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A Comprehensive User Acceptance Evaluation Framework of Intelligent Driving Based on Subjective and Objective Integration—From the Perspective of Value Engineering

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Abstract

Intelligent driving technology is expected to reshape urban transportation, but its promotion is hindered by user acceptance challenges and diverse technical routes. This study proposes a comprehensive user acceptance evaluation framework for intelligent driving from the perspective of value engineering (VE). The novelty of this framework lies in three aspects: (1) It unifies behavioral theory and utility theory under the value engineering framework, and it extracts key indicators such as safety, travel efficiency, trust, comfort, and cost, thus addressing the issue of the lack of integration between subjective and objective factors in previous studies. (2) It establishes a systematic mapping mechanism from technical solutions to evaluation indicators, filling the gap of insufficient targeting at different technical routes in the existing literature. (3) It quantifies acceptance differences via VE's core formula of V = F/C, overcoming the ambiguity of non-technical evaluation in prior research. A case study comparing single-vehicle intelligence vs. collaborative intelligence and different sensor combinations (vision-only, map fusion, and lidar fusion) shows that collaborative intelligence and vision-based solutions offer higher comprehensive acceptance due to balanced functionality and cost. This framework guides enterprises in technical strategy planning and assists governments in formulating industrial policies by quantifying acceptance differences across technical routes.

Keywords: intelligent driving; user acceptance; value engineering; technical route

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1. Introduction

Intelligent driving is a technology that is expected to gradually emerge in urban transportation within 10 years and reshape the entire smart city landscape [1]. However, the promotion of intelligent driving technology faces multiple obstacles. As shown in Figure 1, the market diffusion of intelligent driving technology can be divided into three stages. Before breaking through the technical threshold, it is mainly tested and demonstrated in specific areas. After the technology is proven to be mature enough, it enters the mass production stage. But during mass production, only a small number of users are willing to try the new technology, such as tech enthusiasts or those who lack confidence in their driving skills. Only when a universally recognized technical ethics concept is formed in society will intelligent driving technology enter the popular application stage and be accepted by more and more ordinary consumers [2].

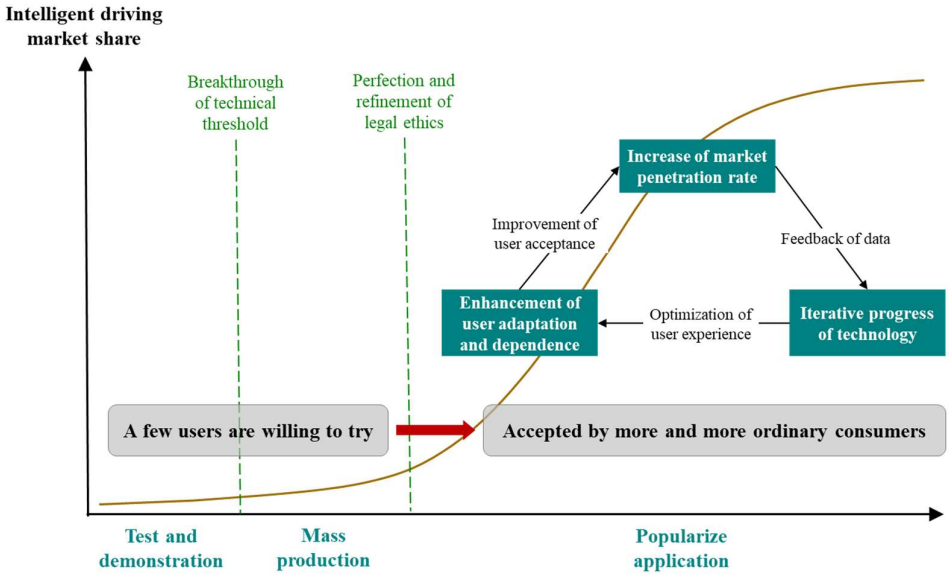


Figure 1. The "S" curve of intelligent driving technology diffusion.

However, the positive cycle of promoting intelligent driving technology currently faces multiple resistances, with user acceptance being the key focus and challenge. On the one hand, the intelligent driving systems that have truly achieved large-scale application remain at the L2 level, still requiring users to pay high attention to driving [3]. On the other hand, representative enterprises such as Xiaomi and Tesla have frequently been exposed to negative public opinions, with users criticizing poor experience and even impacts on driving safety. Acceptance, as an indicator often used to reflect the degree of market recognition of technology, has a significant impact on consumers' car purchase decisions and the innovation diffusion of the technology [4].

At the same time, the development of intelligent driving is in a stage of contention among multiple approaches, with multiple technical routes coexisting [5]. Tesla and XPeng have fully bet on end-to-end solutions based on vision, while Huawei and Waymo adhere to the multimodal fusion of visual and radar data. In addition, debates on single-vehicle intelligence and collaborative intelligence have been raging in both industry and government circles [6]. Intelligent driving systems under different technical routes have distinct functional features and cost structures, so their user acceptance should logically differ [7]. Therefore, this study aims to establish a comprehensive evaluation model to quantify users' acceptance of intelligent driving under different technical routes, thereby guiding enterprises in technological strategy planning and assisting the government in formulating industrial policies.

This paper is structured as follows: Section 2 reviews relevant research in the field and identifies existing gaps. Section 3 proposes an acceptance evaluation framework for different intelligent driving technical routes. Section 4 details the evaluation submodels within the framework. Section 5 demonstrates the practical application value of the proposed framework through a case study. The final section concludes the research and provides recommendations.

2. Literature Review

2.1. Fundamental Theoretical Models

The research on technical acceptance mainly relies on two fundamental theoretical systems: behavioral theory and utility theory.

