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Exploring the Use of Artificial Intelligence in Racing Games in Engineering Education: A Systematic Literature Review

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Using Reinforcement Learning to Optimize Performance of AI Agents in Racing Games in Engineering Education: A Systematic Literature Review

Abstract

Over the past couple of years, artificial intelligence (AI) has undergone numerous breakthroughs and advancements, developing, and refining itself into a remarkable and versatile technological asset in various different fields and domains in automated machinery. As AI continues to evolve, it emerges as a pivotal tool in research development and in different fields of learning, including engineering education in racing games. This paper presents a systematic literature review (SLR) that delves into the subject of artificial intelligence and machine learning and how it can be used to optimize the performance of AI agents in online racing games and simulators such as Track Mania, Gran Turismo, and The Open Racing Simulator (TORCS). The usage of these racing simulators is crucial as they not only provide a platform for entertainment but also a safe and reliable simulator for researchers and developers to test different AI/ML algorithms such as reinforcement learning (RL), providing a cost-effective and risk-free learning environment for users.

The SLR focuses on the development and optimization of AI agents and finds from research in online engineering education. Information for this SLR was gathered from seven different online scholarly sources including Google Scholar, Web of Science, IEEE Explorer, Engineering Village, EBSCOhost, ScienceDirect, and Wiley Online Library. The search process to ensure the inclusion of only relevant articles included screening by title, screening by abstract, screening by full-text, and a full synthesis of each targeted article. This methodological approach involving the combination of multiple scholarly sources and the utilization of a systematic screening process ensures a set of robust and reliable articles in providing a comprehensive literature review of the current state of AI in online racing games and its implications in engineering education. A total of twenty articles published between 2013 to 2023 met inclusion criteria, and the synthesis of these articles highlighted four themes: agent performance optimization, AI technologies applications, machine learning paradigms, and the racing simulation environment. Using these identified themes, the SLR explores the integration of AI in online racing games and simulators, shedding light on the intricate interplay and dynamics between AI technologies and the virtual racing environment.

Introduction

Due to AI's rapidly advancing technology and accessibility, the AI landscape has undergone substantial growth over the years. The trajectory of AI's growth demonstrates its prominence in the tech field and emphasizes its potential usage and roles in the foundation of future tech industries. The development of AI technology not only transformed it into a powerful tool but also paved the way for its integration into various fields of technology, expanding possibilities and revolutionizing research and development [1]. In the dynamic domain of AI technology, racing games emerge as a captivating platform for experimentation which offers a safe, cost-effective, and efficient environment for pushing the boundaries of both game development and AI development [2-3]. With the progression of AI, many companies are striving to implement it into their technology and machines, especially in cars [4-5]. Because of this, there is a high demand for experimentation and research in this field to ensure safety and optimization [6]. As the integration of AI becomes increasingly more sought after, the intersection between AI in racing games and the real world becomes more relevant, especially as more companies are incorporating automotive vehicles into their agenda.

AI and machine learning has always been a major topic in the gaming industry. However, in the early days of AI development, AI was only included in simpler, less complex games such as Go and Chess where the AI bot is only given a certain set of rules to follow in order to beat the opponent [3], [7]. Though, since then, the objective has changed, transitioning to more complex and versatile algorithms following and learning rules through an evolutionary process of trial and error. Racing games and simulators have been a hot topic for area of study as they serve as an optimal environment for visualization, configurations, versatility, and data collection. One racing simulator in particular was widely used among researchers and that is TORCS, more details discussed in theme IV. Because of the ever-growing AI technology, there is a need for further research in the optimization of AI agents, using racing games as a platform for testing and development [6]. By incorporating additional research, we’re able to bridge the gap between theoretical concept and practical concepts, offering a unique and engaging medium for engineers to further apprehend their knowledge of AI principles.

A systematic literature review (SLR) on the implementation of AI/ML algorithms in racing games for optimization was conducted to delve into the capabilities, limitations, future opportunities, and current knowledge of AI in racing games. An organized, methodical process of text screening, data extraction, and data synthesis was employed to guide the systematic literature review process. The objective of this paper is to investigate and summarize the intricate interplay between AI and ML methodologies and racing games, and how their data can potentially be used in real-world implementations. Furthermore, the study also aims to connect these findings back to the field of engineering education, providing a comprehensive overview of the subject matter.

This study seeks to respond to the overarching question: “*What are the current trends, state and future of research on the use of AI/ML to optimize the performance of AI agents in racing games?*” This paper is divided into three main sections. The first section addresses the general overview of AI in racing games, examining the need for exploration, progression over the years, reoccurring challenges, algorithms and frameworks, and the topics correlation to engineering education. Next, the second section delves into the structural overview of the SLR, exploring the processes involved in constructing the literature review. The third section of the findings discusses the common themes categorized through the synthesis of the sampled articles, along with the codes of each theme.

AI in Racing Games Overview

The interplay between AI and gaming has seen an exceptional amount of progression over the years, with racing games emerging as an ideal testing bed for researchers to explore and experiment with different AI/ML algorithms [3], [7-9]. These games provide a remarkably realistic simulation of the real world, giving the user the ability to customize their vehicles and select different tracks to play on, creating a dynamic environment where these implemented algorithms must learn to adapt to varied terrains and circuits. In this section, we will be discussing the intricate relationship between AI/ML and racing games, addressing why there is a recent need for exploration in this specific gaming genre; discussing its progression over the years, challenges AI/ML developers faced, the different algorithms used, and correlation towards engineering education.

The Need for Exploration

The usage of AI has picked up widespread popularity, causing an uproar in the tech industry in the past decade. The need for exploration of AI in racing games stems from the potential challenges, development, and education implications associated with its integration [1]. Racing games and simulators serve as a reliable learning environment for researchers to gather vast amounts of data. This data-driven approach can be used to optimize designs, algorithms, and frameworks that can relate to the real world, aiding in the development of electric vehicles (EVs) and other AI-related programs [10-13]. Racing games offer a controlled yet dynamic environment for refining algorithms. This simulation allows researchers to test different scenarios determining areas for progress, challenges people are faced, and its relation to real-world problems. Not only do the simulations help in the development of AI in the tech industry, but they also act as an engaging platform for engineers and developers to learn and enhance their skills in AI/ML algorithms and frameworks.

