A Comprehensive Overview of Architectural Analysis and Testing Evaluation for Autonomous Driving Decision-Making and Planning Methods

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Abstract—**The decision-making and planning module plays a crucial role in the context of rapidly advancing autonomous driving technologies. Despite extensive research in autonomous driving decision-making and planning, systematic reviews are still lacking, aligning with the prevailing paradigm of large-scale models to consolidate diverse architectures and methodologies. This review systematically categorizes decision-making architectures, critically analyzes the advantages and limitations of various technical approaches, and synthesizes scenario-specific performance metrics within evaluation frameworks. Multiple performance evaluation methodologies are proposed to enhance testing reliability through quantitative validation protocols. These comprehensive analyses aim to establish standardized criteria for algorithm selection and application boundaries, providing actionable guidance for researchers and engineers. This allows stakeholders to identify issues during testing phases and develop more efficient validation strategies.**

Index Terms—**Autonomous Driving, Decision-making and Planning, Architecture Classification, Performance Evaluation.**

I. Introduction

THE criticality of the decision-making and planning module in autonomous driving systems is self-evident. Recent years have seen multidimensional technological evolution in this domain, driven by concurrent advancements in hierarchical, reactive, and end-to-end architectures, along with breakthroughs in search-based algorithms, data-driven methods, and large model technologies. As a core metric for evaluating autonomous driving capabilities and the system's key component, it translates sensor-derived environmental data into executable driving strategies and trajectory plans [1]. This module critically governs vehicle safety, driving efficiency, traffic coordination, energy consumption optimization, user experience, and system reliability. To establish standardized criteria for algorithm selection and application boundaries while enabling precise issue diagnosis during testing, this study contributes:

- A comparative analysis of three primary architectures—hierarchical, reactive, and end-to-end—accompanied by discussions of their respective advantages and limitations.
- It further classifies decision-making and planning methods from the perspectives of search-based, data-driven, and large-scale models, while discussing the common scope and examples within each category. Search-based methods include traditional search, heuristic search, and more; data-driven methods leverage big data and machine learning technologies to support decision-making, and large-scale model decision-making and planning employ deep learning and reinforcement learning technologies, demonstrating significant potential in addressing complex problems.
- The study subsequently synthesizes performance testing metrics and proposes evaluation methodologies to enhance benchmarking frameworks for autonomous driving systems.
- Finally, it emphasizes existing challenges, future development trends, and obstacles in decision-making and planning.

A comprehensive understanding of the decision-making and planning framework, methods, and evaluation schemes not only fosters the advancement of autonomous driving decision-making and planning technology but also lays a strong foundation for achieving higher levels of reliability in autonomous driving.

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II. Architectures for decision-making planning

Autonomous driving systems comprise three core functional layers: perception, decision-making and planning, and execution control. Decision-making and planning synthesize environmental data from perception modules as a critical functional layer to generate safe, efficient, and regulation-compliant driving strategies and trajectory plans. This process incorporates static and dynamic obstacle avoidance and adaptability to complex traffic scenarios [2] [3]. The module must account for vehicular social behaviors, enabling effective interaction with other road users (e.g., pedestrians, vehicles) through behavioral prediction. Such capability is achieved by simulating the social behavioral patterns of surrounding agents to anticipate their intentions and potential actions [2] [4]. Rather than treating path planning and behavioral decision-making as isolated tasks, the module integrates these functions into a unified framework to ensure operational coherence [2]. This hierarchical integration encompasses three core components: global route planning, behavioral decision-making, and local trajectory optimization. By integrating these layers, the system enhances computational efficiency while ensuring decision consistency and safety.

Building on theoretical and practical advancements, this study categorizes decision-making architectures into three paradigms: hierarchical, reactive, and end-to-end frameworks. These paradigms exhibit distinct characteristics in logical layering and environmental interaction mechanisms. Subsequent sections will systematically analyze their theoretical foundations, application boundaries, and comparative features, as summarized in Table 1.

TABLE I
DECISION-MAKING AND PLANNING SYSTEM ARCHITECTURE

Paradigm	Advantages	Disadvantages
Hierarchical	High safety and strong interpretability	Data transmission loss, computational delays, error accumulation issues, high system construction and maintenance costs.
Reactive	Minimal storage space usage, robustness in response to immediate changes, strong real-time capabilities	Lack of global planning and optimization, limited intelligence level, complex coordination mechanisms, weak predictive and inferential capabilities.
End-to-End	Simple architecture, capable of automatically learning complex mappings and processing high-dimensional data	Strong data dependency, high computational resource requirements, black-box nature, poor generalization ability.

A. Hierarchical Decision-Making and Planning Architecture

As the most fundamental and interpretable architectural paradigm in autonomous driving, hierarchical design achieves task specialization through layered decoupling. Its defining characteristic is decomposing the decision-making process into a three-tiered sequential system: global path planning, behavioral decision-making, and local motion planning [3]. As illustrated in Figure 1, this architecture allows for granular problem-solving through top-down task decomposition, enhancing system interpretability and safety assurance. The modular structure enables independent updates and optimizations, facilitating advanced intelligent control implementations.

The canonical implementation in Baidu Apollo 7.0 [5] demonstrates this hierarchy: its global planning layer generates kilometer-level reference paths using HD maps, the behavioral layer manages lane-level strategies via finite state machines (FSMs), while the motion planning layer employs quadratic programming algorithms to produce second-level control commands. 2023 California DMV testing data reveals that this architecture achieved 0.18 interventions per thousand miles in structured highway scenarios, outperforming end-to-end architectures' 0.53 interventions [6], validating the safety advantages inherent in hierarchical decoupling.

