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NAVIGATION CONTROL IN AUTONOMOUS VEHICLES USING ARTIFICIAL INTELLIGENCE: A RECENT COMPREHENSIVE STRUCTURED REVIEW

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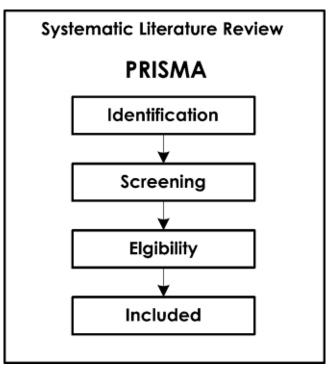
Graphical abstract



Abstract

Navigation control plays a critical role in the performance and safety of autonomous vehicles, especially in dynamic and uncertain environments. Recent advances in artificial intelligence (AI) have led to the development of intelligent control strategies that improve lateral control, path tracking, and decision-making capabilities. The systematic review was performed with the PRISMA method in order both to comply with and evaluate alternatives. Through systematic searches in Scopus, Web of Science and IEEE databases a total of 30 primary studies were identified and reviewed, which fell under three broad themes: Reinforcement Learning and Fuzzy Logic Control Approaches; Neural Networks and AI Control Strategies; and Hybrid Control Strategies and Advanced Path Planning. The selected articles were then examined and discussed to evaluate their roles in improving the vehicle performance, stability and behaviour adaptivity. The findings indicate that AI based control navigation substantially increases the capabilities of autonomous vehicles, and more research will consequently refine those techniques for broad use.

Keywords: Autonomous vehicles, neural networks, fuzzy logic, reinforcement learning, navigation control

Abstrak

Kawalan navigasi memainkan peranan penting dalam prestasi dan keselamatan kenderaan autonomi, terutamanya dalam persekitaran yang dinamik dan tidak menentu. Kemajuan terkini dalam kecerdasan buatan (AI) telah membawa kepada pembangunan strategi kawalan pintar yang meningkatkan kawalan sisi, penjejakan laluan dan keupayaan membuat keputusan. Semakan sistematik telah dilakukan dengan kaedah PRISMA untuk kedua-duanya untuk mematuhi dan menilai alternatif. Melalui carian sistematik dalam pangkalan data Scopus, Web of Science dan IEEE, sejumlah 30 kajian utama telah dikenal pasti dan disemak, yang termasuk dalam tiga tema umum: Pembelajaran Pengukuhan dan Pendekatan Kawalan Logik Kabur; Rangkaian Neural dan Strategi Kawalan AI; dan Strategi Kawalan Hibrid dan Perancangan Laluan Lanjutan. Artikel yang dipilih kemudiannya diperiksa dan dibincangkan untuk menilai peranan mereka dalam meningkatkan prestasi kenderaan, kestabilan dan penyesuaian tingkah laku. Penemuan menunjukkan bahawa navigasi kawalan berasaskan AI meningkatkan dengan ketara keupayaan kenderaan autonomi, dan juga lebih banyak penyelidikan akan seterusnya memperhalusi teknik tersebut untuk kegunaan luas.

Kata kunci: Kenderaan autonomi, rangkaian saraf, logik kabur, pembelajaran pengukuhan, kawalan navigasi

1.0 INTRODUCTION

Autonomous vehicles (AVs) are one of the most impressive uses of artificial intelligence (AI) that has revolutionised several sectors. AI control techniques are essential to promote efficient, stable and accurate autonomous navigation in modern transportation. The need for navigational autonomy is important because of the complex dynamics and uncertainties that occur on the road, such as changing weather patterns, unpredictable driver behaviour, and changing traffic patterns [1][2][3]. Advances in machine learning, deep learning and reinforcement learning have pushed AI-based navigation control systems to override human decisions to improve safety, optimise traffic and reduce transport-related [4][5]. As cities and countries around the world move towards cleaner, more efficient and less efficient transport infrastructure, the pursuit of fully autonomous navigation is not only a technical challenge but also a socially relevant one.

Due to the need to maintain smooth navigation, AI-based control systems used in AVs use complex algorithms and technologies to implement laterally accurate and effective control for vehicles to respond quickly to dynamic environmental inputs [6]. Control strategies such as neural networks, fuzzy logic, and hybrid control mechanisms have a good ability to realise important timing adjustments for path planning, trajectory detection, and obstacle avoidance [7][8][9]. This type of control mechanism is essential for safe navigation across various terrains, whether structured or unstructured. The ability of AI systems to learn from data sets enables continuous improvement in predictive accuracy and decision-making speed. As AVs face uncertain and mixed traffic conditions, these skills become essential, not only improving the performance of individual vehicles but also contributing to a more coordinated traffic environment. Advanced AI control systems make it possible to handle the inherent uncertainty in human-dominated situations, where machine learning models must quickly assess sensor data, predict potential hazards and make appropriate decisions.

The integration of AI control techniques in autonomous navigation is an important step towards the realization of AVs. Figure 1 [10] illustrates how the AV system structure embeds this control strategy. As shown by the entire study of recent developments in neural networks, fuzzy logic, reinforcement learning and hybrid approaches, AI greatly improves the safety and efficiency of AVs and brings the industry one step closer to a world where autonomous transport is common and effective. Overall, this review provides a detailed understanding of these AI-based strategies, highlights their role and impact in achieving smooth navigation control, and establishes a foundation for future research in this rapidly growing field.