Behavioral theory regards individuals as the initiators of accepting innovative technologies, assuming that all external variables influence technological acceptance behavior

by affecting personal acceptance intentions, with users' personal factors as the core variables [8]. Many scholars have developed various technical acceptance models based on behavioral theory, such as the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Innovation Diffusion Model (IDM). Panagiotopoulos et al. conducted an online sampling survey among drivers aged 18–70 based on an extended TAM, and they found correlations between factors such as perceived usefulness, perceived ease of use, perceived trust, and social influence and intelligent driving acceptance through regression analysis [9]. Hartwich et al. set up experimental and control groups for intelligent driving simulation experiments according to the moderator variables of the UTAUT, revealing differences in the acceptance of intelligent driving among users with different test-drive experiences and age groups [10]. Talebian et al. examined respondents' personal characteristics and the information sources relied on when evaluating intelligent driving through questionnaires, and they developed an innovation diffusion algorithm by combining the innovative characteristics of intelligent driving and social system variables, thereby obtaining an S-curve of intelligent driving market penetration [11]. When applied to research on intelligent driving acceptance, behavioral theory takes more account of users' subjective factors and is supported by numerous sociological theories, making it more consistent with real-life scenarios. However, it also has obvious limitations: indicators involving users' subjective psychology are difficult to quantify accurately, so the reliability of research results is questionable. In addition, due to the numerous differences among individuals, massive data support is required to determine the main factors, leading to a high threshold for research implementation.

Utility theory posits that an innovative technology can generate multiple utility values for users, and the total utility value helps users make consumption decisions [12]. Based on utility theory, academia mainly focuses on the consumption value of intelligent driving technology, including the functional value, social value, and emotional value. Khan et al. evaluated the safety benefits, such as reduced traffic accidents, achieved through the deployment of three safety functions in the United States: lane departure assistance, blind spot monitoring warning, and forward collision warning [13]. Fagnant and Kockelman summarized the impacts of autonomous driving vehicles in terms of accident reduction, travel time saving, energy efficiency improvement, and parking convenience, estimating that each autonomous driving vehicle can generate nearly USD 4000 in annual benefits [14]. The core advantage of utility theory is that specific technical indicators related to utility values are relatively objective, making them easier to quantify and evaluate accurately. However, the challenge lies in the difficulty of reasonably distinguishing between various utilities and measuring their relative importance. Since specific weights cannot be determined, the constructed models often fail to reflect differences among individuals.

2.2. Internal Heterogeneity of Acceptance of Intelligent Driving

Identifying the key influencing factors of intelligent driving acceptance is insufficient, and further analysis of its internal heterogeneity is more worthy of attention. Portouli et al. found that, since buses are one of the lowest-cost public transport vehicles, intelligent driving reduces operating costs, minimizes human operational errors, and improves bus safety, thus being more readily accepted by commuting users [15]. Nordhoff et al. argued in their research that intelligent driving shuttles in closed parks offer better safety and compatibility, making them more socially acceptable [16]. Winter et al. believed that, if intelligent driving can complete urgent special tasks faster and safer, special vehicles such as ambulances may be the products most easily accepted by the public [17]. From the perspective of travel opportunities, Bansal et al. found that, for groups such as the elderly, children, and people with disabilities, shared intelligent driving vehicles can more

conveniently address their travel needs, making them more acceptable to these groups [18]. Rödel et al. found that users' attitudes toward intelligent driving systems and perceived behavioral control both decrease with the improvement of system automation, with specific usage intentions peaking at the L2 stage and significantly declining after L3 [19].

The study of the internal heterogeneity of the acceptance of intelligent driving is essentially a process of deconstructing and reconstructing the complex technology–user interaction relationship. It not only breaks the traditional research assumption of "unified acceptance" but also provides the industry with a "divide-and-conquer" implementation path, and, more importantly, it promotes policies and society to welcome the era of intelligent driving with a more inclusive and scientific perspective.

2.3. Limitations of Existing Literature

By reviewing the existing literature, three main limitations were found:

- **Failure to integrate subjective and objective factors into a unified model**: The transformation of human social life by intelligent driving is multi-layered and multi-dimensional, with both subjective and objective factors being critical considerations for acceptance. The two foundational theories in current research—behavioral theory and utility theory—focus on subjective and objective factors, respectively, but a single perspective fails to adequately reveal the technology diffusion mechanism. For instance, Jing et al. noted that most studies on autonomous vehicle acceptance focus on either psychological factors (e.g., trust and perceived risk) or technical metrics (e.g., safety and efficiency), lacking a framework that bridges these two dimensions [20]. Similarly, Bansal et al. pointed out that the fragmentation of subjective and objective evaluations hinders a comprehensive understanding of user acceptance [18].
- **Lack of systematic and scientific acceptance evaluation research**: Before enterprises develop intelligent driving technologies and apply them to specific vehicle models, they often seek to predict user acceptance. However, current studies either remain at the level of analyzing influential relationships between different factors or suffer from significant subjective ambiguity, lacking evaluations based on specific technical solutions. Hewitt et al. acknowledged that existing acceptance models (e.g., AVAM) mainly explore the correlations between variables (e.g., trust and acceptance) but rarely provide quantifiable evaluation tools for specific technical configurations [4]. Talebian et al. also noted that most diffusion models rely on macro-trends rather than technical solution-specific assessments [11].
- **Research objects failing to focus on different technical routes**: It is already known that different technical routes in intelligent driving must exhibit acceptance heterogeneity. However, how to map technical differences to acceptance, what mechanisms should be followed, and what quantitative characterization methods should be adopted are questions that remain to be explored. Malik et al. reviewed collaborative autonomous driving technologies but did not address how technical differences affect acceptance [5]. Liu et al. compared cost differences across technical routes but highlighted the lack of research linking these differences to acceptance metrics [7].