However, limitations persist: reliance on precise global environment models may lead to sensor over-dependence, while information transmission latency and task

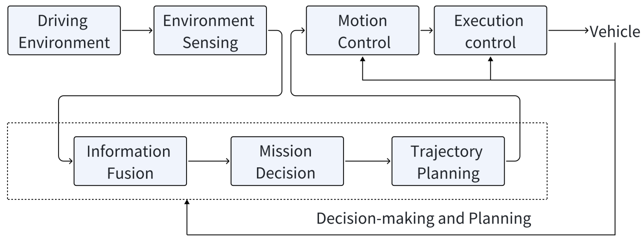

Fig. 1. Hierarchical Architecture

fragmentation can cause operational inefficiency and error accumulation. Furthermore, constraints on system reliability arise since failures in individual modules may cascade into global performance degradation, leading to substantial maintenance costs. In San Francisco urban testing scenarios, a 0.8-second synchronization delay between global and motion planning layers increased construction zone obstacle avoidance response time to 1.5 seconds—58% slower than end-to-end architectures [7]. Moreover, LiDAR malfunctions accounted for 47% of local planning module failures, highlighting vulnerabilities due to tightly coupled module interdependencies [8].

B. Reactive Decision-Making and Planning Architecture

As shown in Figure 2, the reactive architecture employs multiple parallel control loops, each encoding primitive behaviors for localized objectives, generating purposeful actions through coordination to achieve multi-level operational capabilities. This structure grants low-level controllers operational independence, eliminating the reliance on high-level processing delays, thus enabling rapid response and robust real-time performance [4]. With distinct behavioral responsibilities across layers, the system achieves flexible state transitions and fault tolerance, maintaining functional integrity even during partial module failures. However, the design must address coordination challenges between control loops and increasing prediction uncertainties as task complexity escalates, constraining the development of advanced cognitive capabilities.

The ”Boss” system, winner of the 2007 DARPA Urban Challenge, exemplifies this paradigm through a hybrid architecture that integrates hierarchical planning with reactive behaviors, utilizing asynchronous process communication for parallel obstacle detection and path planning. DARPA's official report indicates a 97% task completion rate in intersection scenarios but reveals a global path replanning frequency of 5.3 instances, resulting in a 9.2% increase in energy consumption over baseline metrics [9].

C. End-to-End Architecture

End-to-end autonomous driving technology streamlines the transformation from visual inputs to driving controls using a unified neural network, removing intermediate steps and manual interventions in conventional systems [10]. Its core strength is autonomously learning complex mapping relationships and avoiding manual feature engineering to minimize data loss and error propagation. The architecture's ability to process high-dimensional data and capture nonlinear correlations is essential for emulating human

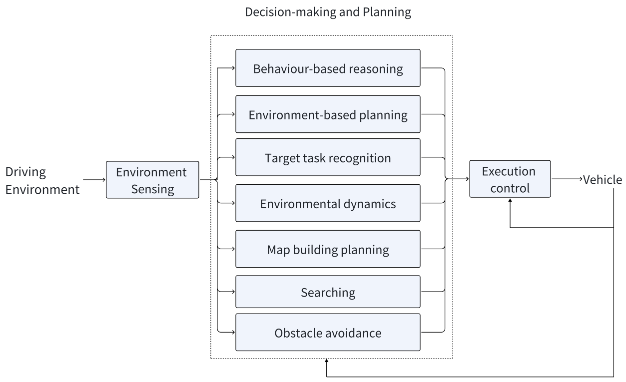

Fig. 2. Reactive Architecture

driving behaviors [11]. Large-scale data training enhances model performance, improving system reliability and safety while allowing seamless integration with perception modules to lower adaptation costs for new scenarios. However, challenges remain, including high computational resource demands and reliance on extensively annotated datasets, which increase training and iteration costs. The black-box nature of neural networks complicates system diagnostics due to limited interpretability. Insufficient generalization capabilities may arise when faced with novel scenarios or edge cases [12].

A representative implementation is the DTPP system co-developed by NTU and NVIDIA, which integrates fragmented components (trajectory generation, interactive gaming) into a single neural network through a differentiable tree-structured policy search. By enabling backpropagation for joint optimization of prediction and decision modules, it achieved 45.7 miles per intervention in the nuPlan Challenge—32% better than modular architectures—with only 0.21m lateral error in construction zones [13]. Another approach, UniAD, utilizes an all-transformer architecture with multi-task co-training for perception-planning coupling, reducing planning errors by 42% to 0.15m in Waymo evaluations [2]. These examples validate the potential of end-to-end architectures in generalizing complex scenarios; however, computational latency (e.g., DTPP's 98ms inference time) and limitations in interpretability remain bottlenecks for deployment.

III. Classification system for decision-making and planning methods

Chapter II established the centrality of decision-making and planning in the technological evolution of autonomous driving. Critical analysis revealed distinct operational paradigms—hierarchical, reactive, and end-to-end architectures—and their strengths and limitations. The modular verification advantages of hierarchical architectures have driven the refinement of search-based algorithms. In contrast, the sensor-to-control direct mapping in end-to-end architectures fundamentally enables data-driven methodologies. The methodology landscape continues to evolve through technological breakthroughs, particularly in large-scale models and deep learning paradigms. Current methodologies are shifting from partitioned problem-solving approaches to holistic joint optimization frameworks.

In response to these developments, this chapter introduces a new taxonomy that integrates existing technical approaches, including search-based algorithms, data-driven strategies, and large-model-enabled paradigms. This framework establishes a systematic theoretical foundation for decision-making in autonomous vehicles while identifying methodological constraints and emerging challenges to guide future research directions.

A. Search-Based Decision-Making and Planning Methods

In autonomous driving, search-based methods constitute a fundamental technical approach for identifying optimal solutions through systematically exploring action paths. This category encompasses traditional, heuristic, dynamic programming, and randomized search algorithms, as outlined below.

- Traditional Search Algorithms

1) Breadth-First Search (BFS): BFS is a blind search strategy that expands nodes layer-by-layer from the root until reaching the target. While it guarantees shortest-path discovery, its high spatial complexity limits its applicability to large-scale problems [14].

2) Depth-First Search (DFS): A memory-efficient blind search that explores individual paths to maximal depth, though it may fail to identify optimal solutions [15].

3) Dijkstra's Algorithm: Widely employed for single-source shortest path problems in graphs with non-negative edge weights. Its efficiency diminishes in obstacle-rich environments but can be improved through parallelization [16].