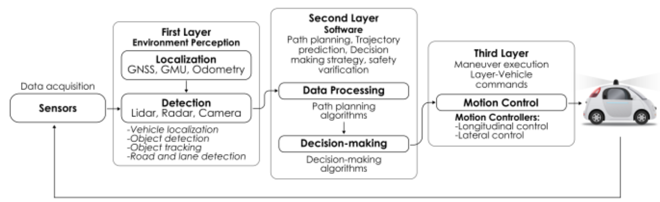


Figure 1 An autonomous vehicles system architecture

This paper contributes to the field by conducting a comprehensive systematic literature review of recent AI-based navigation control strategies for autonomous vehicles, specifically focusing on studies published between 2023 and 2024. It categorizes the reviewed works into three main themes: Neural Networks and AI Control Strategies, Reinforcement Learning and Fuzzy Logic Approaches, and Hybrid Control Strategies and Advanced Path Planning. Review findings have identified critical knowledge gaps and research opportunities that can guide future investigations and practical applications.

This paper is organized as follows: Section 2 presents the research background on autonomous vehicle navigation and the role of AI. Section 3 outlines the methodology for the systematic literature review, including the PRISMA framework and article selection criteria. Section 4 presents the analysis of the reviewed articles grouped under three main themes with a synthesis of key findings, identified research gaps and recommendations for future work. Section 5 summarizes the key findings and broader implications for the development of autonomous vehicle technologies.

2.0 LITERATURE REVIEW

The control of AV has evolved significantly, especially in lateral control approaches, due to the increasing need for efficient and dynamic systems [11][12][13]. Effective lateral control systems are the core of AV safety as they determine an AV's capacity to maintain the correct lane position, manoeuvre through different road conditions, and guarantee vehicle stability in real-world dynamic conditions[14] [15].

Recent years have seen the integration of sophisticated AI-driven methodologies, with neural networks, reinforcement learning, hybrid approaches, and fuzzy control strategies leading the field. All of these methods take advantage of the large amount of data to allow AVs to make decisions in real-time based on environmental inputs [16][17]. Based on this foundation, the lateral control has been developed with the help of the neural network-based approaches that are considered to be the cornerstone in the development of the AVs with the models that can learn from the large sets of the driving scenarios [18], [19]. Unlike traditional rule-based systems, neural networks are quite different from traditional rule-based systems; they can learn the complex patterns that exist in large volumes of sensory data and permit AVs to make decisions in real time based on those huge data sets. For instance, deep neural networks (DNNs) show high effectiveness in the processing and synthesis of big data from lidar, radar, and vision systems to predict and execute precise lateral control actions [20]. Convolutional neural networks (CNNs) have been used in image-based lateral control tasks in which real-time interpretation of visual data such as lane markings, roadsides and other vehicles is important [21]. Improvements in this neural network have ensured AV safety through accuracy, reduced lateral motion, and functionality to sudden changes to the environment [22].

In addition to neural networks, reinforcement learning (RL) has been established as a dynamic and adaptive lateral control method for autonomous vehicles (AVs) operating in unpredictable environments [23], [24]. Iterative learning allows autonomous vehicles to refine control strategies to adapt to the high variability of real-world road conditions. In this study, reinforcement learning models are used to enable autonomous vehicles to learn lane keeping behaviours by optimising reward functions that encourage smooth and stable trajectories [25]. Control based on reinforcement learning allows for ongoing adaptation to lane deviations and maintains lane accuracy in complex situations such as curved roads and heavy traffic [26], [27]. Additionally, reinforcement learning (RL) lateral control has been extended with transfer learning, allowing RL models trained in simulations to be adapted to real world conditions. This approach reduces field testing costs and provides effective lateral control [28], [29], [30]. These advancements further reinforce reinforcement learning as a fundamental method of autonomous vehicle lateral control, allowing for adaptable and responsive maneuvers in dynamic settings. Fuzzy control strategies improve the adaptability of autonomous vehicle lateral control in the face of uncertainties in complex road environments. In the meantime, fuzzy control strategies can improve the adaptability of autonomous vehicle lateral control in the face of uncertainty in complex road environments. Fuzzy logic provides the ability for autonomous vehicle systems to operate effectively in ambiguous sensor data conditions such as in bad weather conditions and unmarked lanes [31], [32]. Lateral control with fuzzy logic can also provide a more complex lateral control method based on the evaluation of many inputs with gradable values instead of only binary states. Neural networks and reinforcement learning equipped with fuzzy control can improve adaptability, especially in unpredictable conditions, by adding a responsive decision-making layer [31], [33].

A hybrid control system combines neural networks, reinforcement learning, and fuzzy logic to increase accuracy and flexibility in lateral control and exploit the positive features of each approach separately. However, single-method approaches are not sufficient for complex environments, and hybrid approaches enable high accuracy and flexibility in lateral control for autonomous vehicles [9], [34], [35]. Lateral control parameters are continuously adjusted using real-time data of the urban environment such as road curvature, traffic density, and weather conditions which can improve the adaptability of autonomous vehicles [36]. Additionally, lateral stability under adverse weather conditions that can severely affect vehicle stability is managed by a hybrid control system using fuzzy logic and reinforcement learning [37]. Real-world driving scenarios show that the hybrid approach effectively balances control accuracy, and adaptability to achieve better lateral accuracy.