The framework proposed in the next section attempts to address the above limitations, achieving a subjective–objective integrated acceptance evaluation for intelligent driving under different technical routes.

3. Acceptance Evaluation Framework

3.1. Selection of Key Indicators

The acceptance of intelligent driving is influenced by multiple subjective and objective factors, which have complex interaction relationships [20]. As shown in Figure 2, based on

many relevant literature surveys, this study comprehensively followed the principles of representativeness, independence, and quantifiability from behavioral theory and utility theory to select and identify key indicators. First, the key factors with the highest frequency of occurrence in relevant studies based on behavioral theory, including perceived usefulness, perceived ease of use, perceived risk, price, perceived compatibility, and social norm, were statistically analyzed. However, since these factors depend largely on user perception, it is difficult to make objective evaluations. Therefore, the correlation between the above key factors and the specific indicators in relevant studies based on utility theory was further analyzed. Finally, we retained product characteristics such as safety, travel efficiency, trust, comfort, and cost that have a strong correlation with consumer perception, and we excluded some weakly related product characteristics, such as symbolic value, mobility, and environmentally friendly.

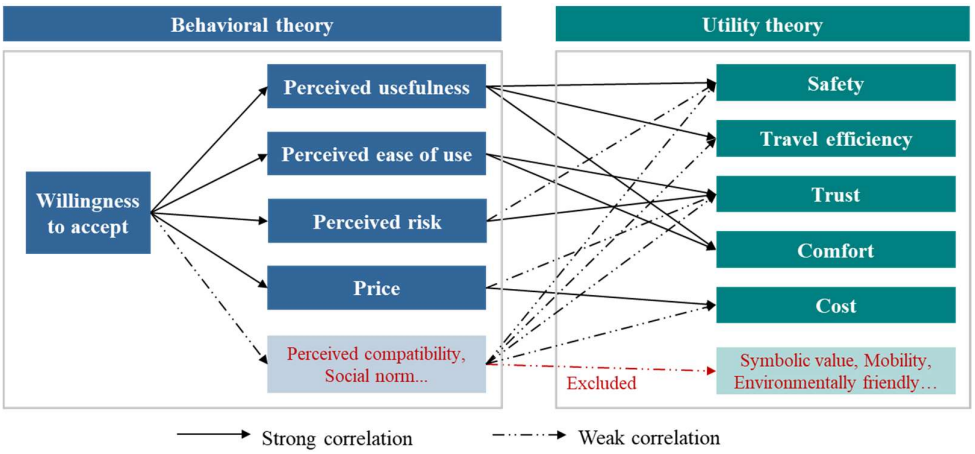


Figure 2. Identification of evaluation indicators of intelligent driving acceptance.

Among the five key indicators finally determined, safety can effectively make users perceive the practicality of intelligent driving and reduce users' sense of unease. Travel efficiency and comfort are also important manifestations of the practical value of intelligent driving. Trust can effectively reduce users' perceived risk and, together with comfort, affect users' perceived ease of use [21]. Cost directly determines the price that users need to pay to accept new technologies.

From an evaluation perspective, safety, travel efficiency, and cost are objective technical and economic indicators that can be scientifically quantified and evaluated in specific scenarios. Trust and comfort are user experience indicators that integrate subjective and objective factors and can be described and quantitatively evaluated through direct or indirect means. They are related to not only specific technical solutions but also some external environmental and personal characteristic factors [22].

3.2. Mapping from Technical Solution to Evaluation Indicator

To reflect the acceptance differences among different technical routes in the final evaluation results, this study proposes a set of mapping relationships from technical solutions to evaluation indicators.

Intelligent driving system solutions consist of a series of hardware and software components. Different technical solutions correspond to varying purchase or operation costs and product functional features. Take safety as an example: its differences mainly stem from product features such as sensing range, sensing reliability, and environmental adaptability. Diverse sensor combinations and V2X technologies endow vehicles with different collision avoidance potentials in traffic accidents [23]. For instance, V2X is proven to eliminate vehicle-sensing blind spots and significantly improve collision avoidance

performance. Lidar, with its long sensing distance and 3D modeling capability, is also recognized for enhancing vehicle safety potential [24].

Similar mapping relationships apply to travel efficiency, trust, and comfort. This study will establish a hierarchical model from technical solutions to product functional features and then to evaluation indicators across different dimensions, which will be detailed in Section 4.

3.3. Evaluation Framework Based on VE

Furthermore, this study incorporates the five key indicators into a unified systematic evaluation framework based on the theoretical concept of VE. VE posits that "value is the ratio of function to cost", aiming to maximize the value of products or systems through function analysis and cost optimization [25]. Its core lies in the definition and quantification of "function", emphasizing the satisfaction of user needs at the lowest lifecycle cost. The "function" in VE is essentially the materialization of "utility" in utility theory—function refers to the use value provided by a product to users, while utility represents users' subjective perception of this value [26]. Utility theory assumes that consumers pursue "utility maximization", guiding resource allocation through marginal utility analysis, which aligns with VE's logic of cost–function trade-offs [27]. VE provides an implementation tool for utility theory—by quantifying functions and controlling costs, it transforms abstract user needs into specific functional indicators and cost control schemes, realizing the materialization and quantification of "utility". The core formula of VE is shown in (1):

$$V = \frac{F}{C} = \frac{\frac{F_i}{\sum F_k}}{\frac{C_i}{\sum C_k}} \tag{1}$$

F denotes the functional score, which, in this study, is obtained through the comprehensive weighting of safety, travel efficiency, trust, and comfort. C represents the cost evaluation value. This study uses the value V to reflect the comprehensive acceptance. Both F and C are normalized to achieve dimensionless processing. When calculating the comprehensive functional score, to avoid uncertainties at the non-technical level, the four functional indicators are treated with equal weights. In practical applications, enterprises can understand the attributes that target user groups pay more attention to based on their own market research, user feedback, big data analysis, and other means, and then they can independently define the weight coefficients of different submodels.