- Heuristic Search Algorithms

4) A Algorithm:* The A* algorithm integrates actual costs with heuristic estimates to efficiently locate the shortest paths, particularly in complex or obstacle-dense environments [17]. Algorithmic efficiency heavily depends on the selection of the heuristic function. For instance, Zhou Chunhui et al. demonstrated the application of the A* algorithm in path planning through its implementation to solve the 8-puzzle problem [18]. Enhanced variants incorporating turn penalty functions, obstacle grid coefficients, and safety margins improve adaptability to intricate road conditions while reducing path length and steering frequency [19].

5) Ant Colony Optimization (ACO): A heuristic algorithm inspired by ant foraging behavior, ACO is designed to solve combinatorial optimization problems such as shortest path identification. It can be adapted through framework extensions for multi-source shortest-path problems involving multiple origins and destinations. For example, assigning virtual destinations to each origin and integrating them into a unified network transforms multi-source problems into single-source formulations. Performance enhancements include directional guidance mechanisms, pheromone redistribution strategies, and dynamic factor-based pheromone concentration updates to accelerate search initiation and prevent excessive pheromone depletion on optimal paths [20]. Quantum-inspired variants redefine ant positions via qubits and replace conventional heuristics with quantum fidelity measures, improving convergence rates and global optimum discovery probabilities [21].

6) Artificial Bee Colony (ABC): ABC is a swarm intelligence algorithm mimicking honeybee foraging behavior. It can address multi-source shortest-path problems. Enhancements such as large-scale neighborhood searches [22], dual-layer evolutionary structures [23], and multi-colony parallel evolution strategies strengthen global exploration capabilities and convergence rates while mitigating premature convergence.

- Dynamic Programming Search Algorithms

*7) D*Lite:* A dynamic path-planning algorithm is designed for rapid path recalculation in changing environments. It updates existing paths locally to accommodate dynamic obstacles. Performance improvements include integrating a safety coefficient to prevent diagonal path traversal through obstacle grid vertices [24]. Enhanced variants based on cell decomposition apply modified Boustrophedon rules to partition environmental maps into cellular units, constructing cell-node graphs. Bidirectional graph search algorithms identify optimal unit sequences for the shortest paths and utilize core grids to guide search directions, accelerating planning efficiency [25].

8) The Floyd-Warshall algorithm: A dynamic programming algorithm computes all pairs shortest paths in a graph. Iterative updates of shortest path estimates between all vertex pairs address the all-source shortest path problem, making it suitable for small-scale graphs [26].

- Randomized Search Algorithms

9) Rapidly-exploring Random Trees (RRT): An efficient strategy for path planning in high-dimensional and nonlinear dynamical systems, which employs random sampling and tree expansion to explore configuration spaces [27]. While RRT may require extensive iterations to identify optimal solutions and faces the risk of local minimum entrapment, improvements such as Luo Hui's two-phase RRT algorithm—utilizing cubic Bézier curves and heuristic functions—enhance path smoothness and continuity [28]. Xu Wan's regionally constrained RRT generates smooth trajectories through intelligent sampling and path pruning, enabling uninterrupted steering maneuvers for vehicles or robots [29].

As decision-making and planning problems increase in scale and complexity, traditional algorithms encounter dual challenges in computational efficiency and solution feasibility, necessitating the integration of novel technical approaches.

B. Data-Driven Decision-Making and Planning Methods

Data-driven methods leverage big data analytics and machine learning to extract actionable insights from real-world driving data, enhancing decision accuracy and scenario adaptability [30]. Key methodologies include:

1) Deep Reinforcement Learning (DRL): As a core methodology, DRL identifies optimal policies by simulating human driving behaviors through various models: deterministic policy gradient-based actor-critic frameworks for continuous action spaces [31], demonstration-augmented DDPG [32], and ECDDPG [33] algorithms that enhance training efficiency, along with proximal policy optimization (PPO) for improved sample complexity through alternating data sampling and objective optimization [34]. Extended applications include Qi Liu et al.'s graph reinforcement learning (GRL) framework, which integrates graph neural networks to model vehicle interactions in dynamic traffic [35]; Yang Guan et al.'s hierarchical architecture that combines model-based RL for multi-path planning [36]; Yuchuan Fu et al.'s hybrid system that merges DRL with expert knowledge to address black-box limitations [37]; and Zhang Qian et al.'s multi-agent RL with goal decomposition for collaborative long-term optimization [38].

2) Mixed-Integer Quadratic Programming (MIQP): For motion planning in complex scenarios (e.g., lane changes), MIQP formulates problems with logical constraints to generate feasible, safe, and comfortable maneuvers. The AutonoVi algorithm [39] exemplifies this approach by incorporating traffic rules and constraints into an optimization framework for path planning.

3) Behavior Cloning and Behavioral Modeling: These methods learn behavioral patterns from real or simulated data for transfer to novel scenarios. Using simplified synthetic datasets, M. Stoll et al. [40]demonstrated reliable and comfortable driving through behavior cloning.

4) Ensemble Learning with Uncertainty Estimation: Ensemble techniques enhance decision safety by integrating motion predictions with uncertainty quantification. Xiaolin Tang et al. [41] developed a deep neural network-based predictor using deep ensembles for uncertainty-aware decisions. At the same time, Yang Hao combined ensemble learning with RL through multi-strategy coordination algorithms that blend human and machine decision logic [42].

5) Genetic Algorithm-Big Data Fusion: Integrating the global search capabilities of genetic algorithms with big data analytics enhances path planning precision. Zhang Caiming et al. [43]proposed a GA-based framework incorporating big traffic data for target vehicle routing.

6) Deep Gaussian Processes with Feedback Control: This approach reduces data requirements while enabling real-time closed-loop control. As demonstrated in [44], deep Gaussian processes with feedback mechanisms achieve smooth driving trajectories under limited training data.

Despite the potential of data-driven methods for handling uncertain information, their performance is not always optimal, particularly in incomplete data, unpredictable environments, or unclear objective functions.

C. Decision-Making and Planning Based on Large Models

In recent years, significant advancements have been made in research on decision-making and planning for autonomous driving, utilizing large models fueled by progress in deep learning and reinforcement learning technologies.