3.0 MATERIAL AND METHODS

3.1 Identification

A rigorous systematic review methodology was applied to collect an extensive body of related literature in this study. The identification process started with choosing core keywords strategically, which were enriched with the help of the identification of relevant terms stemming from the dictionary, thesauri and encyclopaedias, and associated with the relevant studies on the topic in previous research studies. Table 1 details these related terms that were then synthesised into comprehensive search strings. This comprehensive foundation allowed for a thorough review of the literature to ensure that factually relevant and in-depth pieces of research were collected. Scopus, Web of Science, and IEEE. This elaborate and structured final approach led to the first recognition of a large set of 1,077 publications that each essentially brought about valuable insights in response to the study's objectives. This comprehensive foundation allowed for a thorough review of the literature to ensure the factually relevant and in-depth pieces of research collected.

Table 1 The search string

Database	Search string
Scopus	TITLE-ABS-KEY (("autonomous vehicle*" OR "Self-driving vehicles" OR "Automated driving systems" OR "Automated driving systems" OR "Autonomous mobility" OR "Driverless technology" OR "intelligent vehicle*") AND ("lateral control" OR "navigation control") AND ("control method*" OR "Trajectory Tracking" OR "control strateg*" OR "artificial intelligent" OR "deep learning" OR "neural-network" OR "neural network" OR "fuzzy" OR "ANFIS" OR " Neuro-Fuzzy" OR " Adaptive Neuro-Control" OR "Neuro PID" OR " Fuzzy PID" OR "machine learning")) AND (LIMIT-TO (PUBYEAR , 2023) OR LIMIT-TO (PUBYEAR , 2024)) AND (LIMIT-TO (SUBJAREA , "ENGI")) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (SRCTYPE , "j")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (PUBSTAGE , "final")) Date of Access: October 2024
WoS	("autonomous vehicle*" OR "Self-driving vehicles" OR "Automated driving systems" OR "Automated driving systems" OR "Autonomous mobility" OR "Driverless technology" OR "intelligent vehicle*") AND ("lateral control" OR "navigation control") AND ("control method*" OR "Trajectory Tracking" OR "control strateg*" OR "artificial intelligent" OR "deep learning" OR "neural-network" OR "neural network" OR "fuzzy" OR "ANFIS" OR " Neuro-Fuzzy" OR " Adaptive Neuro-Control" OR "Neuro PID" OR " Fuzzy PID" OR "machine learning") (Topic) and 2024 or 2023 (Publication Years) and Article (Document Types) and English (Languages) and Engineering or Automation Control Systems (Research Areas) and Engineering (Research Areas) Date of Access: October 2024
IEEE	("autonomous vehicle*" OR "Self-driving vehicles" OR "Automated driving systems" OR "Automated driving systems" OR "Autonomous mobility" OR "Driverless technology" OR "intelligent vehicle*") AND ("lateral control" OR "navigation control") AND ("control method*" OR "Trajectory Tracking" OR "control strateg*" OR "artificial intelligent" OR "deep learning" OR "neural-network" OR "neural network" OR "fuzzy" OR "ANFIS" OR " Neuro-Fuzzy" OR " Adaptive Neuro-Control" OR "Neuro PID" OR "PID" OR "machine learning") Filter: 2024 or 2023 (Publication Years) and Journal (Document Types) Date of Access: October 2024

3.2 Screening

In the preliminary screening phase, 956 papers were excluded because they did not fit within the scope of the study's objectives. An additional 123 papers were rigorously screened against defined inclusion and exclusion criteria in the subsequent screening stage. The review focused on primary research articles as the core sources of actionable insights, and excluded systematic reviews, meta-syntheses, meta-analyses, books series, book chapters, and conference proceedings to keep the focus on the most recent empirical research. To reflect the most recent advancements in AI-based navigation control for autonomous vehicles, the selection was intentionally limited to English-language publications from the most recent two-year period (2023–2024). This narrow window was chosen to capture cutting-edge developments and ensure that the review reflects the current state of the art. After following these stringent criteria, an additional 27 publications were excluded, leaving a curated, highly relevant set of sources that perfectly matches the study's goals.

Table 2 The selection criterion is searching

Criterion	Inclusion	Exclusion
Language	English	Non-English
Timeline	2023 – 2024	< 2023
Literature type	Journal (Article)	Conference, Book, Review
Publication Stage	Final	In Press
Subject	Engineering	Besides Engineering

3.3 Eligibility

The eligibility stage is a critical component of this systematic literature review (SLR), designed to ensure that only the most relevant and high-quality studies are included in the final analysis. This review started with 96 articles accessed and carefully reviewed against pre-defined criteria to determine whether they were in line with the study on Navigation Control in Autonomous Vehicles using Artificial Intelligence. During this process, 66 articles were excluded for various reasons: Some titles were not clearly related to the topic and did not indicate a strong relevance to AI driven navigation control in autonomous vehicles, while some abstracts were not sufficiently related to the study's focus on lateral control using AI methodologies. Furthermore, the lack of full text access for some articles hindered the comprehensive evaluation of their methodology and findings. After this rigorous eligibility check, 30 articles remained to be analysed. These are the most valuable and relevant articles in the study. This eligibility process was critical to ensuring that the final systematic literature review (SLR) contains only high quality, accessible, and highly relevant studies, thereby improving the robustness, and relevance of the review's outcomes.

3.4 Data Extraction and Analysis

An integrative analysis was used as the primary assessment approach in this study to review a wide range of quantitative research designs. This strategy was primarily aimed at identifying relevant topics and subtopics associated with the study. The first step toward thematic development was data collection. The authors performed extensive analysis of 30 selected publications (refer to Figure 2 and Table 2), extracting assertions or content relevant to the study focus, Navigation Control in Autonomous Vehicles using Artificial Intelligence.

