.; Gui, Y.; Zhang, J. ATAC-based car-following model for level 3 autonomous driving considering driver's acceptance. *IEEE T. Intell. Transp.* **2021**, *23*, 10309–10321. [CrossRef]
4. Wang, Z.; Wu, Y.; Niu, Q. Multi-sensor fusion in automated driving: A survey. *IEEE Access* **2019**, *8*, 2847–2868. [CrossRef]
5. Tan, H.; Zhao, F.; Song, H.; Liu, Z. Quantifying the impact of deployments of autonomous vehicles and intelligent roads on road safety in China: A country-level modeling study. *Int. J. Environ. Res. Public Health* **2023**, *20*, 4069. [CrossRef]
6. Higgins, A.; Paevere, P.; Gardner, J.; Quezada, G. Combining choice modelling and multi-criteria analysis for technology diffusion: An application to the uptake of electric vehicles. *Technol. Forecast. Soc.* **2012**, *79*, 1399–1412. [CrossRef]
7. Bansal, P.; Kockelman, K.M. Forecasting Americans' long-term adoption of connected and autonomous vehicle technologies. *Transport. Res. A-Pol.* **2017**, *95*, 49–63. [CrossRef]
8. Shabanpour, R.; Golshani, N.; Shamshiripour, A.; Mohammadian, A.K. Eliciting preferences for adoption of fully automated vehicles using best-worst analysis. *Transport. Res. C-Emer.* **2018**, *93*, 463–478. [CrossRef]
9. Abraham, H.; Lee, C.; Brady, S.; Fitzgerald, C.; Mehler, B.; Reimer, B.; Coughlin, J.F. Autonomous vehicles, trust, and driving alternatives: A survey of consumer preferences. *Mass. Inst. Technol. AgeLab. Camb.* **2016**, *1*, 2018–2034.
10. Dixon, G.; Hart, P.S.; Clarke, C.; O'Donnell, N.H.; Hmielowski, J. What drives support for self-driving car technology in the United States? *J. Risk. Res.* **2020**, *23*, 275–287. [CrossRef]
11. Bösch, P.M.; Becker, F.; Becker, H.; Axhausen, K.W. Cost-based analysis of autonomous mobility services. *Transp. Policy* **2018**, *64*, 76–91. [CrossRef]
12. Abe, R. Introducing autonomous buses and taxis: Quantifying the potential benefits in Japanese transportation systems. *Transport. Res. A-Pol.* **2019**, *126*, 94–113. [CrossRef]
13. Turoń, K.; Kubik, A. Economic aspects of driving various types of vehicles in intelligent urban transport systems, including car-sharing services and autonomous vehicles. *Appl. Sci.* **2020**, *10*, 5580. [CrossRef]
14. Bailo, C.; Dziczek, K.; Smith, B.; Spulber, A.; Chen, Y.; Schultz, M. The great divide: What automotive consumers are buying vs. auto & supplier investments in future technologies, products & business models. *Cent. Automot. Res.* **2018**, *1*, 1–3.
15. Ongel, A.; Loewer, E.; Roemer, F.; Sethuraman, G.; Chang, F.; Lienkamp, M. Economic assessment of autonomous electric microtransit vehicles. *Sustainability* **2019**, *11*, 648. [CrossRef]
16. Wadud, Z. Fully automated vehicles: A cost of ownership analysis to inform early adoption. *Transport. Res. A-Pol.* **2017**, *101*, 163–176. [CrossRef]

17. 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]
18. Liu, Z.; Zhang, W.; Zhao, F. Impact, challenges and prospect of software-defined vehicles. *Automot. Innov.* **2022**, *5*, 180–194. [CrossRef]
19. Paukert, C. Why the 2019 Audi A8 Won't Get Level 3 Partial Automation in the US. Roadshow. Available online: https://www.cnet.com/roadshow/news/2019-audi-a8-level-3-traffic-jam-pilot-self-driving-automation-not-for-us (accessed on 13 July 2022).
20. Clark, J.R.; Stanton, N.A.; Revell, K. Automated vehicle handover interface design: Focus groups with learner, intermediate and advanced drivers. *Automot. Innov.* **2020**, *3*, 14–29. [CrossRef]
21. Yang, D.; Jiao, X.; Jiang, K.; Cao, Z. Driving space for autonomous vehicles. *Automot. Innov.* **2019**, *2*, 241–253. [CrossRef]
22. Wang, J.; Huang, H.; Li, K.; Li, J. Towards the unified principles for level 5 autonomous vehicles. *Engineering-PRC* **2021**, *7*, 1313–1325. [CrossRef]
23. Meyer, M.A.; Sauter, L.; Granrath, C.; Hadj-Amor, H.; Andert, J. Simulator coupled with distributed co-simulation protocol for automated driving Tests. *Automot. Innov.* **2021**, *4*, 373–389. [CrossRef]
24. Ndikumana, A.; Tran, N.H.; Kim, K.T.; Hong, C.S. Deep learning based caching for self-driving cars in multi-access edge computing. *IEEE T. Intell. Transp.* **2020**, *22*, 2862–2877. [CrossRef]
25. Liu, Y.; Yu, H.; Xie, S.; Zhang, Y. Deep reinforcement learning for offloading and resource allocation in vehicle edge computing and networks. *IEEE T. Veh. Technol.* **2019**, *68*, 11158–11168. [CrossRef]
26. Cao, Y.; Wang, N.; Xiao, C.; Yang, D.; Fang, J.; Yang, R.; Chen, Q.A.; Li, B. Invisible for both camera and lidar: Security of multi-sensor fusion-based perception in autonomous driving under physical-world attacks. In Proceedings of the 2021 IEEE Symposium on Security and Privacy, San Francisco, CA, USA, 24–27 May 2021.