1) LLMs (Large Language Models): LLMs have demonstrated their potential in autonomous driving applications. The model can output the vehicle's subsequent motion by inputting surrounding objects as textual prompts into LLMs, along with their coordinate and velocity information [45]. This approach highlights the critical importance of spatial recognition and compliance with traffic rules for autonomous driving.

2) The BEVGPT model: The BEVGPT, a generative pre-trained large model, integrates driving scene prediction, decision-making, and motion planning, underscoring the significance of incorporating various modules in autonomous driving tasks [46]. This framework makes driving decisions based on Bird's Eye View (BEV) images through a two-stage training process—initially training a causal transformer with vast autonomous driving data, followed by online fine-tuning with a simulator to learn scene prediction and decision-making. The model can predict trajectories for the next 4 seconds and scenes for the next 6 seconds, ensuring the feasibility and smoothness of the trajectory.

3) DriveMLM: DriveMLM, developed by SenseTime, is a multi-modal large model that achieves closed-loop autonomous driving by integrating multi-modal inputs and behavioral planning states. This framework utilizes multi-modal LLMs to bridge the gap between language-based decisions and vehicle control commands, demonstrating the potential application of LLMs in closed-loop autonomous driving simulators [36]. This method improves the efficiency and safety of autonomous driving systems by standardizing decision states and utilizing existing motion planning modules. In practical applications, DriveMLM achieved a driving score of 76.1 in the CARLA Town05 Long test, outperforming the Apollo baseline by 4.7 points under the same settings [47], proving the effectiveness of its model.

4) Apollo ADFM: Apollo ADFM, released by Baidu, is the world's first L4-level autonomous driving large model. It reconstructs autonomous driving based on large model technology, featuring ultra-long-tail scene detection and high-order scene semantic understanding capabilities, enabling fully unmanned autonomous driving. It employs a variety of advanced technologies and methods. For example, it uses a semi-definite relaxation-based collaborative planning and control framework with ADMM (Alternating Direction Method of Multipliers), which helps solve non-linear and non-convex optimization problems, thereby improving computational efficiency and real-time performance [48]. Additionally, Apollo adopts the Adaptive Pole Grid method, an algorithm designed based on local search space, which effectively avoids collisions and smooths paths [49].

5) UniAD: The UniAD, a general large model for perception and decision-making integration proposed by the CVPR 2023 best paper, improves the accuracy and robustness of prediction and planning tasks through efficient multi-modal data fusion and advanced planning algorithms. This approach not only enhances the performance of detection and tracking tasks but also significantly reduces prediction errors and collision rates [50].

6) DriveGPT4: DriveGPT4, developed by Haomo AI, is a generative large model trained on 40 million kilometers of mass-produced vehicle driving data, with a parameter scale of 120 billion. It primarily addresses cognitive decision-making issues in autonomous driving. It can predict low-level control signals and optimize performance through a customized, visual instruction-tuned dataset. This method allows DriveGPT4 to excel in various tasks and generalize to more unseen scenarios via zero-shot learning [51]. DriveGPT4 possesses the potential to handle distributed scenarios and recognize intentions, enabling it to make informed decisions in real driving situations, such as direction recognition and traffic light identification [52].

7) Drive-WM: The first end-to-end autonomous driving world model, Drive-WM, proposed by the Institute of Automation at the Chinese Academy of Sciences, generates high-fidelity driving scenes through joint spatial-temporal modeling. Drive-WM employs a model predictive control (MPC)-based method for behavioral planning. This approach allows vehicles to adjust their driving paths and speeds based on current road conditions and surrounding environments, ensuring safety and efficiency [53]. Drive-WM also explains its decisions, enhancing transparency and user trust in autonomous driving systems. This aspect is crucial for public acceptance and adoption of autonomous driving technology.

8) DriveVLM: DriveVLM, a large visual-language model arising from a collaboration between Tsinghua University and Li Auto, integrates visual perception and language understanding capabilities to enhance autonomous driving systems' decision quality and safety. DriveVLM incorporates the strengths of large language models, enabling it to comprehend and process natural language instructions and dialogues related to driving. This integration allows the system to respond to preset commands and adjust its behavior based on real-time dialogues [54].

9) Drive-OccWorld: The Drive-OccWorld model, collaboratively developed by Zhejiang University and Huawei, innovatively integrates semantic and motion condition normalization, enhancing prediction and planning performance in autonomous driving. It also provides a flexible behavioral condition interface, improving the model's controllability [55].

Large model-based decision-making and planning showcase immense potential in autonomous driving. However, despite these promising advancements, challenges and limitations remain. For instance, real-time planning under uncertainty is critical, as autonomous vehicles must engage in short-term and long-term planning in complex, dynamic environments [56]. Furthermore, integrating prediction and planning is essential for safe, efficient, and comfortable driving [57]. Challenges also arise in effectively blending different functional modules, managing uncertainty, improving real-time performance, and reliably deploying these technologies in vehicles.

IV. Evaluation Strategy

As autonomous driving technologies evolve from search-based approaches to data-driven and large model paradigms, decision-making and planning systems face challenges such as insufficient adaptability to complex environments, inadequate safety assurance, and limited interpretability. To address these challenges, this work proposes a four-dimensional evaluation framework encompassing fundamental performance, robustness, safety, and interpretability, enabling a comprehensive multi-perspective assessment of decision-planning systems. The schematic diagram of the evaluation methodology in this article is shown in Figure 3.

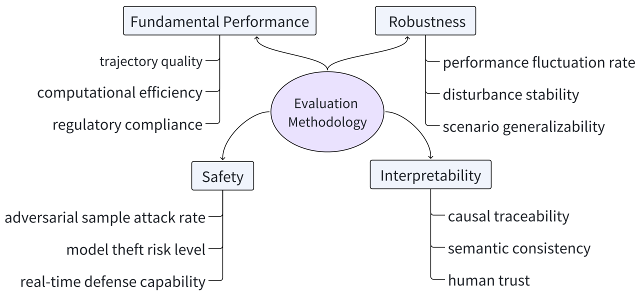

Fig. 3. Evaluation Methodology

A. Fundamental Performance Evaluation

Fundamental performance evaluation examines the essential capabilities of decision-planning systems in nominal environments, using metrics encompassing trajectory quality, computational efficiency, and regulatory compliance.

