Artificial Intelligence in Motorsport: A Scoping Review of Applications, Challenges, and Research Gaps

Radu C. Lucaciu[1], Cornelia Aurora Győrödi[2]
Doctoral School of Engineering Studies-Department of Computer Science and Information Technology,
University of Oradea, Oradea, Romania[1]
Department of Computer Science and Information Technology, University of Oradea, Oradea, Romania[2]

***Abstract*—This study presents a state-of-the-art review of Artificial Intelligence and Machine Learning applications in motorsport, with a particular focus on Formula 1. As modern racing generates increasingly large volumes of high-frequency telemetry data, traditional physics-based analysis methods have proven insufficient to capture the complex, non-linear relationships between vehicle, driver, and environment. AI has emerged as a critical tool for extracting actionable insights from this data across six core domains: vehicle performance optimization, race strategy, autonomous racing and real-time decision support, telemetry and race data analysis, driver coaching and simulation, and predictive maintenance. This review further examines transferable methodologies from adjacent fields — particularly autonomous driving research — and assesses their relevance to high-performance motorsport contexts. A systematic analysis of peer-reviewed publications and preprints reveals a highly uneven distribution of research, with race strategy and vehicle optimization relatively well-covered, while predictive maintenance and computer vision applications remain largely unexplored.**

Keywords*—*Artificial Intelligence; Machine Learning; motorsport; Formula 1; scoping review; PRISMA-ScR; race strategy optimization; telemetry analysis

I. INTRODUCTION

Recently, motorsport competition has developed substantially under the influence of technology and data-driven decisions. The current telemetry systems and high precision sensors, as well as modern and performance data collection infrastructure provide a way to collect massive volumes of data in near-real time. Different variables, ranging from engine, suspension or gearbox parameters to tyre temperature and degradation, driver behaviour or environmental temperature and pressure are collected and used for complex analysis to provide technical and strategic insights but the volume, data-generation speeds and both linear and non-linear dependencies between variables have outgrown the capabilities of traditional methods of analysis. In this context, Artificial Intelligence has emerged as an ideal tool for high performance motorsport, capable of transforming raw data into valuable insights for performance optimisation.

To ensure conceptual clarity and consistency throughout this review, the key terms used in the literature are defined here in a hierarchical manner. Artificial Intelligence (AI) is used as an umbrella term encompassing any computational method capable of extracting complex patterns, generating predictions, or making decisions based on data, including both traditional and modern approaches. Machine Learning (ML) refers to the subset of AI in which models learn from data without being explicitly programmed, covering supervised learning (e.g., regression, classification), unsupervised learning (e.g., clustering), and reinforcement learning (RL). Deep Learning (DL) is a further subset of ML that employs multi-layered neural network architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based models. Finally, the term “data-driven models” is used more broadly to include both ML-based approaches and non-ML statistical methods such as multivariate regression or principal component analysis, provided they learn relationships directly from data rather than from first-principles physics. The relationships between these terms are hierarchical: DL $\subset$ ML $\subset$ AI, while data-driven models partially overlap with ML but also include classical statistical methods. Throughout this study, the most specific applicable term is used in each context; when referring to the overall field or to studies that employ multiple approaches, the general term “AI” is used.

However, adopting AI in motorsport is not a simple process. Racing cars operate at the extreme physical limits: heavy acceleration and deceleration, massive cornering speeds and lateral G-force loads, rapid degradation of tyres and complex strategic decisions like optimal pit strategies, the correct choice of tyre compounds and even technical choices such as mechanical and aerodynamic vehicle setup. In these conditions, standard physics-based models can become too complex or expensive (e.g. CFD simulations or multi-variable analysis) and can sometimes miss non-linear correlations between various components: car, driver and environment. AI, on the other hand, is extremely versatile at detecting and extracting these patterns from vast amounts of data, offering a very pragmatic way of modeling complexity.

Formula 1 has long been considered the technological pinnacle of motorsport and it makes sense that academic research and motorsport industry have converged in multiple areas. Deep reinforcement learning has been applied to autonomous racing using telemetry data [1], sim racing telemetry has been used to predict performance with high accuracy [2], and autonomous racing projects have become real-life laboratories for testing perception, planning and control models at high speeds and variable conditions [3]. AI is no longer just a theoretical research subject: it is a mandatory tool which confers a real competitive advantage, capable of influencing various aspects of performance motorsport, from strategic choices to car setup and even driver coaching and selection.