3.4. Methodology Workflow

The proposed evaluation framework follows a three-step analytical process to quantify user acceptance across technical routes (as shown in Figure 3):

- Step 1: Technical solution decomposition. Each intelligent driving solution (e.g., single-vehicle intelligence vs. collaborative intelligence) is disassembled into hardware components.
- Step 2: Indicator mapping and quantification. Based on the mapping mechanism (Section 3.2), technical features are translated into the five key indicators: safety, travel efficiency, trust, comfort, and cost. Each indicator has a corresponding quantitative evaluation submodel.
- Step 3: Comprehensive acceptance calculation. Using VE's V = F/C (Section 3.3), the functional score (F) is derived by weighting safety, travel efficiency, trust, comfort, and cost (C) via the TCO. The final value (V) reflects the comprehensive acceptance.

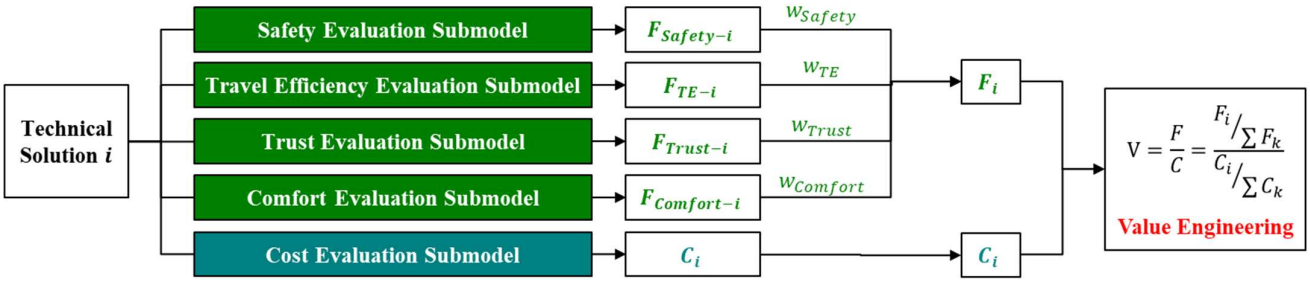


Figure 3. Methodology workflow of the acceptance evaluation framework.

4. Evaluation Submodels

Within the framework of VE, this study develops five evaluation submodels for four functional indicators and cost. All submodels are independent of each other, and a single submodel can provide references for product decisions. For analysis from the user's perspective, all submodels are evaluated at the single-vehicle level.

4.1. Cost Evaluation Submodel

This study employs the Total Cost of Ownership (TCO) to identify the cost differences among different technical routes of intelligent driving. The research team proposed a TCO evaluation model in Reference [7], which covers one-time hardware and software purchase costs, as well as energy consumption, data traffic, and maintenance costs throughout the vehicle's lifecycle. This model decomposes intelligent driving technical solutions into minimum functional units, such as sensors, controllers, and actuators. By quantifying parameters such as the type, quantity, cost, and power consumption of each component, it can accurately identify and evaluate the cost composition. The symbolic definitions of the subdivided cost indicators are shown in Table 1, and the specific model formulas can be found in Reference [7].

Table 1. TCO composition of intelligent driving.

Subdivided Cost	Symbol	Definition
Hardware Cost	C_H	Accumulate according to hardware category, quantity, and market pricing.
Software Cost	C_S	A proportional estimation is made by combining system complexity and software richness.
Energy Consumption Cost	C_E	Calculated according to component power, vehicle life, service time, and charging cost.
Data Traffic Cost	C_D	Setting the average annual cost according to the networking demand.
Maintenance Cost	C_M	The annual maintenance cost is in direct proportion to the cost of software and hardware.

$C_HC_SC_EC_DC_M$ The TCO shown in Table 1 captures the full lifecycle cost, avoiding the underestimation of long-term economic burdens for users. Compared to traditional cost models (e.g., marginal cost analysis), the TCO aligns with user decision-making habits (consumers prioritize long-term affordability over the initial price). It enables a fair comparison across technical routes: e.g., lidar fusion solutions have higher initial hardware costs but may reduce maintenance costs due to their higher reliability.

4.2. Safety Evaluation Submodel

This study uses collision avoidance effectiveness (CAE) to characterize the safety of intelligent driving. In road traffic, intelligent driving vehicles interact with other participants, leading to various collision accidents. Interactions between vehicles may cause frontal collisions, rear-end collisions, side collisions, and angle scraping collisions; interactions between vehicles and people may cause pedestrian collisions and cyclist collisions; interactions between vehicles and roads may cause obstacle collisions, rollovers, and falling accidents [28]. Different intelligent driving technical solutions have different collision avoidance effectiveness in different accident scenarios. The research team proposed a method based on multi-sensor coupling to evaluate this in Reference [24], and the specific formula is as follows (2):

$$CAE_{k,group} = 1 - \prod_{j=1}^{13} \left(1 - CAE_{k,j}\right)^{x_j} \quad (2)$$

$CAE_{k,group}$ represents the collision avoidance effectiveness of multi-sensor unit combinations for accident type k, while $CAE_{k,j}$ denotes the collision avoidance effectiveness of a single sensor unit j for accident type k, with x_j being the quantity of sensor unit j. This study considers the collision avoidance effectiveness of 13 sensor units for various traffic accidents, including vehicle-mounted sensors, roadside sensors, and V2V technologies. Formula (2) uses the local discrete approximation method to achieve collision avoidance effectiveness coupling at three levels:

- **Increase in Sensor Quantity** → Expanded sensing coverage angle and mutual verification of sensing results → enhanced collision avoidance effectiveness.
- **Heterogeneous Sensor Combination** → Extended sensing coverage and increased types or dimensions of sensing information → enhanced collision avoidance effectiveness.
- **Vehicle–Road and Vehicle–Vehicle Collaborative Sensing** → Expanded sensing coverage and increased types or dimensions of sensing information → enhanced collision avoidance effectiveness.