Trajectory quality quantifies path optimality through metrics of length and curvature continuity. Computational efficiency assesses real-time performance via planning latency and memory utilization. Compliance verifies legal boundaries by statistically analyzing frequencies of traffic rule violations. Empirical studies indicate that search-based methods excel in structured road networks. For instance, Dijkstra's algorithm achieves trajectory errors below 0.3 m in static maps [58], yet exhibits exponential growth in replanning latency in dynamic scenarios. Data-driven methods show 0.5 m trajectory errors on the nuScenes benchmark [59] with consistent 50 ms response times, though they experience a 15% compliance degradation compared to traditional approaches. While Wayve's GPT-Drive enhances trajectory smoothness in complex intersections, it requires post-hoc rule engines to mitigate the risks of wrong-way driving [60].

B. Robustness Evaluation

Robustness evaluation quantifies the stability and adaptability of decision-planning systems under dynamic disturbances, parameter perturbations, and anomalous inputs. Core metrics include performance fluctuation rate, disturbance stability, and scenario generalizability.

The performance fluctuation rate, calculated as the ratio of trajectory errors before and after non-adversarial natural perturbations, directly reflects system resilience. Lower ratios indicate superior robustness, representing minimal performance degradation under sensor noise or environmental transients.

Disturbance stability quantifies tolerance thresholds through the minimum adversarial perturbation distance—the smallest sensor input deviation (e.g., ± 500 lux illumination changes or ± 5 cm LiDAR noise) the system can withstand while maintaining safe planning. Higher thresholds indicate stronger disturbance resistance. For example, traditional search methods achieve more than 90% disturbance stability in static maps but exhibit a 40% replanning failure rate in dynamic scenarios like pedestrian intrusions [61], revealing sensitivity to transient disturbances. Adversarially trained data-driven methods enhance adaptability: studies [62] report lane retention improvement from 68% to 89% under sudden illumination changes. However, trajectory deviations increase by 2.1 × in rain and fog conditions, indicating unresolved robustness challenges in adverse weather.

C. Safety Evaluation

Safety evaluation identifies vulnerabilities in data-driven models against adversarial attacks, privacy breaches, and malicious tampering. Key metrics include the adversarial sample attack rate, model theft risk level, and real-time defense capability.

The adversarial sample attack rate measures the probability of planning failures induced by perturbed LiDAR point clouds or camera images. Higher rates indicate weaker security. Studies show that adversarial perturbations can increase lateral errors by 300% in end-to-end models, with adversarial road textures leading to wrong-way driving [63].

Model theft risk quantifies the similarity between proxy models (constructed via distillation or trajectory reconstruction attacks) and original models. For example, proxy models achieve Dynamic Time Warping (DTW) distances less than or equal to 0.3 in trajectory reconstruction, indicating near-identical path planning to original systems [63].

Real-time defense requires low-latency anomaly detection and high interception rates. Multimodal attacks increase path deviation by 45%, necessitating the use of security sandboxes to isolate critical modules [64]. Expanding attack surfaces demand comprehensive dynamic protection frameworks.

D. Interpretability Evaluation

Interpretability evaluation deciphers the decision logic of black-box models by quantifying the alignment between model outputs and human cognition. Metrics include causal traceability, semantic consistency, and human trust.

Causal traceability utilizes SHAP (Shapley Additive Explanations) values to quantify the contributions of sensors to decisions. Higher SHAP values indicate greater sensor influence and enhanced system transparency. Li Shengbo et al. [60] demonstrated that camera-dominant decisions under lighting interference lead to increased misjudgments. By dynamically reweighting multi-sensor fusion (e.g., prioritizing radar SHAP values), the misjudgment rates decrease by 50%, thereby enhancing system robustness.

Semantic consistency evaluates the alignment between planned trajectories and human intent. Custom simulation tests [60] reveal that models lacking semantic explanations achieve 72% of intent matching in complex intersections. Counterfactual explanation tools that perturb obstacle speeds improve matching rates to 89% and reduce misjudgments by 21%.

Human trust is quantified via EEG θ-wave energy and subjective Likert-scale ratings. Higher θ-wave energy indicates greater user unease with system decisions. A driving simulator experiment by Wu Zheng et al. [65] showed that when trust scores reach 4, the takeover frequency drops by 60%; if θ-wave energy exceeds 30 μV, takeover probability surges by 80%.

V. Future Development Trends

Despite the remarkable research achievements in both domestic and international fields of decision-making and planning for autonomous vehicles, numerous technical challenges persist at this stage. Future research endeavors ought to prioritize the following aspects:

1) Versatile High-Generalization Large Models: Developing models capable of adapting to diverse driving environments to address the current limitations in generalization and training efficiency. The development of universal large models that can accommodate a variety of driving environments and scenarios is a significant research direction in the field of autonomous driving. Currently, autonomous driving models face several challenges, including low environmental exploration efficiency, slow initial training speed, poor generalization ability, low training efficiency, and limited applicability in various scenarios. These models must possess a high degree of generalization capability to make accurate decisions when encountering unseen situations.

2) Self-Learning and Evolutionary Decision-Making and Planning Algorithms: Leveraging principles from modern bionics inspired by biological neural intelligence, the development of decision-making and planning algorithms with capabilities for self-learning, self-evolution, and self-upgrade will be crucial for comprehensively enhancing the intelligence level of autonomous driving. Integrating bionic principles into algorithms primarily involves drawing inspiration from nature, simulating biological perception, decision-making, and adaptation mechanisms to improve algorithm performance and adaptability.