Progression Over the Years

AI in gaming development has indeed evolved throughout the years, marked by significant strides in both technological capabilities and overall player gaming experience. In the early years (1980s-1990s), there was very little research on AI as it was in its early stages of development, especially in gaming. AI agents in racing games were underdeveloped as they were only able to work with simple rule-based algorithms to control computer agents. These agents were limited to a set of rules, following predetermined paths and constricted maneuverability. The first occurrence of an AI bot in a racing game is in a game called Pole Position by Namco, seen in Figure 1 below.

Figure 1: The First AI Bot Seen in a Racing Game [14]

As AI computational power developed, researchers began to incorporate more adaptable and dynamic frameworks into their design such as neural networks and reinforcement learning [1], [3], [8], [10-13], [15-16]. These frameworks and algorithms significantly contributed to their growth, allowing the agent to be more adaptable to its dynamic surroundings. Another notable breakthrough in this area picked up in the early 2010s, was in the implementation of a data-driven experiment [8], [15], [17]. As more data-driven frameworks started to be used, the collection and gathering of in-game relevant data became crucial in the development process of the agent. Collectively, over the past three decades, the development of AI agents in racing games has rapidly improved; beginning from undemanding, straightforward rule-based algorithms to more complex and adaptable techniques that involve specific data manipulation.

Identified Challenges

Despite remarkable advancements in the integration of AI/ML algorithms and technologies in racing games, developers are often faced with difficult tasks regarding the dynamics of the game. One main issue that developers face is the task of having a versatile, real-time decision-making AI agent. Oftentimes, these agents are coded with predefined rules and decision trees that are specific to certain scenarios and configurations, limiting their ability to navigate more freely and diversely around different tracks. This poses a problem, especially if the purpose of incorporating these methods is aimed at using them in the real world for automated vehicles. The challenge lies in creating an AI algorithm that can go beyond scope, enabling itself to be able to adapt and maneuver itself through diverse and changing terrain. However, achieving such conditions requires more complex and continuously refined algorithms, models, and frameworks [2-3], [9], [15], [18]. The pursuit is to create AI agents that not only can navigate themselves through a map but also exhibit a high level of strategic thinking and high-speed decision-making that mimics the behavior of a human player [19-21].

Algorithms and Frameworks

The progress in the integration of AI agents in racing games has been fueled by the continuous research and development of the algorithms and frameworks used in refining the performance of the agents. These modified algorithms allow the agents to develop more sophisticated and complex movement and navigation through the track, making them more adaptable in their surroundings. The main techniques that developers tend to use the most are: reinforcement learning, neural networks, actor-critic, ray tracing, and imitation learning [2-3], [8], [12], [16]. There are a variety of other algorithms, however, these are the ones that are mainly incorporated in the reviewed articles. Through the literature search, it was evident that reinforcement learning (RL) is the most widely used algorithm, consistently picked due to its high versatility and adaptability compared to other algorithms.

RL is often preferred as it has a unique ability, allowing the AI agent to ‘communicate’ with its environment, opening more gateways for development in programs, especially in game development [11], [15], [18]. In this method, there are two main components, the agent and the environment. The environment reveals itself and its current data in the form of the state, S; and the agent makes its move in the game by taking actions, A. The agent knows whether it's doing a good job by the reward function, which is a function that the agent receives back from the environment before the next state to improve itself [8], [10], [12-13], [22]. This type of functionality gives the agent leeway to more versatile movements as it is continuously learning through different evolutionary states. Furthermore, the prevalence of the reinforcement learning method in the selected articles emphasizes its capabilities and effectiveness in creating autonomous agents. As the field of AI in racing games continues to progress, there is a potential avenue for new improvements upon algorithms that may top RL, either by building on to the pre-existing algorithm, or by making an entirely new one [11], [23]. So, while RL has proven itself to be a highly reliable and adaptable technique, the dynamic nature of research and development in the field of AI is ever-changing, suggesting new potential for further advancements and optimized methods when it comes to racing games.

Correlation to Engineering Education

The use of AI/ML in racing games not only serves as a reliable testing ground but also serves as an excellent resource for students and engineers to learn and get their hands into basics of the game and AI/ML development, many of these engineers also attend research and AI conventions where they would network and explore different research and methodologies, aiding them in their journey in AI development [23]. Many racing simulators, including TORCS, display sensors and parameters while the agent is on the track to capture its velocity, speed, Rotations Per Minute (RPM), lap time, etc... (More details are provided later in theme IV). This helps users to better visualize what's going on and see things that need to be adjusted. Observing these parameters helps the user to better understand the cause-and-effect relationships of certain components and alterations, helping to identify mistakes and see where to improve [15], [24-25]. The simulator essentially becomes a virtual laboratory for engineers to experiment on, learning from mistakes, and moving forward without any risk of action. This not only gives engineers a better understanding of AI/ML, but it also helps them cultivate a mindset of experimentation and data management.

Methods

The SLR process includes three components in the selection and categorization of research articles. The first involves using specific search terms related to the topic to explore various articles in different databases and scholarly sources. In this review, a total of five search terms were used in the selection process, the five search terms are: (1) Artificial Intelligence + Racing Games, (2) Artificial Intelligence + Performance Optimization + Racing Games, (3) AI Agents + Racing Games, (4) Machine Learning + Racing Games, and (5) Machine Learning + Performance Optimization + Racing Games. Next, the five search terms were then individually searched in seven different online databases including Google Scholar, Web of Science, Compendex/Engineering Village, EBSCOhost, ScienceDirect, IEEE Explorer, and Wiley Online Library. This process of searching played a pivotal role in curating the most applicable and reliable articles in this review. The SLR process and structure/format used in this paper was referred from several existing SLR studies [26-28]. The following questions served as a structured blueprint for research and the selection of publications.

1. How are the sampled articles distributed in terms of:
    a. Publication Year?
    b. Affiliated country of first author?
    c. Scholarly Resources?
    d. Disciplinary techniques?
2. How are the articles included selected in terms of:
    a. Includes AI/ML techniques?
    b. Reliability of Article?
    c. Relevant to research topic? (Racing Games, Optimization, Racing Simulators)
3. What was most commonly employed:
    a. Methodologies?
    b. Technological Frameworks?

   c. AI/ML algorithms?
   d. Simulation environment used?
4. What key takeaways were observed from the retrieved articles:
   a. Theme/trends?
   b. Future Work?
   c. Implications?
   d. Sample Sizes?

Lastly, five exclusion criteria (EC) were determined to eliminate nonrelevant articles, keeping the ones that are most associated with the topic. The selection process and filtering of articles for the SLR are presented in Figure 2 below.