Despite this growing adoption, no comprehensive scoping review has systematically mapped the extent and nature of AI research across the various motorsport application domains. Existing reviews tend to focus on narrow sub-topics: Betz et al. [3] provide a thorough survey of autonomous racing but do not address race strategy, telemetry analysis, or predictive maintenance; Kuutti et al. [4] and Elallid et al. [5] survey deep learning and reinforcement learning for autonomous driving, a field adjacent to motorsport but with fundamentally different performance objectives; and Arena et al. [6] review predictive maintenance in the broader automotive sector without addressing the specific constraints of competitive racing. What differentiates the present analysis from these prior works is its cross-domain scope: rather than focusing on a single technique or application area, this review maps the full landscape of AI research in motorsport, identifies the connections between application domains, and highlights the gaps that remain unexplored. A scoping review approach, following the PRISMA-ScR framework, is particularly well-suited to this purpose given the heterogeneous body of literature available — spanning peer-reviewed journals, conference proceedings, and publicly available preprints — and the exploratory nature of the research landscape.

The primary objective of this scoping review is to systematically map the existing body of research on AI and ML applications in motorsport across defined thematic categories, providing a comprehensive overview of how these technologies are currently being applied and studied. Building on this mapping, the review further aims to identify which application domains are well-covered in the literature and which remain underexplored, to examine transferable methodologies from adjacent fields — particularly autonomous driving — and assess their relevance to high-performance motorsport contexts, and to highlight key research gaps and propose directions for future investigation.

The review is structured around the PCC (Population, Concept, Context) framework: the *Population* comprises published academic works addressing motorsport engineering, autonomous driving and competition; the *Concept* is the application of AI and ML techniques; and the *Context* is motorsport competition, with a particular focus on Formula 1 and related high-performance racing series.

II. METHODS

A. Protocol and Registration

This scoping review was conducted following the methodological framework proposed by Arksey and O'Malley [7] and refined by Levac et al. [8], and is reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analysis extension for Scoping Reviews (PRISMA-ScR) checklist [9]. No formal protocol was registered prior to conducting the review.

B. Eligibility Criteria

Sources of evidence were included if they met the following criteria: 1) addressed the application of AI or ML methods to any aspect of motorsport or high-performance vehicle operation; 2) were published in peer-reviewed journals, conference proceedings, or as verifiable preprints and theses; or 3) were relevant cross-domain works from autonomous driving research with plausible conceptual relevance to motorsport contexts.

Sources were excluded if they: 1) focused exclusively on conventional rule-based or purely physics-based approaches without any data-driven component; 2) addressed motorsport only in a marginal or illustrative capacity; or 3) were not available in English.

The primary temporal focus was literature published from 2020 onwards, reflecting the period during which deep learning and large-scale data-driven approaches became systematically adopted in both academic research and applied motorsport engineering. However, selected earlier works were included where they provided essential historical context or represented foundational contributions to the field.

C. Information Sources

Literature was retrieved from three primary academic databases: Scopus, IEEE Xplore, and Google Scholar. The searches were conducted on February 7th 2026 with a further refining search on May 23rd 2026. Reference lists of included articles were also hand-searched to identify additional relevant sources.

D. Search Strategy

Searches were conducted using combinations of the following keywords: *motorsport*, *Formula 1*, *artificial intelligence*, *Machine Learning*, *deep learning*, *reinforcement learning*, *telemetry*, *race strategy*, *tyre degradation*, *autonomous racing*, *driver coaching*, and *predictive maintenance*. Boolean operators (`AND`, `OR`) were applied to combine domain-specific and methodological terms, for example: *"Machine Learning AND motorsport"* or *"reinforcement learning AND race strategy"*. The full search string for Scopus was: `TITLE-ABS-KEY((``artificial intelligence'' OR ``machine learning'' OR ``deep learning'' OR ``reinforcement learning'') AND (``motorsport'' OR ``Formula 1'' OR ``race strategy'' OR ``autonomous racing''))`. Table I presents the search strategy per database.

E. Selection of Sources of Evidence

All records retrieved from the database searches were first screened by title and abstract for relevance to AI/ML applications in motorsport or closely related high-performance vehicle domains. Full texts of potentially relevant articles were then assessed against the eligibility criteria. To enhance consistency, the eligibility criteria were pilot-tested on a subset of 15 randomly selected records prior to full screening, and the criteria were iteratively refined based on this pilot phase. In cases of ambiguity regarding inclusion, articles were retained for full-text review to minimize the risk of excluding relevant work. Additionally, a random sample of 10 previously screened records was re-screened at the end of the process to verify consistency of the applied criteria.