3) Interpretability of End-to-End Models: End-to-end algorithm frameworks utilize raw sensor inputs to generate motion plans for vehicles rather than focusing on separate tasks such as detection and motion prediction. The advantages of joint feature optimization for perception and planning are rapidly evolving with this approach [66]. However, the precision and responsiveness of end-to-end solutions rely on complex network architectures, large-scale training datasets, and substantial computational resources. Due to the closed nature of end-to-end models, their decision-making processes lack transparency, making it difficult to explain and trace issues when they arise, which does not align with the high reliability, safety, and trustworthiness required for autonomous driving. Therefore, future research should focus on breaking through the nonlinear, high-dimensional mapping mechanisms of end-to-end models, elucidating their internal hierarchies and multidirectional dynamic feedback patterns to enhance model interpretability and predictive accuracy, thereby ensuring the stability and reliability of decision-making and planning outcomes. 4) Interactive Planning and Personalized Decision-Making: Interactive planning can address complex decision-making challenges by emphasizing human-machine interaction, flexibility, a scientific approach, and public participation [67]. In future driving scenarios, it is essential to consider the decision-maker's preferences for plans and to fully leverage known objective information to achieve better decision-making outcomes through human-machine interaction. Moreover, suppose the driving behaviors of autonomous vehicles align with those of human drivers and can be recognized and accepted by other road users. In that case, it will facilitate smooth interactions in mixed traffic environments. This further underscores the importance of personalized decision-making and planning design.

5) Collaborative Optimization Algorithms for Multimodal Data: In dynamic real-world traffic scenarios, numerous interactive factors with complex attributes, such as time-varying and nonlinear characteristics, exist. In addition to considering the vehicle's dynamic information, it is crucial to integrate a wide array of environmental data from various sensors. In response to this challenge, future research must develop a robust multi-objective collaborative optimization algorithm capable of managing multimodal data. This algorithm will uncover and utilize the complementarity and exclusivity among objectives, achieving balance and coordinated optimization amid dynamic changes.

6) Collaborative Intelligence and Smart Transportation Systems: Autonomous driving technology necessitates constructing a highly intelligent and collaborative decision-making and planning system. This system places vehicles as intelligent nodes within the traffic network, capable of independently executing complex decision-making and planning while engaging in real-time interaction and collaboration with other traffic participants.

At the micro level, autonomous vehicles simulate game theory and interactions among multiple agents to understand better and predict dynamic changes in the surrounding environment. Based on multi-agent collaborative interaction, this swarm decision-making approach emphasizes the importance of continuous, strong interactive behaviors, such as exploratory games, in algorithm design, thereby enhancing the adaptability and robustness of decision-making.

At the macro level, the development of intelligent transportation systems offers broader informational support and decision-making space for autonomous driving. Through the collaboration of vehicle-road-cloud, autonomous vehicles can overcome the limitations of onboard sensors to achieve comprehensive perception, thus addressing safety hazards caused by incomplete information. This collaborative mechanism expands the perception range of individual vehicle intelligence and fosters the deep integration and mutual empowerment of various elements within the transportation system.

Looking to the future, research will focus on integrating the complexity of multi-agent interactions with the benefits of intelligent transportation systems to create a unified decision-making and planning framework. This framework will enhance the structural consistency and systematic nature of swarm decision-making, promoting the realization of personalized and human-like driving experiences and providing new momentum and direction for the development of autonomous driving technology.

VI. Conclusion

This paper presents a comprehensive overview of the architectures, methodologies, and evaluation strategies in autonomous driving decision-making and planning while also outlining future development trends. Regarding architectures, the paper delves into the strengths and weaknesses of hierarchical, reactive, and end-to-end architectures. The classification of methods at this level provides a detailed account of various decision-making and planning approaches, including search-based algorithms, data-driven strategies, and large model technologies, supported by numerous examples. Additionally, the paper proposes a four-dimensional evaluation framework encompassing fundamental performance, robustness, safety, and interpretability, offering a robust tool for comprehensive system assessment. Future research will continue to address existing technical challenges while exploring novel methodologies and technologies to achieve safer, more efficient, and reliable autonomous driving systems.

REFERENCES

[1] Y. Guan, Y. Ren, S. E. Li, H. Ma, J. Duan, and B. Cheng, "Integrated decision and control: Towards interpretable and efficient driving intelligence," *arXiv preprint*, 2021.

[2] Y. H. et al., "Planning-oriented autonomous driving," *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2023, pp. 17 853–17 862.

[3] P. Hang, C. Lv, C. Huang, J. Cai, Z. Hu, and Y. Xing, "An integrated framework of decision making and motion planning for autonomous vehicles considering social behaviors," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 12, pp. 14 458–14 469, 2020.

[4] P. Wu, F. Gao, X. Tang, and K. Li, "An integrated decision and motion planning framework for automated driving on highway," *IEEE Trans. Veh. Technol*, vol. 72, no. 12, pp. 15 574–15 584, Dec. 2023.

[5] D. Kim, G. Kim, H. Kim, and K. Huh, "A hierarchical motion planning framework for autonomous driving in structured highway environments," *IEEE Access*, vol. 10, pp. 20 102–20 117, 2022.

[6] C. DMV, "2023 autonomous vehicle disengagement reports," CA DMV-ADV23, Tech. Rep., 2023.

[7] NHTSA, "Response latency analysis in hierarchical ads," DOT HS 813 672, Tech. Rep., 2023.

[8] S. International, "Failure mode analysis of modular autonomous systems," SAE Tech. Paper 2023-01-0876, Tech. Rep., 2023.

[9] DARPA, "Urban challenge final report," DARPA-TR-07-50, Tech. Rep., 2007.

[10] M. B. et al., "End to end learning for self-driving cars," *arXiv preprint*, 2016.

[11] H. Liang, "Spatiotemporal feature fusion for end-to-end driving decision algorithms and simulation," Ph.D. dissertation, Univ. Electron. Sci. Technol. China, 2019.

[12] W. L. et al., "A multi-task fusion strategy-based decision-making and planning method for autonomous driving vehicles," *Proc. Italian Nat. Conf. Sensors*, 2023.

[13] Z. Huang, P. Karkus, B. Ivanovic, Y. Chen, M. Pavone, and C. Lv, "Dtpp: Differentiable joint conditional prediction and cost evaluation for tree policy planning in autonomous driving," *2024 IEEE International Conference on Robotics and Automation (ICRA)*, 2024, pp. 6806–6812.

[14] M. A. Javaid, "Understanding dijkstra's algorithm," *SSRN*, 2013.