Exclusion Criteria**:** The exclusion criteria used in this study are,

EC1: Articles that are not English will be excluded
EC2: Articles not between 2013 – 2023 will be excluded
EC3: Articles not related to racing games will be excluded
EC4: Articles not addressing Artificial Intelligence, Machine Learning, or Reinforcement Learning will be excluded
EC5: Work-in-progress or short papers will be excluded

Data Collection and Analysis

In this review, a total of 696 articles were retrieved using the five search terms and seven databases previously listed. After that, 200 duplicate articles through the seven databases were removed, leaving 469 articles for abstract screening. Through abstract screening 379 articles were removed in consideration of the five exclusion criteria listed above, leaving 90 articles left for full-text screening. After full-text screening, only 22 publications were selected for the final review. However, after the process of detailed review, two articles were eliminated as they did not properly fit the criteria of the topic, leaving 20 articles in the final list of the systematic literature review.

The final synthesizing phase was done using a series of Microsoft Excel spreadsheets. These spreadsheets were used to heavily aid in facilitating ideas and objectives in this review, while addressing research questions, organizing data, and creating a systematic examination of key findings. This Excel file was used to capture and record data including the: year of publication, authors, country affiliated (of first author), title, goal/purpose/questions, codes, software or hardware, usage of TORCS, research design/methodology, framework, number of experiments/trials (same sizes), data type collected, data analysis techniques/methods, findings, implications, and future work. This Excel file greatly contributed to the writing process of this review and mapped a general overview of the main themes, topics, and ideas giving leeway into the writing process. Another Excel file was created for the purpose of sorting and organizing specific themes, these themes were determined by the overall codes that were categorized by each article. In this Excel file, four different themes were listed, each having their own codes, descriptions, exemplar studies, and research and practice implications.

Throughout these phases of research and information gathering, weekly meetings were regularly held with the second author, to serve as a quick review through the searching, synthesis, analysis, and data collection phase. This collaborative approach has enhanced the cohesiveness of the review, ensuring and allowing for a further comprehensive overview of the chosen topic.

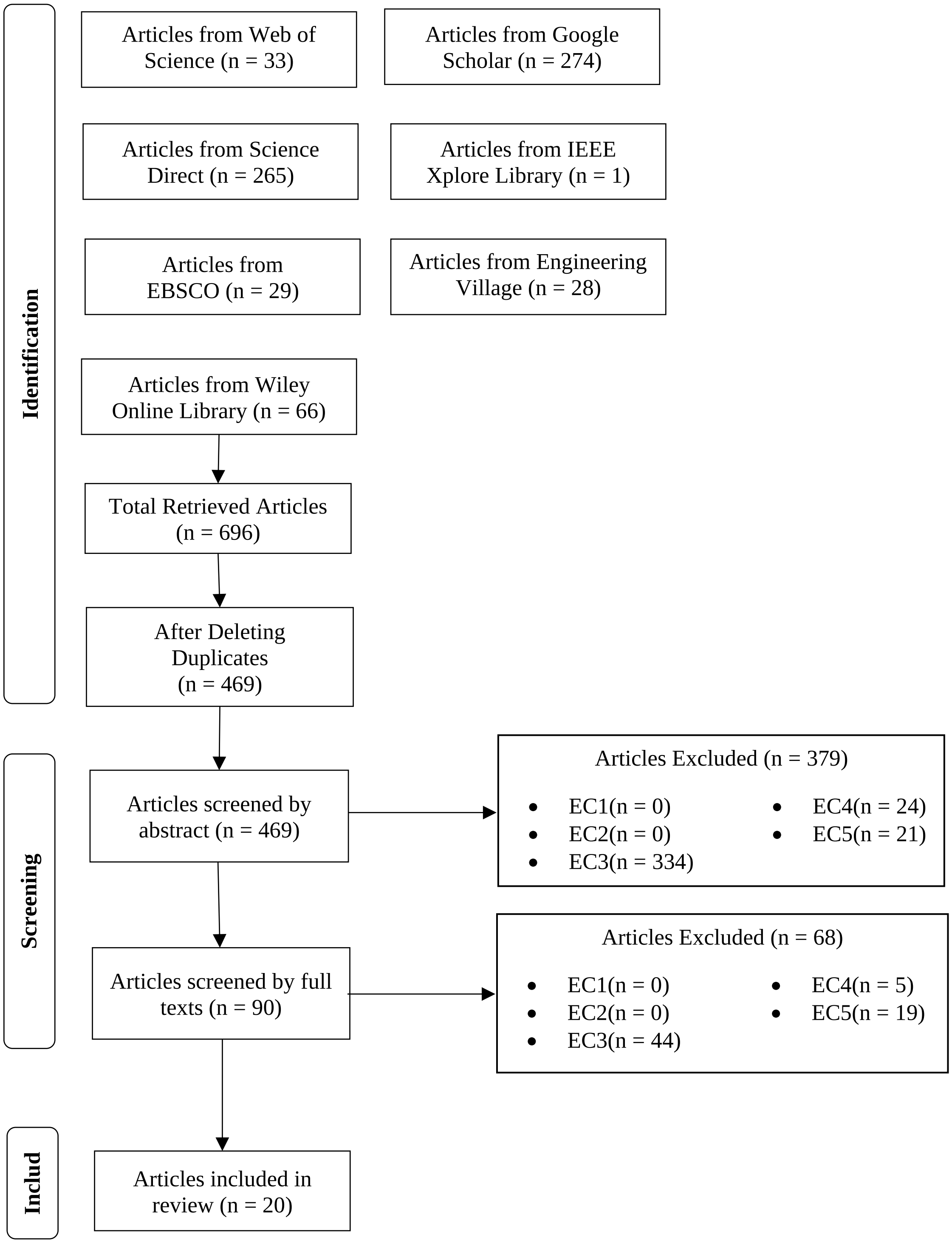

Figure 2: Systematic Literature Review – Article Selection Process

Strengths and Limitations of a SLR

In the pursuit of understanding and synthesizing relevant, reliable, and pre-existing data and research, the systematic review methodology has proven to be a well-grounded approach, ensuring meticulous analyzation of the research topic. Some of its key strengths are rigorous selection process, comprehensive data synthesis, and structured overview. This SLR methodology also does an excellent job of minimizing biases and ensuring the inclusion of all relevant articles by using predefined criteria through a systematic step-by-step process. The utilization of Microsoft Excel spreadsheets in the synthesizing phase greatly aided the process in providing a well-structured overview of the main topics, methodologies, and ideas of each selected article. This type of systematic approach allows for a thorough examination of key findings, facilitating a more in-depth analysis of the literature. Moreover, the SLR method has proven to be a viable option when it comes to meticulous data collection and article analysis, serving as a beneficial tool for researchers and readers to gather the appropriate information. However, as with any methodology, there are specific limitations. One main concern this methodology is faced with is the availability of certain literature. This could pose as a serious complication, especially for some research topics, as the main idea of a SLR is to use pre-existing literature to create an overview of the research topic and evidently, if there are none –to-little available research on a topic, then this methodology would be greatly limited. Another potential limitation when conducting an SLR are the time and resource constraints. The nature of a SLR is often more time consuming when compared to other methodologies, strict adherence and commitment to the systematic process requires a vast amount of time, carefully picking and analyzing articles. However, despite these limitations, the SLR still positions itself as a powerful tool for in-depth analysis of existing literature, giving a well formalized overview of the chosen subject.