4.3. Travel Efficiency Evaluation Submodel

Intelligent driving can optimize travel efficiency by leveraging different functional features at three levels, namely, single-vehicle, traffic flow, and road network levels, and the optimizations at these three levels are decoupled [29]. Based on the principles of independence, representativeness, and comprehensiveness, this study selects 12 functional features related to traffic efficiency from existing studies. Table 2 illustrates the influence mechanism of different functional features on travel efficiency.

In traffic engineering, non-technical factors such as vehicle penetration rate, traffic flow, and road conditions all affect travel efficiency. However, users often lack perception of travel efficiency in non-congested scenarios [30]. Therefore, this study focuses on the maximum value of travel efficiency optimization by intelligent driving in extreme scenarios, and it uniformly uses the Transit Time Optimization Rate (TTOR) for characterization. Each functional feature in Table 2 has its own maximum TTOR, and the corresponding traffic scenarios are different. For example, $\boldsymbol{F_{TE,1}}$, $\boldsymbol{F_{TE,2}}$, and $\boldsymbol{F_{TE,3}}$ achieve the maximum traffic efficiency improvement benefits in the single-lane congestion scenario, two-lane lane-changing scenario, and single-lane vehicle-following scenario, respectively [31,32]. Due to the significant spatiotemporal dynamics and regional differences in the occurrence frequency of different scenarios and their contribution to overall traffic efficiency, there is currently no universal quantitative statistical method or standard weight in the academic community. For as objective an evaluation as possible, the weights of each functional feature in Table 2 are determined by an expert team after deliberation based on the road

characteristic parameters of typical cities, as well as the driving behavior habits and style characteristics of typical drivers [33,34]. Weighting is then performed at three levels—the single-vehicle, traffic flow, and road network levels—with the final "point–line–plane" coupling of travel efficiency achieved through Equation (3):

$$TTOR_{total} = 1 - (1 - TTOR_{vehicle}) \times \left(1 - TTOR_{flow}\right) \times (1 - TTOR_{network}) \quad (3)$$

Table 2. Optimization mechanism of intelligent driving on travel efficiency.

Level	Functional Feature	Optimization Mechanism	Weight
Single Vehicle	$F_{TE,1}$: (Connected and) Automatic longitudinal cruise control	Reduce the headway	0.8
	$F_{TE,2}$: (Connected and) Automatic lateral lane change control	Improve lane change efficiency	0.2
Traffic Flow	$F_{TE,3}$: Cooperative control of multi-vehicle-following	Reduce the fluctuation of vehicle-following speed	0.2
	$F_{TE,4}$: Cooperative control of ramp confluence	Improve the confluence efficiency of ramps	0.2
	$F_{TE,5}$: Cooperative control of signal lamp and multi-vehicle speed	Improve the traffic efficiency of signalized intersections	0.3
	$F_{TE,6}$: Intelligent traffic at signalless intersections	Improve the traffic efficiency of signalless intersections	0.2
	$F_{TE,7}$: Efficient speed planning of road sections	Increase the speed of road traffic	0.1
Road Network	$F_{TE,8}$: Efficient travel route planning	Improve the load balance of the road network	0.3
	$F_{TE,9}$: Efficient route speed planning	Improve the speed of the known route	0.1
	$F_{TE,10}$: Coordinated guidance of regional vehicle paths and lanes	Reduce unnecessary lane-changing behavior	0.3
	$F_{TE,11}$: Multi-signal and multi-vehicle speed cooperative control	Reduce the total waiting time at multiple intersections	0.2
	$F_{TE,12}$: Multi-vehicle speed cooperative control in road network	Reduce unnecessary speed limit sections	0.1

4.4. Trust Evaluation Submodel

Trust directly determines the quality of users' experience when using intelligent driving functions. If users lack trust in the technology, it may even increase drivers' attentional burden [35]. Trust is an indicator influenced by both subjective and objective factors. On the one hand, the reliability of the technology itself forms the objective foundation of trust; on the other hand, social, corporate, and individual factors can all affect users' subjective trust perception. Therefore, this study classifies trust into objective trust and subjective trust, assigning each a weight of 0.5.

This study adopts Chowdhury et al.'s combined credibility model for autonomous driving vehicles, which integrates the trustworthiness of components (sensors, controllers, and actuators) and data (positioning and V2X) into system-level trustworthiness using Dempster–Shafer theory and uncertainty logic operations [36]. The model quantifies hardware reliability (e.g., sensor failure rates and controller response accuracy) and data trustworthiness (e.g., V2X message integrity and positioning error margins) to form an objective trust baseline.

For subjective trust, a multi-index evaluation system covering social, corporate, and individual dimensions is proposed through expert deliberation. The influence mechanisms, evaluation methods, and weights of sub-indicators are shown in Table 3:

Table 3. Multi-index evaluation system of subjective trust of intelligent driving users.