[15] V. K. Garg, "Removing sequential bottleneck of dijkstra's algorithm for the shortest path problem," *arXiv preprint*, 2018. [Online]. Available: https://api.semanticscholar.org/CorpusID:57189188

[16] Y. Ye, F. Wei, and X. Cai, "Fast dijkstra algorithm based on parallel computing," *Comput. Eng. Appl.*, vol. 56, no. 6, pp. 58–65, 2020.

[17] Y. Liu, J. Du, and Q. Zhang, "Performance comparison of a* and dijkstra algorithms based on path optimization," *Mod. Electron. Tech*, vol. 40, no. 13, pp. 181–186, 2017.

[18] C. Zhou and S. Li, "Research on dijkstra algorithm and a* algorithm," *Softw. Guide*, no. 1, pp. 102–103, 2007.

[19] L. Hu, Y. Ye, and C. Huang, "Vehicle path planning using variable neighborhood a* algorithm based on driving risk field," *Model. Simul*, vol. 13, no. 3, pp. 2367–2380, 2024.

[20] Y. Yuan, Y. Liu, and B. Wu, "A modified ant colony algorithm to solve the shortest path problem," *Proc. Int. Conf. Cloud Comput. Internet Things*, 2014, pp. 148–151.

[21] L. Zhao, Y. Dong, and T. Jiang, "Solving shortest path problem via quantum ant colony optimization algorithm," *Inf. Technol. Informatization*, no. 12, pp. 112–115, 2019.

[22] Z. Lin, "Improved artificial bee colony algorithm for bi-level vehicle routing problems," Ph.D. dissertation, South China Univ. Technol, 2024.

[23] D. Zhao and Y. Zhang, "Multi-population parallel artificial bee colony algorithm based on bi-level evolution," *Comput. Eng. Des*, vol. 36, no. 1, pp. 6–12, 2015.

[24] N. D. et al., "Improved path planning method based on d* lite algorithm," *Mach. Tool Hydraul*, vol. 50, no. 2, pp. 167–171, 2022.

[25] Y. Zhang and M. Shi, "Improved d* lite path planning algorithm based on cell decomposition," *J. Chongqing Univ. Posts Telecommun. (Nat. Sci.)*, vol. 33, no. 6, pp. 1007–1013, 2021.

[26] X. Zhou, "Research on shortest path problem and its solutions," *Comput. Knowl. Technol*, vol. 6, no. 6, pp. 1403–1412, 2010.

[27] S. M. Lavalle, "Rapidly-exploring random trees: A new tool for path planning," *The annual research report*, 1998.

[28] H. L. et al., "Improved two-stage smooth rrt search algorithm," *Comput. Eng. Appl*, vol. 58, no. 12, pp. 74–84, 2022.

[29] W. X. et al., "Global path planning algorithm based on improved rrt*," *Control Decis*, vol. 37, no. 4, pp. 829–838, 2022.

[30] Y. W. et al., "A survey on datasets for decision-making of autonomous vehicle," *arXiv preprint*, 2023.

[31] T. L. et al., "Continuous control with deep reinforcement learning," *Proc. Int. Conf. Learn. Represent. (ICLR)*, 2015.

[32] S. Zuo, "Research on intelligent decision control for autonomous vehicles based on deep reinforcement learning," Ph.D. dissertation, Harbin Inst. Technol, 2018.

[33] R. Li, "Research on intelligent vehicle decision control based on model-integrated deep reinforcement learning," Ph.D. dissertation, Hefei Univ. Technol, 2020.

[34] J. S. et al., "Proximal policy optimization algorithms," *arXiv preprint*, 2017.

[35] Q. L. et al., "Graph reinforcement learning-based decision-making technology for connected and autonomous vehicles: Framework, review, and future trends," *Proc. Italian Nat. Conf. Sensors*, 2023.

[36] Y. G. et al., "Integrated decision and control: Towards interpretable and efficient driving intelligence," *arXiv preprint*, 2021.

[37] Y. F. et al., "Hybrid autonomous driving guidance strategy combining deep reinforcement learning and expert system," *IEEE Trans. Intell. Transp. Syst*, vol. 23, no. 7, pp. 11 273–11 286, 2022.

[38] Q. Zhang, T. Li, and C. Bai, "Hierarchical decision optimization method based on multi-agent reinforcement learning," *J. Univ. Electron. Sci. Technol. (Soc. Sci. Ed.)*, vol. 24, no. 6, pp. 90–96, 2022.

[39] A. B. et al., "Autonovi: Autonomous vehicle planning with dynamic maneuvers and traffic constraints," *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, 2017, pp. 2629–2636.

[40] M. S. et al., "Scaling planning for automated driving using simplistic synthetic data," *arXiv preprint*, 2023.

[41] X. T. et al., "Prediction-uncertainty-aware decision-making for autonomous vehicles," *IEEE Trans. Intell. Veh*, vol. 7, no. 3, pp. 849–862, 2022.

[42] H. Yang, "Research on multi-strategy collaborative decision system based on deep reinforcement learning," Ph.D. dissertation, Huazhong Univ. Sci. Technol., 2020.

[43] C. Zhang and Z. Liu, "Target vehicle path planning method integrating genetic algorithm and big data," *Microelectron. Comput*, vol. 37, no. 6, pp. 89–92, 2020.

[44] W. F. et al., "Learn to make decision with small data for autonomous driving: Deep gaussian process and feedback control," *Proc. IEEE Intell. Veh. Symp.*, 2020, pp. 1–11.