Findings

This section outlines the different findings discovered during the selection, screening, and analysis portion of the SLR. Firstly, reoccurring trends since 2013 have been selected as the number of publications by year of each article, the number of articles based on country affiliation, different types of AI frameworks and algorithms used, sampling methods/sizes, and the racing environments. Second, each article was categorized into one or more of the four varying themes, each theme was then provided with a description, two exemplar studies, research implications, and practice implications. Lastly, a comparison of overlapping codes and keywords assigned to each article is described. Additionally, potential avenues for future work are discussed followed by an overall summary encapsulating the key findings found in the review.

Year of Publication

From 2013 to 2023, there has been a substantial amount of research conducted on the topic of AI in racing games. In this review, 696 articles were found relating to this topic. However, of the 696 founded articles only 20 articles were able to make it to the final synthesizing phase. Despite the extensive work done from 2013 to 2023, the recent five years have shown to have witnessed a surge in research on the intersection of AI and racing games. This trend in the past couple of years reflects the advancements of technology in both the AI and the gaming industry recently. This emphasizes the growing recognition in the fields of machine learning, artificial intelligence, and gaming.

First Author Country of Affiliation

There were twelve countries affiliated with the first author within the twenty articles found. Of these twenty articles, a majority of them were published from the U.S. (20%) and China (20%), followed by Egypt (10%) and Poland (10%), and the rest, consisting of Canada, Netherlands, Switzerland, Germany, Australia, Brazil, Spain, and South Africa (5%). These results indicate the prominence of research done in the U.S. and China compared to other countries potentially because this SLR only includes research articles written in English (EC 1). However, it may also be due to the fact of growing research and technological advancements in correlation to the population of these first world countries. Such resources, technology, and connections in varying countries may contribute to the difference in research conducted in this topic. Table 1 shows the number of countries of affiliation with the first author in this research.

Table 1. Countries of Affiliation of First Author

#	Country	Frequency	Percentage (%)
1	United States	4	20
2	China	4	20
3	Egypt	2	10
4	Poland	2	10
5	Canada	1	5
6	Netherlands	1	5
7	Switzerland	1	5
8	Germany	1	5
9	Australia	1	5
10	Brazil	1	5
11	Spain	1	5
12	South Africa	1	5

AI Frameworks and Algorithms

Five main AI frameworks/algorithms were used in the application of these AI agents, they are reinforcement learning, neural networks, algorithmic trees, imitation learning, and other varying ones (waypoint system, steady state, and simulation alterations) [12], [16], [23], [29-31]. Of the five strategies found, reinforcement learning was found to stand out as the most widely favored one, being featured in thirteen out of the twenty articles (65%); followed by neural networks, algorithmic trees, and imitation learning all with two occurrences (10%); and finally, by the other methods used in three articles (15%). It is noteworthy that some articles were included in more than one category as they were found to use multiple frameworks/algorithms, indicating the potential opportunity for new areas of research with the flexibility of these frameworks and algorithms. Such versatility might offer researchers new opportunities for advancements, exploring different methodologies in providing a comprehensive and optimal understanding of different methodologies in AI. Because of this, Table 2 below will not add up to 100% as there are overlapping methods.

Within these five strategies, there exist various subcategories specifying the different techniques used in each distinct algorithm. For example, the most frequently encountered algorithm encompasses seven different techniques found, that is Deep Reinforcement Learning, Whale Optimization, Actor-Critic Method, Continuous Action, Policy Optimization, and Deep Q Networks [12-13], [15], [18], [32-35]. These seven listed techniques were found under the category of reinforcement learning while reviewing the articles. Table 2 shows the different methodologies used in the twenty articles as well as the techniques found in each methodology. Note that the number of techniques used will not sum up to the frequency of the methods used, this is due to the utilization of multiple techniques in each article.

Table 2. AI Frameworks and Algorithms of Sampled Articles

#	Methods	N	%	Techniques	N	%
1	Reinforcement Learning	13	65	- Deep Deterministic Policy Gradient	5	25
				- Actor-Critic Algorithms	5	25
				- Policy Optimization	4	20
				- Deep Reinforcement Learning	3	15
				- Deep Q Networks	2	10
				- Continuous Action	1	5
				- Whale Optimization	1	5
2	Neural Networks	2	10	- Differential Evolution	2	10
				- Convolutional Neural Networks	1	5
				- Feed Forward Artificial Neural Networks	1	5
3	Algorithmic Trees	2	10	- Behavior Trees	3	15
				- Decision Trees	2	10
				- Random Forests	2	10
4	Imitation Learning	2	10	- Not indicated	-	-
5	Others	3	15	- Waypoint System with Vector Calculations	1	5
				- Waypoint System with Conditional Monitoring System	1	5
				- Trigger Detection	1	5
				- Vehicle Controlling	1	5
				- Opponent Manager	1	5

Sampling Methods and Size

The sampling methods/sizes were found to vary across the twenty articles, this is due to the numerous amounts of methodologies the researchers used in implementing their AI agent. Because of this, it is difficult to depict the exact sampling sizes in each article in a table so each article will be grouped by their sampling sizes based on certain ranges. However, the sampling methods in these articles all seem to have reoccurring trends. All the sampling methods were tested over a racing simulator. Additionally, the majority of the sampling methods were done similarly, each on different tracks for tests, using different algorithms and reward signals over a generational data collecting environment. Some sampling methods even used real, human drivers in racing games to act as a control variable for the purpose of overtaking and comparison [25], [36]. Table 3 shows the different track testing methodologies used during the experiments while Table 4 illustrates the approximate number of sample sizes employed in the articles.