Dimension	Sub-Indicator	Psychological Mechanism	Evaluation Method	Weight
Social	Technical permeability	Group psychology [37]	Market statistics	0.2
	Standard regulation	Endorsement of government credibility [38]	Regulation evaluation	0.2
	Public opinion atmosphere	Frame effect and cognitive narration [39]	Internet word frequency analysis	0.1
Corporate	Brand reputation	Anchoring effect and value identification [40]	Third-party brand power survey	0.3
Individual	Familiarity	Behavior inertia and path-dependence mechanism [41]	Large-scale user survey	0.1
	Habitual preference	Perceptual deviation and inertia overcoming cost [42]	Big data analysis of driving behavior	0.1

4.5. Comfort Evaluation Submodel

Comfort is also an indicator influenced by both subjective and objective factors. At the technical level, comfort can be characterized by quantifiable objective indicators such as NVH (noise, vibration, and harshness), speed mutation rate, human takeover frequency, and control smoothness. On the other hand, users often express discomfort through subjective descriptions like motion sickness, driving style mismatch, or unexpected driving routes.

Vehicle design contexts (e.g., chassis system, interior layout, and seat design) form the basic comfort foundation, while this study pays more attention to the functional features in intelligent driving systems that can achieve comfort improvement. This study establishes a multi-index evaluation system distinguishing objective and subjective influences based on 12 key comfort-related functional features. The selection of the 12 comfort-related functional features was informed by a systematic review of the existing literature on intelligent driving comfort, combined with empirical insights from user experience studies [43–45]. These studies identified core functional features through multi-method research, including driving simulator experiments, real-world road tests, and expert Delphi surveys. The 12 functional features cover both objective technical attributes (directly controllable by intelligent driving systems) and subjective experience-related attributes (closely linked to human–machine interaction), ensuring a balanced reflection of comfort mechanisms specific to intelligent driving. Table 4 shows the optimization mechanism, evaluation method, and weight of each functional feature on comfort.

Table 4. Multi-index evaluation system of comfort of intelligent driving users.

Dimension	Functional Feature	Optimization Mechanism	Evaluation Method	Weight
Objective	$F_{comfort,1}$: Automation	Reduce the driver's attention load	SAE classification standard	0.25
	$F_{comfort,2}$: Continuous trajectory planning	Improve horizontal NVH	Comparative analysis based on experts	0.05
	$F_{comfort,3}$: Bump minimization	Improve vertical NVH	Comparative analysis based on experts	0.05
	$F_{comfort,4}$: Ecological driving strategy	Reduce sudden acceleration and deceleration	Comparative analysis based on experts	0.05
	$F_{comfort,5}$: Smooth lateral control	Improve control stability	Comparative analysis based on experts	0.05
	$F_{comfort,6}$: Continuous curvature path planning	Reduce the change rate of curve speed	Comparative analysis based on experts	0.05

Table 4. *Cont.*

Dimension	Functional Feature	Optimization Mechanism	Evaluation Method	Weight
Subjective	$F_{comfort,7}$: Scenario adaptation	Improve the fluency of human–computer interaction	Driving simulator test	0.15
	$F_{comfort,8}$: User-friendly takeover strategy	Improve the user experience when taking over	Driving simulator test	0.10
	$F_{comfort,9}$: Custom driving mode	Provide a variety of alternative driving styles	Driving simulator test	0.10
	$F_{comfort,10}$: Personalized control parameters	Reduce carsickness	Driving simulator test	0.05
	$F_{comfort,11}$: Street framework planning	Improve the consistency of driving expectations	Comparative analysis based on experts	0.05
	$F_{comfort,12}$: Track tracking of other cars	Reduce unexpected paths	Comparative analysis based on experts	0.05

5. Case Application

5.1. Selection of Evaluation Objects

Currently, intelligent driving is in a critical period of transitioning from middle-level human–machine codriving to high-level machine-dominated driving. There are mainly two aspects of controversy in the industry regarding technical routes: one is single-vehicle intelligence versus collaborative intelligence, and the other is sensor combination.

Regarding the former discussion, it is generally believed in the industry that collaborative intelligence, by enabling joint perception and decision-making between vehicles and roads, can reduce vehicle-end hardware configuration and improve safety, travel efficiency, and comfort. However, it may also lead to drawbacks such as increased networking requirements, increased software complexity, and heightened data trust risks.

The discussion on the latter mainly involves three strategies: vision-only perception, fusion perception emphasizing high-precision mapping, and fusion perception emphasizing lidar. Different sensor combinations result in varying costs and functional features.

As referenced in [7], Figure 4 shows the codes of different routes and the corresponding intelligent driving technical solutions. At the sensor level, distinctions are made between cameras with different pixels, millimeter-wave radars with different detection distances and dimensions, and lidar with different sensing ranges and accuracies. The number before the "*" in Figure 4 means the number of corresponding sensors. At the map level, maps with different resolution accuracies are differentiated. At the communicator level, a distinction is drawn between 4G and 5G connections, where a 5G connection is a necessary condition for realizing collaborative intelligence. On this basis, the computational capability requirements of each solution are evaluated, measured in Tera Operations Per Second (TOPS). In addition, all intelligent driving vehicles are equipped with steer-by-wire and brake-by-wire systems as standard.

5.2. Data Source and Evaluation

For each technical route in Figure 4, this study evaluates their TCO, CAE, TTOR, trust, and comfort.

For the TCO, the specific model formulas and parameters can be found in Reference [7]. Among them, parameters that change over time, such as hardware unit prices, vehicle electricity prices, and vehicle data traffic prices, are updated to the latest values.

For the CAE, the $CAE_{k,j}$ data of each sensor unit j facing different accident types k is derived from Reference [24]. Based on Formula (2), the $CAE_{k,group}$ of each technical route facing different accident types can be obtained. The comprehensive CAE of a technical solution can be obtained by weighting $CAE_{k,group}$ according to the proportion of each

accident type. The proportion data of each accident type is obtained from the 2024 Statistical Yearbook of China's Road Traffic Accidents.