[45] K. Tanahashi, Y. Inoue, Y. Yamaguchi, H. Yaginuma, D. Shiotsuka, H. Shimatani, K. Iwamasa, Y. Inoue, T. Yamaguchi, K. Igari, T. Horinouchi, K. Tokuhiro, Y. Tokuchi, and S. Aoki, "Evaluation of large language models for decision making in autonomous driving," *ArXiv*, vol. abs/2312.06351, 2023. [Online]. Available: https://api.semanticscholar.org/CorpusID:266162537

[46] P. Wang, M. Zhu, H. Lu, H. Zhong, X. Chen, S. Shen, X. Wang, and Y. Wang, "Bevgpt: Generative pre-trained large model for autonomous driving prediction, decision-making, and planning," *ArXiv*, vol. abs/2310.10357, 2023. [Online]. Available: https://api.semanticscholar.org/CorpusID:264146375

[47] W. Wang, J. Xie, C. Hu, H. Zou, J. Fan, W. Tong, Y. Wen, S. Wu, H. Deng, Z. Li, H. Tian, L. Lu, X. Zhu, X. Wang, Y. Qiao, and J. Dai, "Drivemlm: Aligning multi-modal large language models with behavioral planning states for autonomous driving," *ArXiv*, vol. abs/2312.09245, 2023. [Online]. Available: https://api.semanticscholar.org/CorpusID:266210476

[48] X. Zhang, Z. Cheng, J. Ma, S. Huang, F. L. Lewis, and T. H. Lee, "Semi-definite relaxation-based admm for cooperative planning and control of connected autonomous vehicles," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 7, pp. 9240–9251, 2022.

[49] Y. L. et al., "Apollo: Adaptive polar lattice-based local obstacle avoidance and motion planning for automated vehicles," *Proc. Italian Nat. Conf. Sensors*, 2023.

[50] T. Ye, W. Jing, C. Hu, S. Huang, L. Gao, F. Li, J. Wang, K. Guo, W. Xiao, W. Mao, H. Zheng, K. Li, J. Chen, and K. Yu, "Fusionad: Multi-modality fusion for prediction and planning tasks

of autonomous driving," *ArXiv*, vol. abs/2308.01006, 2023. [Online]. Available: https://api.semanticscholar.org/CorpusID:260378760

[51] Z. Xu, Y. Zhang, E. Xie, Z. Zhao, Y. Guo, K.-Y. K. Wong, Z. Li, and H. Zhao, "Drivegpt4: Interpretable end-to-end autonomous driving via large language model," *IEEE Robotics and Automation Letters*, vol. 9, pp. 8186–8193, 2023. [Online]. Available: https://api.semanticscholar.org/CorpusID:263605524

[52] L. Wen, X. Yang, D. Fu, X. Wang, P. Cai, X. Li, T. Ma, Y. Li, L. Xu, D. Shang, Z. Zhu, S. Sun, Y. Bai, X. Cai, M. Dou, S. Hu, B. Shi, and Y. Qiao, "On the road with gpt-4v(ision): Early explorations of visual-language model on autonomous driving," *ArXiv*, vol. abs/2311.05332, 2023. [Online]. Available: https://api.semanticscholar.org/CorpusID:265067382

[53] Y. W. et al., "Driving into the future: Multiview visual forecasting and planning with world model for autonomous driving," *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, 2024, pp. 14 749–14 759.

[54] C. Cui, Z. Yang, Y. Zhou, Y. Ma, J. Lu, and Z. Wang, "Personalized autonomous driving with large language models: Field experiments," *2024 IEEE 27th International Conference on Intelligent Transportation Systems (ITSC)*, pp. 20–27, 2023. [Online]. Available: https://api.semanticscholar.org/CorpusID:266335383

[55] Y. Yang, J. Mei, Y. Ma, S. Du, W. Chen, Y. Qian, Y. Feng, and Y. Liu, "Driving in the occupancy world: Vision-centric 4d occupancy forecasting and planning via world models for autonomous driving," *AAAI Conference on Artificial Intelligence*, 2024. [Online]. Available: https://api.semanticscholar.org/CorpusID:271957449

[56] P. Cai and D. Hsu, "Closing the planning-learning loop with application to autonomous driving," *IEEE Trans. Robot.*, vol. 37, no. 3, pp. 998–1011, 2021.

[57] S. Hagedorn, M. Hallgarten, M. Stoll, and A. Condurache, "The integration of prediction and planning in deep learning automated driving systems: A review," *IEEE Transactions on Intelligent Vehicles*, 2023. [Online]. Available: https://api.semanticscholar.org/CorpusID:260775752

[58] B. P. et al., "A survey of motion planning and control techniques for self-driving urban vehicles," *IEEE Trans. Intell. Veh.*, vol. 1, no. 1, pp. 33–55, 2016.

[59] Y. C. et al., "A survey of end-to-end autonomous driving systems," *J. Image Graph.*, vol. 29, no. 11, pp. 3216–3237, 2024.

[60] S. L. et al., "A review of driving behavior assessment indicators for autonomous vehicles," *China J. Highway Transp.*, vol. 38, no. 1, pp. 304–323, 2025.

[61] B. Z. et al., "Complexity evaluation method for continuous test scenarios of autonomous vehicles," *J. Jilin Univ. (Eng. Ed.)*, pp. 1–12, 2024.

[62] L. Min, "Research on functional safety testing and evaluation methods for autonomous driving of intelligent connected vehicles," *Auto Test Rep.*, no. 11, pp. 41–43, 2024.

[63] L. X. et al., "A review of driving risk assessment methods for autonomous vehicles," *J. Automot. Eng.*, vol. 14, no. 5, pp. 745–759, 2024.

[64] Y. Dong, H. Chen, J. Chen, Z. Fang, X. Yang, Y. Zhang, Y. Tian, H. Su, and J. Zhu, "How robust is google's bard to adversarial image attacks?" *ArXiv*, vol. abs/2309.11751, 2023. [Online]. Available: https://api.semanticscholar.org/CorpusID:262083772

[65] Z. Wu, B. Han, and Y. Ma, "Research on driver takeover capability in human-machine cooperative autonomous driving environment," *Spec. Veh.*, no. 6, pp. 81–84, 2023.

[66] Y. Hou, C. Wang, J. Wang, X. Xue, X. L. Zhang, J. Zhu, D. Wang, and S. Chen, "Visual evaluation for autonomous driving," *IEEE Transactions on Visualization and Computer Graphics*, vol. 28, no. 1, pp. 1030–1039, 2022.

[67] W. Schwarting, J. Alonso-Mora, and D. Rus, "Planning and decision-making for autonomous vehicles," *Annu. Rev. Control Robot. Auton. Syst*, vol. 1, pp. 187–210, 2018.