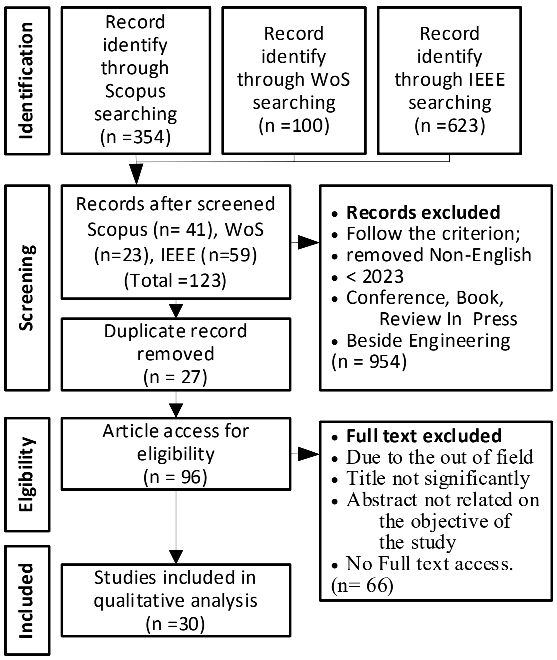


Figure 2 PRISMA flow chart [38]

A review of major studies in the field identified trends in approaches and key findings. The authors worked together to develop evidence-based frameworks specific to the context of the research. An audit trail was kept during the data analysis to capture working interpretations, preconceptions configured around what, and thoughts–questions that emerged while processing the data. The authors conducted comparisons to investigate inconsistencies in framework development to preserve conceptual consistency. During a collaborative and methodical discussion process, the authors quickly settled any arising differences, demonstrating the rigour of the conceptual design process and its inherent coherence. To ensure the validity of the problems, thorough examinations were conducted. This stage of review aimed to identify any areas of confusion or irrelevance in the subthemes and, in this way, verify the presence of domain validity in their evaluation, enhancing the total reliability of the assessment. By establishing domain content validity, the review phase assisted in providing assurance of the clarity, relevance, and adequacy of each subtheme. The questions are as follows:

1. What are the challenges and solutions related to the implementation of neural networks and AI control techniques in navigation control for autonomous vehicles?
2. In what way do reinforcement learning, fuzzy logic, and hybrid control approaches improve the accuracy and stability of navigation control in autonomous vehicles under various and complex driving conditions?

4.0 RESULT AND DISCUSSION

This section categorises analysis the primary data (Table 3) into several approaches. Each is based on one of three primary themes: Neural Networks and AI Control Strategies, Reinforcement Learning and Fuzzy Logic Control Approaches, and Hybrid Control Strategies and Advanced Path Planning. The analysis of each theme outlines how these approaches enhance the adaptability, safety, and efficiency across different conditions for autonomous vehicles.

4.1 Neural Networks and AI Control Strategies

Autonomous vehicle development has made substantial progress, particularly in terms of lateral control, tracking, and navigation—all of which are vital components for safe and optimal driving. The approach of neural networks, with the help of other forms of AI, has become more popular in terms of dealing with the millions of dynamics and uncertainties.

These methods can be utilised in response to the real-time decision-making, trajectory fidelity, and vehicle robustness requirements. The Neural Networks and AI Control Strategies theme refers to research efforts to further improve these controls such that vehicles can achieve accurate tracking and adaptation in dynamic environments. Recent research has emphasised utilising the capabilities of neural networks to enhance lateral, tracking control, and to tackle real-world scenarios such as different road conditions and dynamic obstacles. For instance, adaptive second-order non-singular terminal sliding mode control with the aid of neural networks. To solve this issue of the unmodeled vehicle dynamics, a radial basis neural network structure is implemented with the triangular neural observer. Abdillah *et al.* [39] proposed a system that aims to enhance autonomous vehicles' lateral control, especially when it is challenging to accurately estimate some state variables. The performance of neural networks integrated with sliding mode control results in better trajectory control. Similarly, Wang et al. [40] introduced a robust H_∞ control method to address the path tracking problem using norm-bounded uncertainty. A new observer for estimating unobservable state variables has been introduced to improve the robustness of the lateral controller and its accuracy, especially in urban and highway environments.