TABLE I. SEARCH STRATEGY PER DATABASE

Database	Records	Date	Search query / strategy
Scopus	51	7 Feb 2026	`TITLE-ABS-KEY(("artificial intelligence" OR "machine learning" OR "deep learning" OR "reinforcement learning") AND ("motorsport" OR "Formula 1" OR "race strategy" OR "autonomous racing"))`
IEEE Xplore	38	7 Feb 2026	`("artificial intelligence" OR "machine learning" OR "deep learning" OR "reinforcement learning") AND ("motorsport" OR "Formula 1" OR "race strategy" OR "autonomous racing")` (Command Search, all metadata)
Google Scholar*	55	7 Feb 2026	Keyword combinations of `machine learning`, `deep learning` and `reinforcement learning` with `motorsport`, `Formula 1`, `race strategy` and `autonomous racing`; first 100 results per query screened; date range 2003–2026.

Google Scholar does not support field-restricted (title/abstract/keyword) searching or fully nested Boolean queries; simplified keyword combinations were, therefore, used and results screened by relevance ranking.

F. Data Charting Process

A data charting form was developed to extract relevant information from each included source. The form was iteratively refined as the reviewer became increasingly familiar with the literature. Data were charted by the primary reviewer and verified through re-reading of the source material. The charting categories included: author(s), year of publication, source type, AI/ML method(s) employed, motorsport application domain, racing context (e.g., Formula 1, Formula Student, autonomous racing), data source used (e.g., real telemetry, simulator, synthetic), and key findings. Additionally, research gaps were identified through a thematic frequency analysis of the charted data. After categorizing all included sources into the six predefined application domains, areas with notably fewer studies relative to other domains were flagged as underexplored. This quantitative threshold-based approach was complemented by a qualitative assessment of the depth of existing research within each domain, considering factors such as methodological diversity, data source variety, and the presence or absence of real-world validation.

G. Data Items

The following data items were extracted from each included source: (1) bibliographic information (authors, year, publication venue); (2) study type (journal article, conference paper, thesis, preprint); (3) AI/ML technique(s) used (e.g., deep learning, reinforcement learning, supervised learning, ensemble methods); (4) primary application domain (vehicle performance, race strategy, telemetry analysis, driver coaching, predictive maintenance, or autonomous racing); (5) motorsport context (Formula 1, Formula Student, MotoGP, autonomous racing, general motorsport); (6) data source (real-world telemetry, simulator data, synthetic/generated data, public API); (7) research approach (simulation-based, experimental, conceptual/survey, or hybrid); (8) technical maturity level, classified using a simplified scale: conceptual or theoretical, simulation-validated, experimentally tested with real data, or deployed in competition; and (9) key findings and contributions.

III. RESULTS

A. Selection of Sources of Evidence

The database searches yielded a total of 144 records (Scopus: 51, IEEE Xplore: 38, Google Scholar: 55). Eight additional sources were identified through reference-list manual search and supplementary targeted searches. After removing 26 duplicates, 126 records were screened by title and abstract, of which 49 were excluded for not meeting the eligibility criteria (primarily papers addressing general AI/ML, sports medicine, or other non-motorsport domains). The remaining 77 articles were assessed in full text, leading to the exclusion of 27 sources (12 focused exclusively on physics-based methods without a data-driven component, 10 addressed motorsport only marginally, 3 were not available in English, and 2 were duplicates of included works by the same authors). In total, 50 sources were included in this scoping review. The selection process is illustrated in the PRISMA flow diagram (Fig. 1).

B. Characteristics of Sources of Evidence

The 50 included sources spanned the period from 2003 to 2026, with the majority (n=38) published from 2020 onwards. Source types included journal articles (n=30), conference papers (n=11), theses and dissertations (n=6) and preprints (n=3). The geographic distribution of first authors was varied, with contributions from Europe, North America, Asia, and the Middle East. The motorsport contexts addressed included Formula 1, Formula Student, MotoGP, Endurance Racing, autonomous racing (e.g., Indy Autonomous Challenge, Roborace), and general motorsport engineering.

C. Data Charting Results

Table II and Table III presents the data extracted from each included source. Papers were categorized into six thematic application domains: Vehicle Performance Optimization (VP), Race Strategy and Real-Time Decisions (RS), Telemetry and Race Data Analysis (TA), Driver Coaching and Simulation (DC), Predictive Maintenance and Reliability (PM), and Autonomous Racing (AR).