Table 3. Track Testing Sampling Methodologies

Sampling Approaches	N	%
Single Bot	5	25
Multiple Bots	7	35
Multiple Iterations	2	10
Multiple Tracks	5	25
Not Recorded	1	5

The Virtual Racing Environments

Ten total racing environments were used in the twenty articles. Of the ten racing environments, TORCS stood out to be the most widely preferred racing simulator when it comes to testing and sampling with 50% of reviewed articles using TORCS. TORCS is generally favored due to its reliability and user-friendly interface. It allows users to quickly access and extract information and use it to perform alterations they need for future tests [2-3], [15], [37].

Table 4. Sample Sizes Found in the Sampled Articles

Sampling Sizes	**N**	**%**
1-10	8	40
11-30	4	20
31-50	3	15
51-100	0	0
101-500	0	0
500-1000	0	0
1000-10000	2	10
Probability Model	1	5
Not Recorded	2	10

Figure 3: The Open Racing Car Simulator (TORCS) [24]

However, it lacks in versatility, and many opt for other alternatives that may provide additional configurations such as different lane numbers, vehicle numbers, track curvature, etc. [8], [29]. Although TORCS is a well-grounded, dependable racing simulator, it has a limited range of tracks and vehicles for the users to test on as opposed to current and further modified ones [8], [17], [29]. Next is the OpenAI racing simulator with 10% of the articles and the rest (Gran Turismo, WRC6, CARLA, Racer Game System, SUMO, Unity, F1Tenth ROS2, and Mario) each being 5%. Table 5 shows the distribution of racing environments used in the reviewed articles.

Table 5. Distribution of Racing Environments Used

#	Racing Environment	N	%
1	TORCS	10	50
2	OpenAI Gym	2	10
3	Gran Turismo	1	5
4	WRC6	1	5
5	Racer Game System	1	5
6	SUMO	1	5
7	Unity, Self-implemented Racing Environment	1	5
8	F1Tenth ROS2	1	5
9	Mario	1	5
10	CARLA	1	5

Themes

A total of fifteen codes were generated from this SLR: Optimization, Evolutionary, Reinforcement Learning, Machine Learning Algorithms, Actor-Critic Method, Trial and Error, Neural Networks, Decision Trees, Forests, Imitation Learning, TORCS, Self-Implemented Racing Environments, OpenAI Gym Libraries, Ahura, Game/Simulator Development. In this section, we will thoroughly explore different themes. Briefly explaining each theme, how they're organized together and delving into two exemplary studies most specific to each theme. Additionally, research and practice implications will be provided for each theme. Table 6 shows the codes associated with each theme along with a brief description of the themes (more in-depth descriptions will be found under each theme).

Table 6. Distribution of articles based on themes and codes

Themes	Definitions	Codes	*N*
Agent Performance Optimization	Topics relating to the optimization of the performance of AI agents in the racing environment. Achievable through the various AI/ML methodologies and techniques.	Optimization Evolutionary	3
AI Technologies Applications	Topics describing the different frameworks and algorithms used in implementing a robust, reliable, and efficient AI model in racing games, capable of self-navigating itself through the course.	Reinforcement Learning Machine Learning Algorithms Actor-Critic Method Trial and Error	13
Machine Learning Paradigms	Topics relating to the synergy of machine learning models and paradigms in order to achieve artificial intellect in AI agents within the racing environment.	Neural Networks Decision Trees Forests Imitation Learning	5
The Racing Simulation Environment	Topics relating to the racing simulation environment itself, emphasizing the pivotal role the racing environment plays in the advancements of both AI/ML and racing games.	TORCS WRC6 Gran Turismo Open AI Gym Library Ahura Game/Simulator Development	9

A total of twenty research articles between 2013 and 2023 were selected after the screening process. These studies were analyzed and placed under four themes: (1) Agent Performance Optimization, (2) AI Technology Applications, (3) Machine Learning Paradigms, and (4) The Racing Simulation Environment. Descriptions covering each theme will be found later in this chapter. Appendix A provides a table that correlates each article to its theme; notably, an article may be associated with multiple themes.

Theme 1: Agent Performance Optimization

Three articles strictly addressed the important elements of optimization techniques found in AI agents. Together, the three articles form a theme that entails employing advanced machine learning techniques, particularly reinforcement learning, to refine and enhance the decision-making abilities of the AI agent's navigation and pathing through the racetrack. Two articles under this theme can be categorized as describing the overall stability and optimization of the overall performance of the car on the track without any safety constraints by using a racing simulator [15], [23]. The objective is to integrate these certain algorithms and techniques shown into educational frameworks, creating an interactive platform for engineering students.

By focusing on how AI agents adapt and enhance their racing abilities through continuous learning and feedback loops through trial and error, the research not only addresses the technical aspects of track optimization but also underscores the educational advantages of such an approach. Lastly, another article [32] discussed the safety of the vehicle and driving while also optimizing the AI Agent to perform rigorous tasks while improving racing abilities by defining risks and safety constraints.

Exemplar Studies

Exemplar studies under this theme (Agent Performance Optimization) highlight the intricate interplay between advanced machine learning techniques and the enhancement of AI Agents' capabilities in the continuous and dynamic racing environment. In study [15] their agent was optimized by the usage of three different machine learning classes: swarm-based, evolution-based, and physics-based methods. Firstly, they used swarm-based techniques, drawing data from collective behaviors observed in the racing environment. This approach allowed the AI agent to mimic the collaborative dynamics seen in swarms, providing room for better adaptation and decision-making on the track. Secondly, they explored the evolution-based method which utilizes the principles of natural selection to iteratively refine and evolve the agents' performances over generations of runs. This adaptive process is aimed to enhance the agent's ability to navigate and respond to evolving challenges within the racing environment. Lastly, [15] incorporated a physics-based method into their framework. By integrating an understanding of the underlying physical dynamics of the racing environment and replicating real-world physics, the AI agent could make more informed decisions, optimizing its movements and interactions with its surroundings.

In another exemplary study, [32] explored the use of a safe Reinforcement Learning algorithm called Parallel Constrained Policy Optimization (PCPO) for autonomous driving. PCPO ensures the safety of both the driver and the vehicle during the training/learning process while also improving its convergence speed and performance. PCPO consists of five main steps: (1) Define Risk, determining what may cause danger or risks; (2) Policy Security Constraint, implementation of the 'safety rules' the agents must follow; (3) Learning with Rules, training the agents while also following the set safety rules given; (4) Balancing Act, helps agents balance out exploration and safety; (5) Repeat and Improve. The five-step PCPO process offers a comprehensive framework that the researchers incorporated into their study that integrates safety considerations seamlessly into their training environment.