Table 3 The primary data

No.	Authors	Title	Year	Source title	S	W	I	Remarks
1	Abdillah M.; Mellouli E.M. [39]	A new adaptive second-order non-singular terminal sliding mode lateral control combined with neural networks for autonomous vehicle	2024	International Journal of Vehicle Performance	/			Neural Networks and AI Control Strategies
2	Wang J.; Wang B.; Liu C.; Zhang L.; Li L.[40]	A Novel Robust H∞ Control Approach Based on Vehicle Lateral Dynamics for Practical Path Tracking Applications	2024	World Electric Vehicle Journal	/			Neural Networks and AI Control Strategies
3	Dong C.; Chen Y.; Wang H.; Ni D.; Shi X.; Lyu K. [41]	An Evolutionary Learning Framework of Lane-Changing Control for Autonomous Vehicles at Freeway Off-Ramps	2023	IEEE Transactions on Vehicular Technology	/	/	/	Neural Networks and AI Control Strategies
4	Chen L.; Liu Y.; Dong P.; Liang J.; Wang A. [42]	An Intelligent Navigation Control Approach for Autonomous Unmanned Vehicles via Deep Learning-Enhanced Visual SLAM Framework	2023	IEEE Access	/		/	Neural Networks and AI Control Strategies
5	Bayuwindra A.; Wonohito L.; Trilaksono B.R. [43]	Design of DDPG-Based Extended Look-Ahead for Longitudinal and Lateral Control of Vehicle Platoon	2023	IEEE Access	/			Neural Networks and AI Control Strategies
6	Tarhini, F; Talj, R; Doumiati, M. [44]	Dynamic and real-time continuous look-ahead distance for autonomous vehicles: an explicit formulation	2024	VEHICLE SYSTEM DYNAMICS		/		Neural Networks and AI Control Strategies
7	Wan J.; Liu H.; Xu M.; Yang X.; Guo Y.; Wang X. [45]	Lane-Changing Tracking Control of Automated Vehicle Platoon Based on MA-DDPG and Adaptive MPC	2024	IEEE Access	/	/	/	Neural Networks and AI Control Strategies
8	Artuñedo A.; Moreno-Gonzalez M.; Villagra J. [46]	Lateral control for autonomous vehicles: A comparative evaluation	2024	Annual Reviews in Control	/			Neural Networks and AI Control Strategies
9	Kim, H; Kee, S.C. [19]	Neural Network Approach Super-Twisting Sliding Mode Control for Path-Tracking of Autonomous Vehicles	2023	ELECTRONICS		/		Neural Networks and AI Control Strategies
10	Hajjami L.E.; Mellouli E.M.; Žuraulis V.; Berrada M.; Boumhidi I. [47]	Neural network optimization algorithm based non-singular fast terminal sliding-mode control for an uncertain autonomous ground vehicle subjected to disturbances	2024	Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering	/			Neural Networks and AI Control Strategies
11	Cai Q.; Qu X.; Wang Y.; Shi D.; Chu F.; Wang J. [48]	Research on Optimization of Intelligent Driving Vehicle Path Tracking Control Strategy Based on Backpropagation Neural Network	2024	World Electric Vehicle Journal	/			Neural Networks and AI Control Strategies
12	Zhang R.-Y.; Zhang B.; Shi P.-C.; Mei Y.; Du Y.-F.; Feng Y.-L. [49]	Research on the High-Speed Collision Avoidance Method of Distributed Drive Electric Vehicles	2023	IEEE Sensors Journal	/			Neural Networks and AI Control Strategies
13	S. Teng; R. Yan; X. Zhang; Y. Li; X. Wang; Y. Wang; Y.	Sora for Hierarchical Parallel Motion Planner: A Safe End-to-End Method Against OOD Events	2024	IEEE Transactions on Intelligent Vehicles			/	Neural Networks and AI Control Strategies

No.	Authors	Title	Year	Source title	S	W	I	Remarks
	Tian; H. Yu; L. Li; L. Chen; F. -Y. Wang [50]							
14	S. Cheng; H. Chen; Z. Wang; B. Yang; C. Lv; K. Nakano [51]	A Game Theoretical Chassis Domain Approach to Trajectory Tracking for Automated Vehicles	2023	IEEE Transactions on Vehicular Technology			/	Reinforcement Learning and Fuzzy Logic Control Approaches
15	W. Xiao; Y. Yang; X. Mu; Y. Xie; X. Tang; D. Cao; T. Liu [52]	Decision-Making for Autonomous Vehicles in Random Task Scenarios at Unsignalized Intersection Using Deep Reinforcement Learning	2024	IEEE Transactions on Vehicular Technology			/	Reinforcement Learning and Fuzzy Logic Control Approaches
16	Jennan N.; Mellouli E.M. [53]	Direct optimal fuzzy logic adapted to sliding mode for lateral autonomous vehicle control	2024	International Journal of Vehicle Performance	/			Reinforcement Learning and Fuzzy Logic Control Approaches
17	J. Zhang; L. Zhang; S. Liu; J. Wang [54]	Event-Triggered Adaptive Fuzzy Approach-Based Lateral Motion Control for Autonomous Vehicles	2024	IEEE Transactions on Intelligent Vehicles			/	Reinforcement Learning and Fuzzy Logic Control Approaches
18	Lian Z.; Shi P.; Lim C.-C.; Yuan X. [55]	Fuzzy-Model-Based Lateral Control for Networked Autonomous Vehicle Systems under Hybrid Cyber-Attacks	2023	IEEE Transactions on Cybernetics	/		/	Reinforcement Learning and Fuzzy Logic Control Approaches
19	Q. Ma; X. Yin; X. Zhang; X. Xu; X. Yao [56]	Game-Theoretic Receding-Horizon Reinforcement Learning for Lateral Control of Autonomous Vehicles	2024	IEEE Transactions on Vehicular Technology			/	Reinforcement Learning and Fuzzy Logic Control Approaches
20	Ren Y.; Xie X.; Li Y. [57]	Lateral Control of Autonomous Ground Vehicles via a New Homogeneous Polynomial Parameter Dependent-Type Fuzzy Controller	2024	IEEE Transactions on Industrial Informatics	/			Reinforcement Learning and Fuzzy Logic Control Approaches
21	Taghavifar, H; Mohammadzadeh, A; Zhang, WJ; Zhang, CW [58]	Nonsingleton Gaussian type-3 fuzzy system with fractional order NTSMC for path tracking of autonomous cars	2024	ISA TRANSACTIONS		/		Reinforcement Learning and Fuzzy Logic Control Approaches
22	Fan, ZX; Yan, Y; Wang, XY; Xu, HZ [59]	Path Tracking Control of Commercial Vehicle Considering Roll Stability Based on Fuzzy Linear Quadratic Theory	2023	MACHINES		/		Reinforcement Learning and Fuzzy Logic Control Approaches
23	C. -J. Lin; B. -H. Chen; J. -Y. Jhang [14]	Type 2 Fuzzy Neural Controller for Navigation Control of an Ackermann Steering Vehicle	2023	IEEE Access			/	Reinforcement Learning and Fuzzy Logic Control Approaches
24	S. Yang; C. Geng [60]	A Longitudinal/Lateral Coupled Neural Network Model Predictive Controller for Path Tracking of Self-Driving Vehicle	2023	IEEE Access			/	Hybrid Control Strategies and Advanced Path Planning
25	Y. Li; Y.	A Merging Strategy Framework for	2024	IEEE Access				Hybrid Control