D. Synthesis of Results

1) Distribution across application domains: The distribution of the 50 reviewed sources across the six thematic categories is presented in Fig. 2. The six application domains were defined a priori based on a preliminary scan of the literature and reflect the principal areas in which AI methods are applied in motorsport: Vehicle Performance Optimization (VP), Race Strategy and Real-Time Decisions (RS), Telemetry and Race Data Analysis (TA), Driver Coaching and Simulation (DC), Predictive Maintenance and Reliability (PM), and Autonomous Racing (AR). Papers with cross-cutting contributions were assigned to the single category most closely matching their

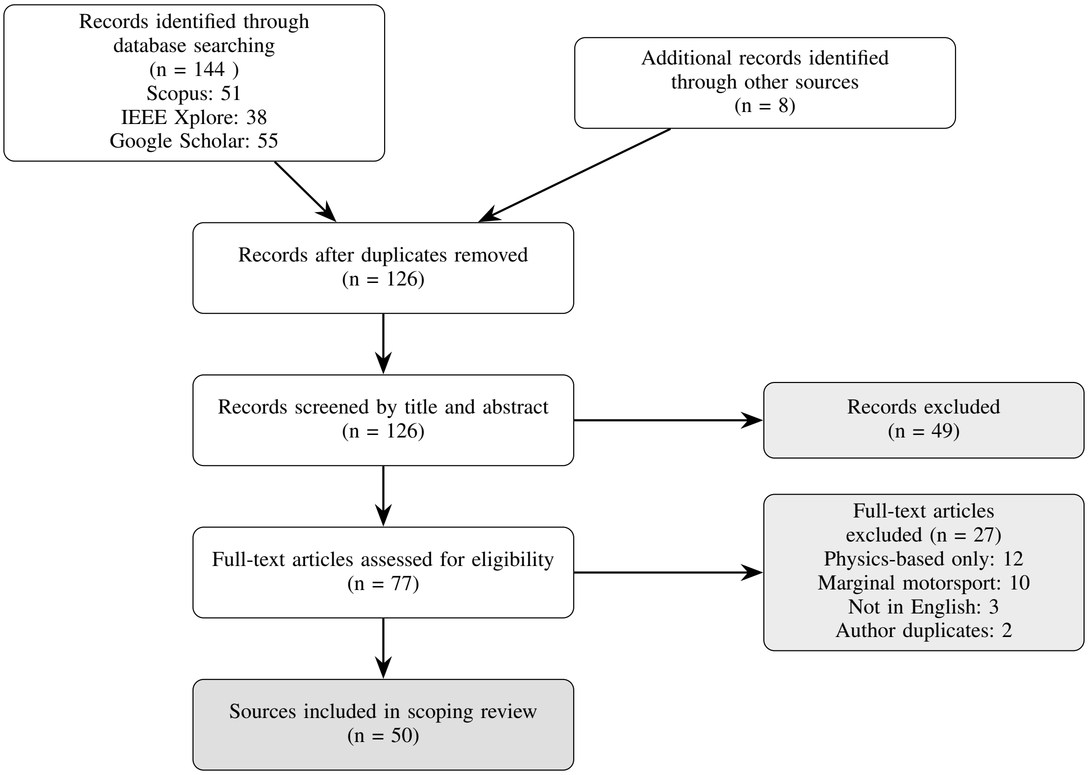

Fig. 1. PRISMA flow diagram illustrating the source selection process.

primary research focus, based on the declared objectives and the principal contribution of each study. In cases, where a paper contributed to multiple domains (e.g., a study combining vehicle dynamics modeling with race strategy), the dominant methodological contribution was used as the classification criterion. As shown in Fig. 2, Race Strategy dominates the current research landscape (n=14), followed by Vehicle Performance Optimization and Autonomous Racing (n=12 each), while Predictive Maintenance remains notably underrepresented (n=2), indicating a significant gap in the literature.

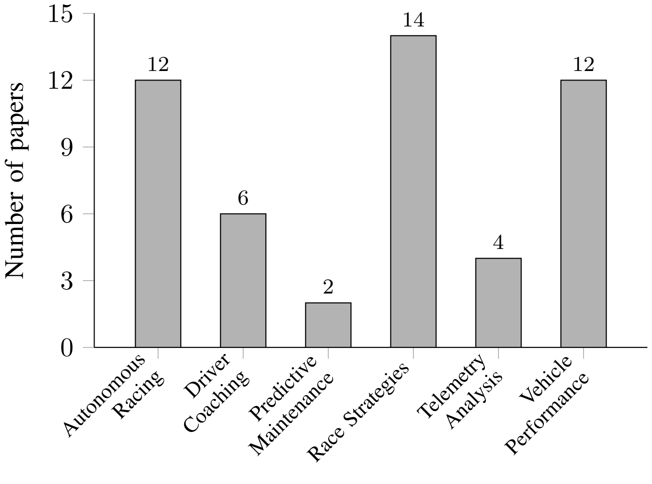

Fig. 2. Distribution of reviewed papers across application categories.