Research Implications
Previous research suggests a need for more in-depth exploration of the field. One study suggests performing experiments to analyze how hyperparameter optimization techniques act in model-based algorithms, investigating if the capabilities of model-based techniques would be enhanced by optimizing their hyperparameters. By optimizing hyperparameters, future research hopes to unravel the intricate dynamics interplay between model-based algorithms and AI agents [15]. Moreover, researchers can further optimize the performance of AI agents by experimenting with newer and more in-depth studies on fitness functions and different classification algorithms to find better patterns and strategies. Through continued exploration and experimentation, researchers can guide the field toward more sophisticated and effective track performances, fostering advancements that align with the ever-growing demands of artificial intelligence in gaming [23], [32].

Practice Implications
The research findings underscore the potential for optimizing AI agents in the context of autonomous racing through advanced machine-learning techniques. To translate these insights into practice, adequate attention must be given to the types of algorithms and models used in developing the AI agent; in addition, the use of hyperparameters and sensors in the racing environment plays a crucial role in the implementation and advancements of the agent as they give insights and data on the performance of the agent throughout the course [15]. Moreover, optimizing AI agents for autonomous racing goes beyond just selecting a model; it involves the intricate adjustments of hyperparameters and the strategic incorporation of sensor inputs, trying different algorithms, and going through various trials and errors in refining the capabilities of the agent [23], [32].

Theme 2: AI Technology Applications
The central topic revolves around the use of Artificial Intelligence and the techniques and algorithms used to implement these AI Agents into the application and their implications. One technique that has been widely used for its robust, reliable, and efficient results is Reinforcement Learning. The use of Reinforcement Learning and Machine Learning Algorithms have been used in this area of study to address complex challenges in diverse domains. These algorithms are the brains of the AI Agents themselves enabling them to make intelligent decision-making through continuous learning and interactions with the environment while examining their adaptability and efficiency/performance in various scenarios and obstacles.

Thirteen articles were categorized under the theme of AI Technology Applications, all of which underscore the importance of AI and machine learning techniques and technological applications in developing an autonomous self-driving vehicle tested in various racing environments. Of the thirteen articles, seven delved into the generalizing implementation of machine learning techniques such as reinforcement learning in End-To-End autonomous car racing/driving [8], [10-13], [15], [18]. For example, [8] explained how state encoders and deep reinforcement learning through data collected from trials and experiments can lead to the development of End-To-End autonomous cars soon. Now, regarding the other six articles, their primary focus lies in the techniques and different types of racing styles (Drifting, Lateral Control, Lane Changing, Overtaking) that can be implemented through the use of AI applications [9], [17], [20], [32], [33], [38]. By synthesizing existing literature, the study aims to provide insights into the current state of these algorithms, their applications in engineering, and potential future developments in this field."

Exemplar Studies

The exemplary studies for this theme were specifically chosen due to their focus on the practical application of reinforcement learning techniques and how they're implemented to better the performance of the agents. These studies were selected as they dive into the techniques and algorithms in machine learning and how they can be used to boost agent performance, they're not just theoretical — these studies provide insights into real-world strategies. In the first study, [12] explored and analyzed the possibility of achieving autonomous driving using synthetic simulators, specifically employing Deep Deterministic Policy Gradient (DDPG) algorithms. DDPG is an algorithm used in reinforcement learning, a type of machine learning. Another key component that [12] used in developing the agent was the utilization of sensor inputs and parameters that the racing simulator gives. These sensors input log data and use reinforcement learning for a reward design technique (agents are given 'rewards' for every good action), however, because the simulator does not have its internal rewarder, the researchers designed their own.

In another exemplar study, [33] implemented these AI technologies, utilizing different types of reinforcement learning frameworks to create an agent that would 'drift' to better its performance. In this study, the researchers used a different type of reinforcement learning method called Soft Actor-Critic (SAC) over DDPG because DDPG is comparatively more difficult to converge due to the limited exploration ability caused by its deterministic behavior. To improve convergence and avoid high sample complexity, [30] opted to use SAC. The goal of this research is to control the vehicle to follow a certain trajectory at high speeds and drift through manifold corners and large sideslip angles like a professional driver would enhance their performance. Their goal of mimicking professional driving skills using reinforcement learning, machine learning algorithms, and other methods and frameworks exemplifies the practical implications of these studies in advancing AI capabilities in dynamic environments.

Research Implications

Further research is needed into (1) scaling higher with more comprehensive research, (2) investigating more complex RL techniques and algorithms, and (3) environment Augmentation. Much research has been shown to be only limited to specific racing tracks and car combinations [9], limiting its ability to be able to dynamically adjust itself when faced with different obstacles and tracks. This specifically poses a challenge in achieving broad generalization and adaptability across diverse racing scenarios. The need for comprehensive research arises from the recognition that current studies may lack the inclusivity required for dynamic challenges. Therefore, further research needs to be done, focusing on the exploration of different RL techniques that are more adaptable to ever-changing, dynamic environments. This proactive approach aims to enhance the robustness and versatility of autonomous racing using different approaches in AI technologies. Addressing these research gaps will contribute to the advancement of AI racing technology, making it more adaptable across different environments [11], [18].

Practice Implications

Ensuring an understanding and knowledge of machine-learning algorithms by familiarizing yourself with online resources, tutorials, open-sourced platforms, and the racing simulator itself.

A good overview of Artificial Intelligence and Machine-Learning technologies heavily aids in determining which model, algorithm, or method is best fitted for a certain topic or area of study. Furthermore, staying updated on the latest research papers, online resources, and publications within the field of AI/ML technologies can provide valuable insights into emerging trends and up-to-date AI applications. By maintaining a proactive approach to learning, researchers and developers can effectively navigate the evolving landscape of AI/ML technologies [12].

Theme 3: Machine Learning Paradigms

This theme includes four articles that revolve around the synergy of machine learning models like Neural Networks, Decision Trees, and Imitation Learning to achieve artificial intellect in AI Agents. These frameworks are used to achieve the most optimal results through search algorithms, trial and error, and continuous learning from given data. Neural Networks are explored for their ability to decipher intricate patterns and facilitate nuanced decision-making within the racetrack. Of the four articles two strictly focus on the implementation of neural networks [2-3]. Decision Trees are used for their structured decision pathways and easy-to-modify data structures. Lastly, in imitation learning, the agents examine human behavior and emulate and learn from such behaviors, implementing it and adapting it into their own skill set. There is only one article covering the topic of imitation learning [39]. Finally, the fourth article covers the implementation of both neural networks and imitation learning [36]. By synthesizing such existing frameworks and literature on these interconnected themes, the research aims to present a holistic understanding of the synergies and applications of Neural Networks, Decision Trees, and Imitation Learning in the optimization of AI agents within engineering.