No.	Authors	Title	Year	Source title	S	W	I	Remarks
	Zhang; Y. Ma [61]	Connected and Automated Vehicles in Multi-Lane Mixed Traffic Scenarios					/	Strategies and Advanced Path Planning
26	L. Zhang; J. Zhang; S. Liu; C. Ren; Y. Kang [62]	Adaptive Backstepping Fuzzy Lateral Motion Control Approach for Autonomous Vehicles	2024	IEEE Transactions on Transportation Electrification			/	Hybrid Control Strategies and Advanced Path Planning
27	J. Fan; X. Wu; J. Li; M. Xu [63]	Deep Reinforcement Learning Based Integrated Eco-Driving Strategy for Connected and Automated Electric Vehicles in Complex Urban Scenarios	2024	IEEE Transactions on Vehicular Technology			/	Hybrid Control Strategies and Advanced Path Planning
28	X. Zhao; Z. Yin; Z. He; L. Nie; K. Li; Y. Kuang; C. Lei [64]	Indirect Shared Control Strategy for Human-Machine Cooperative Driving on Hazardous Curvy Roads	2023	IEEE Transactions on Intelligent Vehicles			/	Hybrid Control Strategies and Advanced Path Planning
29	X. Li; X. Gong; Y. -H. Chen; J. Huang; Z. Zhong [65]	Integrated Path Planning-Control Design for Autonomous Vehicles in Intelligent Transportation Systems: A Neural-Activation Approach	2024	IEEE Transactions on Intelligent Transportation Systems			/	Hybrid Control Strategies and Advanced Path Planning
30	A. LelkÃ³; B. NÃ©meth [66]	Optimal Motion Design for Autonomous Vehicles With Learning Aided Robust Control	2024	IEEE Transactions on Vehicular Technology			/	Hybrid Control Strategies and Advanced Path Planning

*Noted: **S**-Scopus, **W**-Web of Siences, and **I**-IEEE

In the field of lane-changing control, Dong *et al*. (2023) [41] proposed an evolutionary learning framework using random forest and backpropagation neural networks with model predictive control (MPC) for freeway off-ramps. Particularly, it demonstrates the performance of neural networks to make decisions and trajectory execution while ensuring safety under heavy traffic situations. In a related study, Chen *et al*. (2023) [42] present visual simultaneous localization and mapping (SLAM) with deep learning-assisted methods for the navigation of autonomous unmanned vehicles. Then, they proposed a method of navigation control that enhances the accuracy of path tracking by 5% for robots through interpreting visual dynamic scenarios with neural networks. Similarly, neural network methods have also been used in vehicle platooning control, as seen in Bayuwindra *et al*. [43] who proposed an extended lookahead in longitudinal and lateral control based on deep deterministic policy gradient (DDPG). The use of neural networks enables the system to adapt to changes in environmental conditions, thus preventing any issues such as cut corners while manoeuvring. Wan *et al*. (2024) [45] also presented a framework that combines multi-agent deep deterministic policy gradient (MA-DDPG) with adaptive model predictive control (AMPC) to solve lane changing in vehicle platoons. This method allows initial speed variations to extend the range of controlled platoons while enabling more efficient inter-vehicle communication via decentralized control strategies for maintaining separation.

Tarhini *et al*. (2024) [44] and Hajjami *et al*. (2024) [47] both looked into the effect of look-ahead distances and sliding mode controllers upon vehicle stability. Consequently, Hajjami added a neural network to optimise sliding mode controllers, while Tarhini's research made a new-form continuous look-ahead distance for real time operation. These strategies offer enhancements in vehicle performance and control precision when experiencing dynamic driving conditions, such as lane changes or rapid manoeuvres. A comparative study of control strategies in different driving scenarios was performed by Artuñedo *et al*. [46] that only reinforces this point of view. Neural network optimisation algorithms have also been applied to path tracking problems. Cai *et al*. (2024) [48] provided a case study demonstrating the ability of backpropagation neural networks to adjust both lateral and vertical control strategies within an MPC framework. This method also greatly increases the adaptability of control systems in changing road conditions and vehicle speeds. Kim and Kee (2023) [19] make extensive use of neural networks to address the chattering caused by super-twisting sliding mode control while keeping good tracking performance when faced with rapid lane changes or other practical situations. In high-speed collision avoidance, it is one of the important applications studied so far that neural networks do best. Zhang *et* *al*. (2023) [49] provided results demonstrating the enhancement of tracking stability under emergency management conditions through the combination of a neural control technique and an adaptive MPC. Sora's hierarchical parallel motion planner was used by Teng *et al*. (2024) [50] to look at how constraints must be met in open-world safety when AI-based controllers are used to handle out-of-bounds events.