2) Research approach and technical maturity: To assess the current state of AI development in motorsport beyond thematic coverage, each included source was classified by its research approach (simulation-based, experimental, conceptual/survey, or hybrid) and by its technical maturity level, using a simplified four-level scale: conceptual or theoretical, simulation-validated, experimentally tested with real-world data, or deployed in competition. The cross-tabulation of these two dimensions is presented in Table IV.

The analysis reveals that the majority of included studies remain at the simulation-validated stage (n=23), relying on simulated or synthetic data to train and evaluate AI models. Only 14 studies have been experimentally validated using real-world data, and merely 5 have demonstrated deployment in actual competition or real-time racing environments — notably Kabzan et al. [37] (learning-based MPC for autonomous racing), Betz et al. [46] (full-stack autonomous racing at the Indy Autonomous Challenge), and Wurman et al. [31] (RL agent outperforming human drivers in Gran Turismo Sport). Eight sources are conceptual or survey papers that synthesize existing knowledge without introducing new experimental results.

This distribution indicates that while AI research in motorsport is growing rapidly, the field remains largely in the simulation and proof-of-concept phase. The gap between simulation-validated methods and real-world deployment is substantial, reflecting both the technical challenges of transferring AI models to the extreme conditions of racing vehicles and the data-access constraints imposed by the secretive nature of the sport. Future work should prioritize bridging this simulation-to-reality gap, particularly through sim-to-real transfer techniques and the

TABLE II. DATA EXTRACTION TABLE OF INCLUDED SOURCES (PRISMA-SCR CHARTING)

Author(s)	**Year**	**Source Type**	**AI/ML Method(s)**	**Cat.**	**Motorsport Context**	**Data Source**	**Key Findings**
Remonda et al.[1]	2021	Preprint	Deep RL (DDPG)	AR	Autonomous racing	Simulator	DDPG agent trained on telemetry data able to autonomously drive race cars
Hojaji et al.[2]	2024	Journal	ML (ensemble, feature selection)	DC	Sim racing	Simulator (ACC)	97.19% prediction accuracy for lap performance; lateral accel., steering angle most significant
Betz et al.[3]	2022	Journal	Survey (RL, MPC, CV)	AR	Autonomous racing	Multiple	Comprehensive survey of autonomous vehicle racing; perception, planning, control
Ishii et al.[10]	2010	Journal	Electronic control	VP	Formula 1	Real telemetry	Early electronic control systems for F1; foundational data acquisition
Besselink et al.[11]	2008	Conference	Data-driven vehicle dynamics	VP	General	Simulation	First integration of data-driven methods for yaw dynamics optimization
Richardson[12]	2017	Thesis	Statistical modeling	VP	General motorsport	Simulation	Tyre performance evolution modeling in real-time simulation environment
Piccinotti[13]	2019	Thesis	Open-loop optimization	RS	Formula 1	Simulation	Open-loop planning approach for F1 race strategy identification
Vesel[14]	2015	Journal	Algorithmic optimization	VP	General motorsport	Simulation	Automated racing line optimization for multiple vehicle types and circuits
Stoll et al.[15]	2013	Conference	Computer Vision	TA	General motorsport	Sparse data	Racecar tracking and visualization using sparse data techniques
Cressell & Tornberg[16]	2018	Thesis	Object recognition, SLAM	AR	Formula Student	Real-world	Object recognition and localization for autonomous racecar
Choo[17]	2015	Thesis	Predictive analytics	RS	Professional motorsport	Race data	Real-time decision-making analytics for professional race strategy
Diasinos et al.[18]	2017	Journal	Numerical/CFD + data	VP	Formula-type	Simulation	Aerodynamic analysis of ride height effects on wing-wheel interactions
Zhang & Zerihan[19]	2003	Journal	Experimental + numerical	VP	General racing	Wind tunnel	Aerodynamics of double-element wing in ground effect
Akin[20]	2024	Thesis	Data-driven optimization	VP	Formula Student	Real + simulator	Data-driven vehicle performance optimization for Formula Student
Sasikumar et al.[21]	2025	Journal	Deep learning (Bi-LSTM, TCN-GRU, CNN)	RS	Formula 1	Public API (FastF1)	Bi-LSTM best for pitstop prediction (F1=0.81); uses SMOTE for class balancing
Rao[22]	2025	Thesis	Ensemble learning	RS	Formula 1	Race data	Predictive model for pitstop strategy using ensemble methods
Rondelli[23]	2022	Journal	Neural networks	RS	Formula 1	Race data	Neural networks to predict tyre strategy in F1
Shakila & Baalaji[24]	2025	Conference	Big data analytics, predictive models	RS	Formula 1	Race data	Survey on optimizing tyre and brake performance using big data analytics
Avignone et al.[25]	2025	Journal	Data mining, visualization	TA	Racing (general)	Telemetry	Mine4Race toolset for telemetry analysis and visualization
Basile[26]	2024	Preprint	Anomaly detection	TA	MotoGP	Telemetry	Anomaly detection techniques applied to MotoGP telemetry data
Theissler et al.[27]	2021	Journal	ML (multiple methods)	PM	Automotive / motorsport	Sensor data	Predictive maintenance via ML; use cases and challenges in automotive
Arena et al.[6]	2022	Journal	Literature review (ML)	PM	Automotive / motorsport	Multiple	Comprehensive review of predictive maintenance in automotive sector
Kuutti et al.[4]	2019	Journal	DL survey (DRL, CNN, RNN)	AR	Autonomous vehicles	Multiple	Survey of DL for autonomous vehicle control; layered architecture
Di & Shi[28]	2021	Journal	RL, physics-AI hybrid	AR	Autonomous vehicles	Multiple	Mixed-autonomy control; from physics-based to AI-guided policy learning
Elallid et al.[5]	2022	Journal	DL, RL survey	AR	Autonomous driving	Multiple	Comprehensive survey of DL and RL in autonomous driving
Pérez-Gil et al.[29]	2022	Journal	DRL (DQN, DDPG)	DC	Autonomous (CARLA)	Simulator	DRL-based vehicle control comparable to classical LQR controllers
Reda et al.[30]	2023	Journal	Hybrid ML (SL + RL)	DC	Autonomous driving	Simulator	Hybrid approach balancing accuracy, finesse, and response time