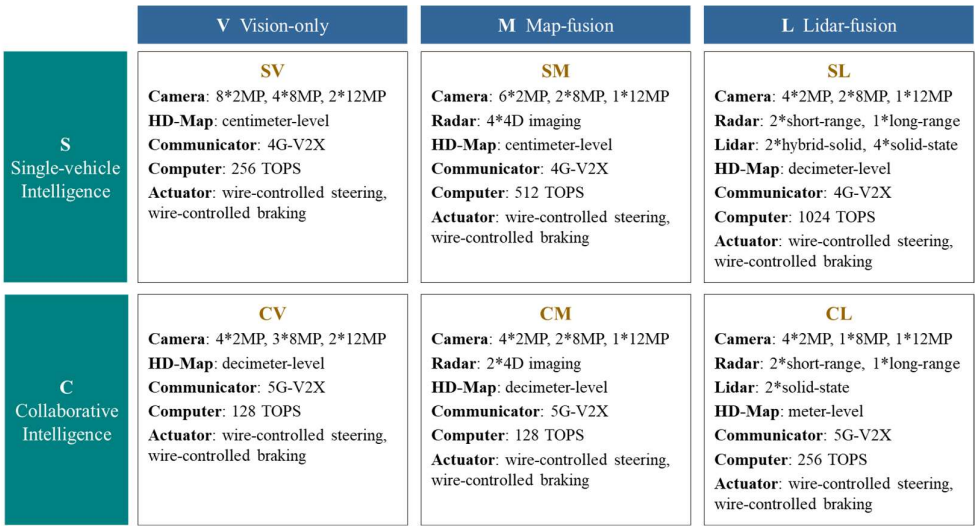


Figure 4. Intelligent driving technical solutions of different routes.

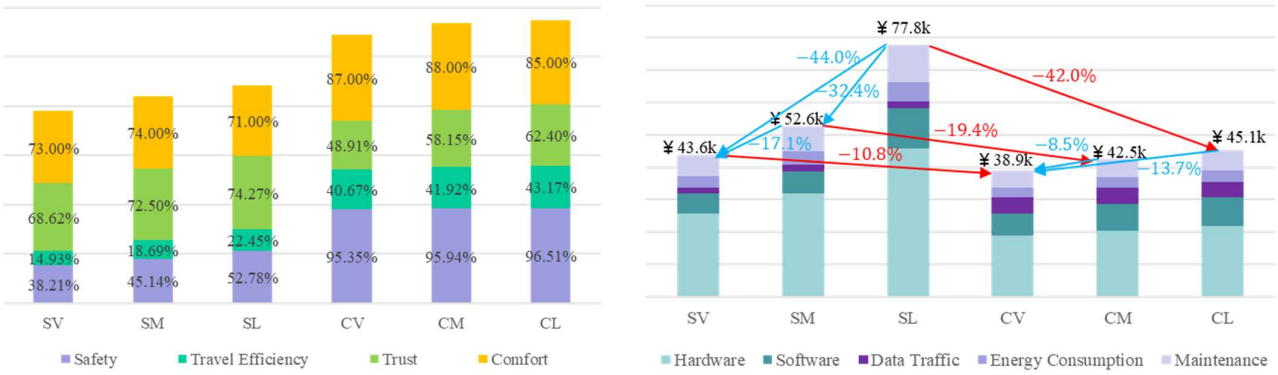
For the TTOR, this study obtains the extreme scenario parameters of each functional feature through an extensive literature investigation, and it verifies them via simulation in VISSIM 2021 software (SP 13) to determine the travel efficiency optimization effects of each functional feature under different technical solutions. Compared with other microscopic simulation tools (such as SUMO, Aimsun, and Paramics), VISSIM has unique advantages in modeling intelligent driving scenarios: On the one hand, VISSIM's driving model better captures the dynamic interactions between intelligent driving vehicles and human-driven vehicles, and it is widely used in research on intelligent driving efficiency. On the other hand, VISSIM natively integrates modules such as V2X communication, adaptive cruise control, and ramp merging coordination, which are the core functional features evaluated in this study. Moreover, it allows for fine adjustments to intelligent driving-specific parameters and strategies (such as perception range, decision-making algorithms, and interactive information), thereby enabling accurate modeling of different technical routes. The specific simulation settings can be found in the papers published by the research team [31,32].

For trust, the evaluation of objective trust directly substitutes the quantity of each hardware unit in Figure 4 into the model in Reference [36], and it uses the hardware reliability and data trustworthiness therein as the underlying parameters. The evaluation of subjective trust generally follows the method shown in Table 3, among which the brand reputation of corporates is uniformly set to 0.5 since it has no strong correlation with technical routes.

For comfort, this study invited several engineers and researchers engaged in the development of intelligent driving systems to conduct comparative evaluations of different technical routes, which were verified in combination with the literature research.

5.3. Results of Case Evaluation

Figure 5 demonstrates a comparison of the functional features and costs of intelligent driving under different technical routes. The red arrow in Figure 5b means the percentage of cost reduction caused by collaborative intelligence under the same perceptual technical route. The blue arrow in Figure 5b means the percentage of cost reduction caused by different sensor combinations under the same intelligent distribution technical route.



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

Figure 5. (**a**) Comparison of functional features of different technical routes; (**b**) comparison of costs of different technical routes.

From the functional feature perspective in Figure 5a, collaborative intelligence achieves safer, more efficient, and comfortable driving by acquiring information from more dimensions, with overall functional features superior to those of single-vehicle intelligence. Multi-modal fusion perception can realize performance complementarity and mutual redundancy among heterogeneous sensors and obtain information from more dimensions, and its overall functional features are superior to vision-only perception. Under the collaborative intelligence route, in accordance with the principle of "placing commonalities on the road and personalities on the vehicle", road-side sensors undertake the main perception tasks, thus leading to a narrowing of functional differences among different sensor combinations on the vehicle side.