To close this section, a review of neural network methods has shown significant performance benefits across a wide range of autonomous vehicle functions. Several knowledge gaps have also been identified. Most studies rely heavily on controlled simulation environments and lack validation under a variety of real-world traffic and weather conditions. Furthermore, many neural models act as 'black boxes', offering limited interpretability and insight into the decision-making process. Future research should therefore focus on improving the interpretability and real-time robustness of these AI control architectures. Furthermore, they should be capable of operating in unstructured real-world environments to ensure safe, reliable and scalable deployment in practical autonomous navigation systems.

4.2 Reinforcement Learning and Fuzzy Logic Control Approaches

Autonomous vehicles have introduced organised control strategies that deal with the challenges of lateral control, trajectory tracking, and navigation, in which some start using more reinforcement learning (RL) techniques and fuzzy logic systems. Such strategies provide useful approaches to enhancing, even developing, decision-making and managing uncertainties while maintaining vehicle stability throughout different driving conditions. The lack of control by autonomous vehicles in less-clear cases has established the necessity of reinforcement learning and fuzzy logic control systems for the vehicle to accomplish high-control tasks such as running around or making more sophisticated manoeuvres with higher accuracy and efficiency.

Researchers have extensively studied the use of fuzzy logic systems for adaptive control. Jennan and Mellouli (2024) [53] proposed a direct optimal fuzzy logic system with a fast terminal sliding mode control (FTSMC) for an autonomous vehicle's lateral control. In this approach, the particle swarm optimisation and butterfly optimisation algorithms are implemented to maximise stability of the vehicle through fuzzy accuracy and minimisation of uncertainty from external disturbances. This strategy not only addresses the chattering problem and exploits faster convergence in sliding mode control but also verifies its efficiency through comparative analysis and demonstrates Lyapunov stability. Similarly, Lian *et al*. (2023) [55] focused on finding an industrial grade fuzzy model-based lateral control system for cyber-physical systems such as autonomous vehicles in conditions of hybrid cyber-attacks. An event-triggered scheme (ETS) is embedded into the control strategies to minimise the risk caused by cyberattacks and information-exchange induced issues while guaranteeing that the vehicle maintains lateral stability and reduces communication burden. Furthermore, Ren *et al*. (2024) [57] also showed that a homogeneous polynomial parameter-dependent fuzzy controller can effectively deal with nonlinearity in vehicle dynamics. Their controller improves control flexibility, ensuring smooth vehicle navigation despite external disturbances and varying road conditions.

Reinforcement learning methods are also becoming popular for autonomous vehicle decision-making and control. Xiao *et al*. (2024) [52] addressed moving vehicles at unsignalized intersections and proposed a deep reinforcement learning framework to control autonomous vehicles in such scenarios, posing a high level of uncertainty, randomness, and time-dependence in the road network. Using an augmented replay buffer and a mixed-attention network, the neural network is trained on essential collision and arrival data, thus improving both safety and efficiency. Meanwhile, Cheng *et al*. focused on trajectory tracking using multiple actuators (2024) [51] addressed integrated longitudinal and lateral control in the chassis domain through a game theoretic coordination approach. This also handles chassis control nonlinearities to maximise vehicle dynamics and improve tracking accuracy over challenging driving conditions. Similarly, Ma *et al*. [56] have also explored the game theory. The game-theoretic receding-horizon reinforcement learning (GTRHRL) strategy is utilised for lateral tracking under agile conditions. The algorithm guarantees convergence to Nash equilibrium and stability in large curvature turns and non-stationary environments.

Innovative adaptive and event-triggered mechanisms have further enhanced fuzzy logic systems. Zhang *et al*. (2024) [54] proposed an event-triggered adaptive fuzzy control system of parameter uncertainty and communication problem management that is developed in lateral control of vehicle. The fuzzy logic system (FLS) approximates the nonlinearities, leading to reduced communications loads and ensuring task performance. Additionally, Fan *et al*. [59] (2023) proposed a fuzzy linear quadratic controller for commercial vehicles for tracking control and roll stability. Improvement in path-tracking accuracy and vehicle safety is subject to the condition that adaptive control aims to ensure that a vehicle can remain stable and make an adjustment to driving conditions, but the process is real-time. Taghavifar *et al*. [58] designed a type-3 fuzzy system integrated with an adaptive fractional-order terminal sliding mode controller (AFOTSC) to tackle this problem while controlling the unpredictability occurring during the path tracking of autonomous vehicles. The system does not only exhibit good performance but also guarantees accurate control even in the presence of measurement errors and disturbances through Lyapunov stability and Barbalat's lemma. Similarly, Lin *et al*. [14] (2023) designed a type-2 fuzzy neural controller (FNC) based on particle swarm optimization for control of an Ackermann steering vehicle. This technique improves navigation precision, and the system operates in unexplored environments using lidar data and systematic fuzzy logic, ensuring a robust control process.

Overall, fuzzy logic and reinforcement learning systems have made unprecedented progress in certain aspects of autonomous vehicle performance in lateral control, decision-making, and trajectory tracking. However, there are still some knowledge gaps that remain to be addressed. Most of the reviewed approaches were designed and tested in simulated environments and lack validation in real-world complex traffic scenarios. Furthermore, the integration of reinforcement learning with fuzzy logic for truly adaptive and safe real-time control is still limited. Therefore, future research should focus on the application of these strategies in field environments that can enhance the interpretability and adaptability of their learning in uncertain dynamic environments.