Categories: VP = Vehicle Performance Optimization; RS = Race Strategy and Real-Time Decisions; TA = Telemetry and Race Data Analysis; DC = Driver Coaching and Simulation; PM = Predictive Maintenance and Reliability; AR = Autonomous Racing.

development of standardized benchmarks.

3) Brief overview of AI usage in motorsport: Although data collection in Formula 1 has been implemented starting with the mid-1980s when teams started using digital systems for data acquisition, analysis was still being done through traditional statistical methods or rule-based systems. Telemetry was collected using burst transmissions from the car during races [10]. During the 1990s, usage of digital technology picked up considerably as modern sensors became prevalent with the advent of active-ride cars [54]. Public research during this period was already treating the potential benefits of algorithmic optimization of vehicle performance.

The early 2000s marked the switch from purely physics-based analysis to hybrid models (physical–data driven) as a response to the greater complexity of racing vehicles. Even though modern Machine Learning was not widely used, the emergence of multivariate regression, non-linear optimisation and solid statistical models was evident. Besselink [11] integrated the first data-driven methodologies, allowing teams to adjust simulation strategies based on historical data. The

TABLE III. DATA EXTRACTION TABLE OF INCLUDED SOURCES — CONTINUED

Author(s)	**Year**	**Source Type**	**AI/ML Method(s)**	**Cat.**	**Motorsport Context**	**Data Source**	**Key Findings**
Wurman et al.[31]	2022	Journal	Deep RL (SAC)	AR	Gran Turismo (sim)	Simulator	RL agent outperformed champion human drivers in GT Sport
Fuchs et al.[32]	2020	Journal	Deep RL	AR	Gran Turismo (sim)	Simulator	Super-human performance in GT Sport via deep RL
Liu & Fotouhi[33]	2020	Journal	ANN, MCTS	RS	Formula E	Simulation	ANN + Monte Carlo tree search for Formula-E race strategy
Garlick & Bradley[34]	2021	Journal	ML (trajectory opt.)	VP	General motorsport	Simulation	Real-time optimal trajectory planning and lap time simulation
Boettinger & Klotz[35]	2023	Preprint	RL, simulation	RS	Nürburgring	Simulator	Comprehensive race simulation for AI strategy decisions
Hojaji et al.[36]	2022	Conference	ML (classification)	DC	Sim racing	Simulator	ML modeling of driver performance in simulated racing
Kabzan et al.[37]	2019	Journal	Learning-based MPC	AR	Autonomous racing	Real-world	Learning-based MPC for autonomous racing
Wurman et al.[38]	2022	Journal	RL survey	AR	Autonomous racing	Multiple	Challenges and opportunities of RL in autonomous racing
Heilmeier et al.[39]	2020	Journal	ANN (strategy)	RS	Circuit motorsport	Race data	Virtual Strategy Engineer: ANN for race strategy decisions
Boiarov et al.[40]	2023	Conference	Computer Vision, ML	TA	General racing	Race photos	RaceLens: ML-based racing photo analysis application
Veerasagar et al.[41]	2025	Journal	RL	RS	Formula 1	Race data	F1 strategy predictor using reinforcement learning
Paparusso et al.[42]	2022	Journal	Stochastic opt.	RS	Hybrid racing	Simulation	Competitors-aware stochastic lap strategy optimization
Remonda et al.[43]	2021	Journal	DRL, behavioral	DC	Professional racing	Simulator	Comparing human vs. autonomous driving in racing simulator