Exemplar Studies

Exemplary studies for this theme were chosen to highlight the importance of machine learning paradigms in the development of autonomous cars. As opposed to the previous theme 'AI Technology Applications' this theme revolves around the use of AI models like neural networks, imitation learning, and decision trees. In the first exemplary, [36] explained how the use of decision trees, random forests, and imitation learning can be opted over reinforcement learning strategies. In this study, they decided that decision trees were more efficient than neural networks as they allow for easier inspection, verification, and tuning by humans. They're also easier to understand and inspect and can be learned in a reasonably short amount of time, even for large training sets. There are three main phases in the construction of decision trees: (1) Growing, which involves adding new nodes to the tree step-by-step. At each step, the algorithm selects the best split to apply to the current set of data; (2) Pruning, the pruning phase involves removing nodes from the tree, this is done to prevent overfitting (when the data becomes too closely fitted to the training data); and (3) Prediction, involves using the decision trees to classify data points. These trees are grouped to become what's known as a 'forest'. Forests are an ensemble learning method that builds multiple decision trees during training and merges them to get a more accurate and stable prediction.

In another exemplar, [39] delved more into the use of supervised learning/imitation learning to create better results in AI agents. In this study, they believed that they could better the performance of the agents by using expert data to guide their training. They let an agent imitate human strategies through expert human data initially. After this imitation learning, when it almost reaches its peak performance through the human data alone, the algorithm gradually becomes an ordinary deep reinforcement learning method and continues to improve through self-learning from there on. These different methods and models of machine learning play a crucial role in the advancement of autonomous cars, the versatility of AI models like neural networks, imitation learning, and decision trees, offers distinct advantages in addressing specific challenges.

Research Implications
[3] suggests future opportunities for Machine Learning Techniques, including (1) balancing game elements, (2) balancing game difficulty, (3) finding design loopholes in games, and (4) making timely decisions. These strategies set a solid blueprint when implementing these machine learning paradigms. Furthermore, additional research is required to investigate new ways to improve the generalization capabilities of the learned control models and address the challenges of learning control models for tasks in more realistic environments [36]. This ongoing research pursuit aims to further refine and extend the applicability of machine learning paradigms in shaping more responsive and adaptable gaming systems.

Practice Implications
Acquiring a comprehensive understanding of machine-learning paradigms such as decision trees, neural networks, random forests, and imitation learning is important for the implementation of such models into the agent. Hence, researchers and developers must devote sufficient time to learning these paradigms and carefully analyzing each model. Additionally, engaging in communication through online resources, competitions, and workshops can serve as valuable avenues for continuous learning and collaborative knowledge exchange. Exploring different paradigms and gaining a comprehensive understanding of each one helps in determining which paradigm would best fit different types of studies. For example, [36] conducted research in which they knew that they wanted to use pre-recorded human data to heighten the performance of their agent, in which case, they used imitation learning to implement their design.

Theme 4: The Racing Simulation Environment
While synthesizing the information from the sampled articles, a significant focal point was dedicated to the racing simulation environment itself. This theme encapsulates a detailed investigation into the intricacies of the simulated racing environment and its pivotal role in shaping the learning experience for AI Agents. These simulations are a huge beneficiary when it comes to research as they allow researchers to test and experiment on virtual vehicles designed with physics and capabilities mirroring those of real-world physical cars. Allowing researchers to test freely without the worry of safety and costs. Many simulators have been used throughout the various papers, however, TORCS seems to be the most widely used one for its sensory and parameter information.

All twenty articles used some type of software car racing simulator, however, only eight seemed to have used something unique that is not TORCS. These eight consist of alternative platforms to that of TORCS, each with their unique advantages and disadvantages. Five articles used different pre-built racing simulators like Gran Turismo, WRC6, GTS, and other open Gym AIs [8-9], [10], [13], [40]. Within the eight articles, there were two articles in which the researchers created their personalized car racing simulator environment to fit their criteria [7], [30]. Lastly, there was one article that built upon TORCS and essentially made a 'new and improved' alternative [17]. Navigating diversity is crucial, as simulators vary in their emphasis on realism. By centering on the racing simulation environment, the research seeks to unravel the challenges and opportunities it presents in engineering education.

Exemplar Studies

The racing simulation environment is possibly the most vital component for researchers when researching autonomous cars as these simulations provide a safe and multi-functional testing environment. Although TORCS is the most popular one, there are many other simulators that researchers prefer like WRC6, Gran Turismo, AI Gym Libraries, Ahura, etc., each with their own benefits and limitations. In the first exemplar study, [3] used TORCS in looking at the broad issues of incorporating learning into games, independently of languages and platforms. The utilization of TORCS helped [3] in gathering information and datasets through hyperparameters and sensors presented in the simulator. One main reason why so many researchers used TORCS is that it not only provides a physically realistic testing environment for researchers but also drastically helps them in logging data by providing sensors and parameters like angles, current lap time, damage, distance from start line, distance raced, fuel, gear, focus, last lap time, opponents, rotations per minute, speed X, speed Y, speed Z, etc. The combination of all these different attributes helps the researcher conduct more thorough and well-backed-up studies and it also helps everyone to learn through gaming.

In another exemplary study, [9] used a different racing simulator called Gran Turismo Sport as a testing ground for tackling high-speed autonomous race-car overtaking. In this study, they used ML techniques to create an agent that will perform exceptionally in an environment where they are tasked to overtake their opponent. The researchers used GTS as the game provided a more diverse and more dynamic set of tracks and various vehicles that they could choose from. GTS was favored for its more contemporary graphics and physics compared to TORCS, highlighting the importance researchers place on the simulation environment's comparison to the real world. The choice of a racing simulation environment is pivotal, relying heavily on the different scenarios and areas of research the researchers are delving into. The chosen platform plays an important role in shaping the landscape of the research, offering various innovations, experimentations, and learning in the dynamic field of autonomous driving.

Research Implications

Potential directions for this theme include (1) the development of a versatile simulator, emphasizing adaptability to a wide range of scenarios and environments (2) providing users with the capability to create and customize parameters and sensors, allowing them to tailor the simulator to best suit their needs, and (3) fostering a well-established collaboration and knowledge-sharing among researchers to establish standardized practices. More research needs to be done in incorporating certain features in the racing environment itself like enabling the controllers in the simulators to generate a map of the track before the race for the agent to 'warm up' and get used to the track to make better decisions and recognize pattern [29].