4.3 Hybrid Control Strategies and Advanced Path Planning

As safety considerations continue to attract attention during the ongoing push for autonomy in both personal advancing and cargo systems, the navigation and control of autonomous vehicles have been impeded and have also been studied more extensively. Hybrid control strategies that integrate various control methods, and AI solutions have proven effective in motion planning, lateral control, and path tracking. The scope of this theme aims for hybrid control strategies to facilitate deployment of deep learning, neural networks, model predictive control (MPC), reinforcement learning (RL), and other AI-based autonomous vehicles in practice.

Yang and Geng (2023) [60] considered model predictive control (MPC) for path tracking by integrating neural networks to improve its performance. By adopting a recurrent neural network (RNN) as an alternative vehicle dynamic model to overcome their user-defined vehicle dynamic models, particularly for the high-speed manoeuvres. This prediction error and control error combination makes such a classical MPC highly sensitive. This hybrid method addresses the previously mentioned challenges by having high prediction fidelity under difficult conditions to effectively minimise control error. Similarly, Zhang *et al*. (2024) [62] described an adaptive backstepping fuzzy control (ABFC) method that combines backstepping and fuzzy logic to handle nonlinear dynamics when unknown disturbances are presented. Simulation results showed that the ABFC strategy is especially capable of providing stable and accurate tracking and control against various vehicle conditions.

For multi-lane traffic scenarios, hybrid control strategies are proposed to deal with merging and lane changes. For instance, Li *et al*. (2024) [61] propose a merging framework integrating lateral speed controlled based vehicle interaction model and merging decision layer for safe pre-merging connected and automated vehicles (CAVs) in heavy congested traffic scenario With real-world dataset training, their model achieved an overlap efficiency of 45% higher than that needed for a safe merge. Similarly, Fan *et al*. (2024) [63] introduced a deep reinforcement learning based eco-driving strategy that simultaneously optimises energy efficiency and travel time for CAVs via integrated longitudinal speed planning with lateral lane change decisions. The results indicated that vehicle-to-everything communication procedures as well as multi-objective reward functions could upgrade the overall control framework of the vehicle. Human-machine cooperative driving also exemplifies hybrid control strategies. Zhao *et al*. (2023) [64] developed an indirect shared control system of autonomous systems and human drivers to allow them to collaborate in sharing control when negotiating a dangerous curvy road. The proposed method employs gaussian process regression (GPR) to perform risk assessment and multi-objective hierarchical MPC controller-based vehicle control, enabling the fusion of human and machine input to achieve safer driving. That collaborative method was validated through driving simulations in which the system successfully handled ambiguous roadway scenarios, and concurrently reduced human-machine mode conflicts. Furthermore, path planning and control optimisation are further explored through neural activation mechanisms and reinforcement learning-based control frameworks. Li *et al*. (2024) [65] proposed a neural activation method for path tracking based on the traffic state to yield robustness and ensure smoothness with respect to evolving environment conditions. In addition, Lelkó and Németh (2024) [66] presented a motion optimisation framework that merges robust $H\infty$ control with the reinforcement learning paradigm to safely control movements of autonomous vehicles. Simulation and experimental results showed that the tracking error can be minimised effectively.

To close this section, although hybrid control strategies show great potential in combining the strengths of various AI methods, there are still critical knowledge gaps that persist. Most of the proposed systems have been validated only in simulated environments. Their application in real-world situations involving unpredictable human interactions, mixed traffic dynamics, and infrastructure constraints is still lacking. Furthermore, many hybrid models lack standardization, making it difficult to compare their effectiveness across use cases. The interpretability of control results, especially in shared control systems involving human-machine collaboration, remains unexplored. Future research should focus on developing standardized evaluation metrics for hybrid controllers, improving their interpretability, and validating them in complex real-world driving environments such as in scenarios involving cooperative behaviour among connected autonomous vehicles.

5.0 CONCLUSION

In conclusion, the review of neural networks, reinforcement learning, fuzzy logic, and hybrid control strategies highlights significant advances in navigation control for autonomous vehicles, especially in enhancing lateral stability, decision-making, and trajectory tracking. The findings reveal several strengths as well as research gaps that should be addressed for future research. Neural network-based models have shown promising real-time performance but still face challenges related to interpretability and validation in unstructured environments. Similarly, reinforcement learning and fuzzy logic approaches have improved adaptability and accuracy of control under uncertainty, yet many remain untested in real-world applications. Meanwhile, hybrid control frameworks effectively integrate various AI methods and offer robustness and flexibility. However, this approach requires further investigation, especially in human-machine collaboration and standardized benchmarking. Therefore, it is essential to address these identified gaps to ensure reliable and transparent AI-based navigation systems for future autonomous vehicle applications.

Furthermore, although this paper focuses on the technical aspects of autonomous navigation, the economic and environmental implications are equally important. Efficiency in navigation and control systems can reduce fuel consumption, maintenance costs and traffic congestion, thus providing economic benefits to industry and end users. From an environmental perspective, smoother driving patterns and AI-driven route optimization contribute to reduced carbon emissions and enhanced integration with electric vehicle technology. In line with this, these benefits highlight the importance of overcoming existing technical challenges to achieve a more widespread and effective implementation of autonomous technology.

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Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper

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