27. Mou, L.; Xie, H.; Mao, S.; Zhao, P.; Chen, Y. Vision-based vehicle behaviour analysis: A structured learning approach via convolutional neural networks. *IET Intell. Transp. Sy.* **2020**, *14*, 792–801. [CrossRef]
28. Li, W.; Yao, N.; Shi, Y.; Nie, W.; Zhang, Y.; Li, X.; Liang, J.; Chen, F.; Gao, Z. Personality openness predicts driver trust in automated driving. *Automot. Innov.* **2020**, *3*, 3–13. [CrossRef]
29. Xue, D.; Cheng, J.; Zhao, X.; Wang, Z. A vehicle-in-the-loop simulation test based digital-twin for intelligent vehicles. In Proceedings of the 2021 IEEE Intl Conf on Dependable, Autonomic and Secure Computing, Intl Conf on Pervasive Intelligence and Computing, Intl Conf on Cloud and Big Data Computing, Intl Conf on Cyber Science and Technology Congress, AB, Canada, 25–28 October 2021.
30. Sun, S.; Zhang, Y.D. 4D automotive radar sensing for autonomous vehicles: A sparsity-oriented approach. *IEEE J-STSP* **2021**, *15*, 879–891. [CrossRef]
31. Wang, H.; Wang, C.; Xie, L. Lightweight 3-D localization and mapping for solid-state LiDAR. *IEEE Robot. Autom. Let.* **2021**, *6*, 1801–1807. [CrossRef]
32. Bjelica, M.Z.; Lukac, Z. Central vehicle computer design: Software taking over. *IEEE Consum. Electron. Mag.* **2019**, *8*, 84–90. [CrossRef]
33. Ni, J.; Hu, J.; Xiang, C. An AWID and AWIS X-by-wire UGV: Design and hierarchical chassis dynamics control. *IEEE T. Intell. Transp.* **2018**, *20*, 654–666. [CrossRef]
34. Clements, L.M.; Kockelman, K.M. Economic effects of automated vehicles. *Transport. Res. Rec.* **2017**, *2606*, 106–114. [CrossRef]
35. Grube, T.; Kraus, S.; Reul, J.; Stolten, D. Passenger car cost development through 2050. *Transport. Res. D-Tr E* **2021**, *101*, 103–110. [CrossRef]
36. Zerfowski, D.; Buttle, D. Paradigm shift in the market for automotive software. *ATZ Worldw.* **2019**, *121*, 28–33. [CrossRef]
37. Khan, J.A.; Khan, S.U.R.; Khan, T.A.; Khan, I.U.R. An amplified COCOMO-II based cost estimation model in global software development context. *IEEE Access* **2021**, *9*, 88602–88620. [CrossRef]
38. Egil, J. Projections for Rising Auto Software Cost for Carmakers. EE Times. Available online: https://www.eetimes.com/projections-for-rising-auto-software-cost-for-carmakers/ (accessed on 17 March 2023).
39. Shi, Y.; Zhang, Q.; He, A.; Pan, A.; Zhang, M.; Li, C.; Liao, Q.; Yang, X.; Wang, Z. A real-world investigation into usage patterns of electric vehicles in Shanghai. *J. Energy Storage* **2020**, *32*, 10–25. [CrossRef]
40. Harms, I.M.; Bingen, L.; Steffens, J. Addressing the awareness gap: A combined survey and vehicle registration analysis to assess car owners' usage of ADAS in fleets. *Transport. Res. A-Pol.* **2020**, *134*, 65–77. [CrossRef]
41. Lazaroiu, G.; Machová, V.; Kucera, J. Connected and autonomous vehicle mobility: Socially disruptive technologies, networked transport systems, and big data algorithmic analytics. *Contemp. Read. Law Soc. Justice* **2020**, *12*, 61.
42. Kaiser, C.; Festl, A.; Pucher, G.; Fellmann, M.; Stocker, A. The vehicle data value chain as a lightweight model to describe digital vehicle services. In Proceedings of the 15th International Conference on Web Information Systems and Technologies, Vienna, Austria, 18–20 September 2019.
43. Ding, Y.; Li, R.; Wang, X.; Schmid, J.; Axhausen, K.W. Heterogeneity of autonomous vehicle adoption behavior due to peer effects and prior-av knowledge. *Transportation* **2022**, *49*, 1837–1860. [CrossRef]
44. Yue, L.; Abdel-Aty, M.A.; Wu, Y.; Farid, A. The practical effectiveness of advanced driver assistance systems at different roadway facilities: System limitation, adoption, and usage. *IEEE T. Intell. Transp.* **2019**, *21*, 3859–3870. [CrossRef]
45. Kuang, X.; Zhao, F.; Hao, H.; Liu, Z. Assessing the socioeconomic impacts of intelligent connected vehicles in China: A cost–benefit analysis. *Sustainability* **2019**, *11*, 3273. [CrossRef]

46. Huang, N.; Jack, W. Tesla Rumored to Reintroduce MMWave Radar. Digitimes. Available online: https://www.digitimes.com/news/a20230117PD203/4d-imaging-radar-adas-mmwave-radar-tesla.html (accessed on 17 March 2023).
47. Power, J.D. Consumers in China Are More Confident About Self-Driving Technologies by Chinese Companies. Global Times. Available online: https://china.jdpower.com/resources/china-self-driving-confidence-index (accessed on 17 March 2023).
48. Athanasopoulou, A.; Reuver, M.; Nikou, S.; Bouwman, H. What technology enabled services impact business models in the automotive industry? An exploratory study. *Futures* **2019**, *109*, 73–83. [CrossRef]