Kavitha et al.[44]	2025	Conference	Survey (AI in F1)	RS	Formula 1	Multiple	Overview of AI applications in Formula One racing
Raji et al.[45]	2022	Conference	Motion planning, MPC	AR	Autonomous racing	Real-world	Multi-vehicle autonomous racing at high speeds
Betz et al.[46]	2022	Journal	Full-stack autonomous	AR	Indy Auton. Challenge	Real-world	Complete autonomous racing software for IAC
Hojaji et al.[47]	2023	Conference	AI, telemetry	DC	Sim racing	Simulator	AI analysis of driving behaviour using telemetry data
Jiménez Elbal et al.[48]	2024	Journal	Optimization (ML)	VP	Electric racing	Simulation	Simultaneous vehicle design and control optimization
Bonini et al.[49]	2023	Conference	ANN, Kalman filter	VP	MotoGP	Real-world	ANN and Kalman filter estimate carbon-brake friction coefficient (μ) for accurate in-race braking-torque computation; validated with real track data
Bonini et al.[50]	2026	Journal	NARX, ANN	VP	MotoGP	Real-world	NARX and ANN estimate the disc/pad friction coefficient (μ) from telemetry; combined with a physical model to compute front-wheel braking torque; validated on multi-track real data
Jain & Morari[51]	2020	Conference	Bayesian optimization	VP	General motorsport	Simulation	Computes the racing line (path and optimal speed profile) via Bayesian optimization; fully data-driven and more efficient than dynamic programming and random search
de Vries et al.[52]	2026	Conference	RL, game-theoretic optimal control	RS	Electric endurance racing	Simulation	Bi-level RL framework for full-race energy allocation and pit/charging strategy; competitor-aware strategies differ fundamentally from single-agent minimum-time approaches
van Kampen et al.[53]	2024	Journal	Bi-level convex optimization (MISOCP)	RS	Electric endurance racing	Simulation	Jointly optimizes stint length, charge time, and pitstop count to maximize distance in a fixed-time endurance race under powertrain thermal limits

adoption of data-driven analysis was accelerated by the FIA's decision to limit track testing in efforts to decrease costs, leading to increased investment in advanced simulations, algorithm optimization and the setup of infrastructures prepared to handle large volumes of data.

After 2010, Machine Learning became widely adopted with its impact on motorsport noticeable in all areas, from car development to driver coaching or marketing. This was possible mainly due to three factors: the increase in computational power leveraging GPUs and cloud infrastructure, the greater volume of telemetry data and the appearance of advanced Machine Learning and Deep Learning models. This marked a shift towards more advanced simulations ranging from tyre degradation over time [12] to optimizing race strategy [13] or analyzing driver behavior [14]. In parallel, the first autonomous racing projects appeared, such as Carolo-Cup and Formula Student Driverless, which introduced new techniques based on Computer Vision [15], high-speed Simultaneous Localization and Mapping (SLAM) [16] and reinforcement learning for car control [17].

Following 2020, AI has started being used systematically in data analysis and performance optimization, with further

TABLE IV. Distribution of Included Sources by Research Approach and Technical Maturity Level.