Practice Implications

The racing simulator is a key foundation when it comes to researching autonomous racing, as it sets the foundation/environment of the research itself. When it comes to determining the racing simulator, adequate attention must be given to certain criteria needing to be met. This includes the simulator's ability to faithfully replicate flexibility, physics, vehicle behavior, and its ability to accurately replicate real-world racing conditions. Additionally, factors such as user-friendly interfaces, accessibility, and compatibility with AI models and algorithms also play a pivotal role in the selection process. By prioritizing these criteria, researchers can ensure that the chosen racing simulator provides a versatile and robust foundation for the research to be conducted [13], [29], [40].

Future Work

This systematic literature review suggests a few possible paths for future research. For example, [30] proposed their research in which they used reinforcement learning frameworks to see which algorithm would be best for drifting cars. By drifting their cars, they're able to better optimize their times on corners and overtake opponents. The utilization of these real-world techniques also works in-game; however, there's an obscure amount of research done on this topic. A suggested future work would be implementing real-world professional maneuvers in these agents, for example, F1 racing tactics like chicane, hairpin, and apex to name a few. Another common potential path mentioned is versatility. Many articles in this SLR designed their model in which they're only limited to the specific racing track and car combination. A potential path moving forward would be scaling models higher with more in-depth research on the AI models, making them more versatile to different maps, composition, terrain, elevation, and possible even obstacles [3], [9], [15], [18], [23]. These suggestions indicate that there is still much to be done in this area of study and potentially even more as AI continues to evolve in the years to come.

Summary

In this study, twenty articles regarding the intersection between AI, optimization, and racing games were critically synthesized, analyzing their year of publication, countries of affiliation by first author, goals/purposes, codes, methodologies, sample sizes/methods, and findings. Subsequently, four distinct themes were found: (1) agent performance optimization, (2) AI technology applications, (3) machine learning paradigms, and (4) the racing simulation environment. Exemplary studies and research and practice implications were summarized for each listed theme. This overview provides a comprehensive literature review of twenty articles curated through the systematic screening process, screening by title, screening by abstract, screening by full-text, full-text reading, and full-text analysis to fully synthesize the information provided in the articles. This SLR delves into the intricate interplay and relationships between AI and racing games and their potential impact in both the technological and gaming industries.

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APPENDIX A: Classification of the reviewed studies based on specific themes

Theme 1: Agent Performance Optimization

Authors	*Country affiliation of first author*	*Title*
Ashraf & Mostafa (2021)	Egypt	Optimizing hyperparameters of deep reinforcement learning for autonomous driving based on whale optimization algorithm
Cotta & J. Fernández-Leiva (2013)	Spain	Car setup optimization via evolutionary algorithms
Wen & Duan (2021)	United States	Safe Reinforcement Learning for Autonomous Vehicles through Parallel Constrained Policy Optimization

Theme 2: AI Technologies Applications

Authors	*Country affiliation of first author*	*Title*
Holubar & Wiering (2020)	Netherlands	Continuous-action Reinforcement Learning for Playing Racing Games: Comparing SPG to PPO
Jaritz & Charette (2019)	Germany	End-to-End Race Driving with Deep Reinforcement Learning
Wang & Jia (2018)	United States	Deep Reinforcement Learning for Autonomous Driving
Savid & Mahmoudi (2023)	Poland	Simulated Autonomous Driving Using Reinforcement Learning: A Comparative Study on Unity's ML-Agents Framework
Portugal & Cruz (2022)	Brazil	Analysis of Explainable Goal-Driven Reinforcement Learning in a Continuous Simulated Environment
Evans & Jordaan (2023)	South Africa	Comparing deep reinforcement learning architectures for autonomous racing
Ashraf & Mostafa (2021)	Egypt	Optimizing hyperparameters of deep reinforcement learning for autonomous driving based on whale optimization algorithm
Wen & Duan (2021)	United States	Safe Reinforcement Learning for Autonomous Vehicles through Parallel Constrained Policy Optimization
Song & Lin (2021)	Switzerland	Autonomous Overtaking in Gran Turismo Sport Using Curriculum Reinforcement Learning
Sallab & Abdou (2016)	Egypt	End-to-End Deep Reinforcement Learning for Lane Keeping Assist
Li & Zhao (2019)	China	Reinforcement Learning and Deep Learning Based Lateral Control for Autonomous Driving
Cai & Mei (2020)	China	High-Speed Autonomous Drifting With Deep Reinforcement Learning
Ye & Cheng (2020)	United States	Automated Lane Change Strategy using Proximal Policy Optimization-based Deep Reinforcement Learning

Theme 3: Machine Learning Paradigms

Authors	*Country affiliation of first author*	*Title*
Long & On (2013)	China	Evolving Controllers for Simulated Car Racing Using Differential Evolution
Muñoz-Avila & Bauckhage (2013)	United States	Learning and Game AI
Yi & Xu (2018)	China	Deep imitation reinforcement learning with expert demonstration data
Cichosz & Pawełczak (2014)	Poland	Imitation Learning of Car Driving Skills with Decision Trees and Random Forests

Theme 4: The Racing Simulation Environment

Authors	*Country affiliation of first author*	*Title*
Evans & Jordaan (2023)	South Africa	Comparing deep reinforcement learning architectures for autonomous racing
Savid & Mahmoudi (2023)	Poland	Simulated Autonomous Driving Using Reinforcement Learning: A Comparative Study on Unity’s ML-Agents Framework
Ye & Cheng (2021)	United States	Automated Lane Change Strategy using Proximal Policy Optimization-based Deep Reinforcement Learning
Jaritz & Charette (2018)	Germany	End-to-End Race Driving with Deep Reinforcement Learning
Song & Lin (2021)	Switzerland	Autonomous Overtaking in Gran Turismo Sport Using Curriculum Reinforcement Learning
Chan & Chan (2015)	Canada	Development of a Car Racing Simulator Game Using Artificial Intelligence Techniques
Bonyadi & Michalewicz (2016)	Australia	Ahura: A Heuristic-Based Racer for the Open Racing Car Simulator
Li & Zhao (2019)	China	Reinforcement Learning and Deep Learning Based Lateral Control for Autonomous Driving
Muñoz-Avila & Bauckhage (2013)	United States	Learning and Game AI