From the cost perspective in Figure 5b, collaborative intelligence can effectively reduce vehicle-end costs, especially when the original vehicle-end configuration is high, with a maximum reduction of 42.0%. Under the single-vehicle intelligence route, vision-only perception has a 44.0% cost advantage over lidar fusion perception and a 17.1% advantage over map fusion perception. Collaborative intelligence can significantly narrow the cost gap between multi-modal fusion and vision-only routes: taking the lidar fusion perception route as an example, the relative cost gap is reduced from 44.0% to 13.7%.

Based on VE, functional indicators and cost indicators are integrated into value to reflect users' comprehensive acceptance. The benchmark scenario assumes equal weights for all functional indicators. Since different user groups may have distinct preferences for different functional indicators, this study also considers several additional scenarios. The specific results are shown in Figure 6.

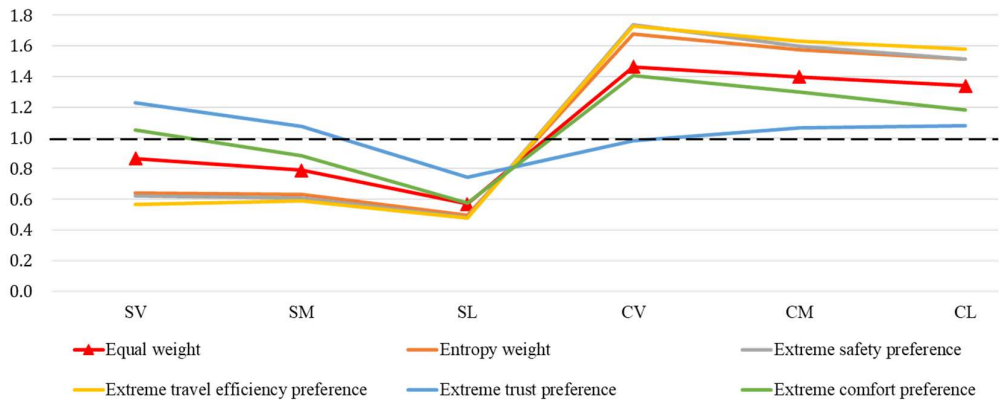


Figure 6. Comparison of value or comprehensive acceptance of different technical routes.

In Figure 6, the extreme preference scenario means setting the weight of a single functional indicator to 1 and the weights of other indicators to 0. The entropy weight scenario refers to setting weights according to the degree of the data variation (measured by information entropy) exhibited by each functional indicator within different technical routes; that is, the greater the internal difference, the greater the weight. In the equal-weight benchmark scenario, collaborative intelligence demonstrates higher acceptance than single-vehicle intelligence as a technical route, with the order of acceptance being vision-only > map fusion > lidar fusion. This finding aligns with the industry's general consensus (governments worldwide are vigorously promoting the construction of vehicle–road cooperation systems, and industry leader Tesla is committed to developing vision-only autonomous driving systems).

In most weighted scenarios, the evaluation results show a high degree of consistency with the benchmark scenario. Only the extreme travel efficiency preference scenario and extreme trust scenario exhibit outliers, but the former is extremely rare, and the latter can be avoided through cognitive education. Therefore, the analysis of different weight scenarios indicates that the model has high robustness and reliability.

6. Conclusions

This study proposes a comprehensive user acceptance evaluation framework for intelligent driving technologies, integrating subjective and objective factors from the perspective of VE. Five core indicators (safety, travel efficiency, trust, comfort, and cost) are selected, combining behavioral theory and utility theory. A mapping mechanism from technical solutions to evaluation indicators is established, bridging technical features with user acceptance. The framework addresses critical gaps in existing research by unifying technical metrics and user experience into a systematic model, enabling a quantitative comparison of acceptance across different technical routes.

Comparative analysis of single-vehicle intelligence vs. collaborative intelligence and sensor combinations (vision-only, map fusion, and lidar fusion) shows that collaborative intelligence and vision-based solutions offer higher comprehensive acceptance due to balanced functionality and cost. The framework's robustness is validated across weighted scenarios, confirming its reliability for practical applications.

The proposed framework not only quantifies user acceptance but also provides a bridge between technical routes and sustainable urban development. By highlighting collaborative intelligence and vision-based solutions as preferred options, it offers actionable insights for enhancing transport sustainability and livability:

- For policymakers, prioritizing collaborative intelligence can guide infrastructure investments (e.g., roadside sensors and 5G-V2X) that optimize traffic flow, reduce energy consumption, and lower emissions—key pillars of sustainable mobility.
- For urban planners, the cost-effectiveness of vision-based solutions accelerates the integration of intelligent driving into shared mobility systems, reducing private car usage, alleviating parking pressure, and freeing up urban space for public facilities (e.g., parks and schools), thereby improving the livability of surrounding areas.
- For enterprises, aligning technical strategies with both user acceptance and sustainability (e.g., reducing lidar dependency to lower production costs and material waste) can drive a virtuous cycle of market adoption and environmental benefits.

The current framework still has certain limitations. For example, the results of evaluation methods for subjective indicators are not close enough to those of real users, and they often rely on some indirect data for assessment. Including users in the evaluation loop is a direction worth exploring. In addition, in future research, based on this framework, the impact of technological progress and policy tools on the acceptance of intelligent driving can

be further analyzed. For instance, by setting different scenarios of technological progress, subsidies, tax incentives, regulatory standards, etc., it is possible to predict how different incentive structures (such as promoting lidar fusion vs. vision-only systems) affect market diffusion and user acceptance.

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