	Concept.	**Simul.**	**Exper.**	**Deployed**	**Total**
Simulation-based	–	19	–	1	20
Experimental	–	–	10	3	13
Conceptual / Survey	8	–	–	–	8
Hybrid	–	4	4	1	9
Total	8	23	14	5	**50**

Technical maturity levels: Conceptual = theoretical proposal or literature review; Simulation-validated = method tested using simulated or synthetic data; Experimentally tested = validated using real-world data; Deployed = demonstrated in actual competition or real-time racing environment.

development in performance prediction[2], autonomous racing and determining optimal racing lines [1]. At this time, autonomous racing has become a lot more prevalent, with events like Indy Autonomous Challenge proving a very promising area of research at the intersection of Artificial Intelligence, Computer Vision and Reinforcement Learning.

4) Vehicle performance optimization: One of the most important applications of AI in motorsport, vehicle performance optimization, relies on the analysis and modelling of complex relations between car setup, environmental conditions and the results obtained on track. Modern race cars operate in a highly non-linear regime, where small changes in parameters such as wing angles, ride height, suspension stiffness or tyre pressure can have a disproportionate effect on lap time, stability and tyre wear. In this context, traditional physics-based simulation tools, while still essential, are increasingly complemented by data-driven models that can learn these complex relationships directly from telemetry and simulation data.

Some of the most common applications of Machine Learning models in this area include estimating vehicle behaviour as a function of aerodynamic configuration and ride height [18], [19], modeling the tyre-track surface interaction and tyre degradation prediction [12] over a stint, or forecasting [20] the reliability and remaining useful life of critical components. Data-backed decisions have been also applied to trajectory planning and individual systems of the vehicle. Jain and Morari [51] compute the racing line, the optimal trajectory and its speed profile along a racing track, using Bayesian optimisation, demonstrating that a fully data-driven design may converge more efficiently than classic programming or random search. At the component level, Bonini et al. [49], [50] utilize deep learning techniques (ANN, Kalman filters and NARX) to estimate the friction coefficient of carbon braking systems based on telemetry data and combine the results with a physics-based model to obtain the braking torque on the front wheel, with results being validated with data recorded in MotoGP races. These models are typically trained using a combination of historical race data, simulator outputs and controlled test runs, allowing them to capture both the physical trends and the empirical behaviour observed in real racing conditions. A key advantage of AI-based approaches is their ability to evaluate a very large number of possible vehicle configurations in a short amount of time. Instead of running a limited set of expensive physical tests or computationally intensive CFD and vehicle dynamics simulations, engineers can use trained models to rapidly scan through thousands of setup combinations and identify those that are most likely to deliver optimal performance under specific track and weather conditions.

Furthermore, these models allow for continuous and incremental updates as new data becomes available, allowing them to adapt to changes in track grip, weather, tyre compounds or even driver style. As a result, vehicle performance optimization becomes an ongoing, data-driven process rather than a one-off calibration task, supporting more informed engineering decisions throughout a race weekend.

5) Race strategies and real-time decisions: Another central pillar is the utilisation of AI as active support for decision making during races, such as choosing the optimum strategy for pitstops [21], [22], the selection of race tyre types [23], [24] or adapting the car's race pace to current environmental and track conditions [17]. Strategic decision-making research extends beyond Grand Prix competitions to endurance racing, where success is typically conditioned by energy and component temperature management over multiple hours of active racing, rather than optimization of a single stint. In the case of fully electric endurance racing, van Kampen et al. [53] simultaneously optimize stint length, battery-charging time and pitstop count to maximize the traveled distance in fixed-duration races while de Vries et al. [52] analyze the same problem through a two-level reinforcement-learning methods which yields competitor-aware energy-allocation and charging strategies that differ fundamentally from single-agent, minimum-time solutions. In a sport, where hundredths of a second matter in the final classification, the ability to make real-time strategic calls can have just as large an impact as pure mechanical car performance.

AI models that support these decisions need to address problems characterized by a high degree of uncertainty. Certain events such as the appearance of the Safety Car, sudden changes in meteorological conditions or reacting to the unpredictable behaviour of other competitors could have a major impact on the race dynamic in a very short interval of time. Additionally, these decisions are often constrained by strict temporal requirements: deciding the optimal time for a pitstop or changing the tyre strategy is a fluid process requiring quick reactions while cars are already on the race track. Another constraint, besides uncertainty and time, is the complex interaction with the other competitors, as a strategy's efficacy is dictated not just by the performance of the team but the competitor's positions, strategies and behaviour. For this reason, problems are often formulated as sequential optimisation or stochastic methods in which the race's future evolution can be probabilistically modeled, where methods like reinforcement learning or predictive models play a pivotal role.

6) Telemetry and race data analysis: Modern motorsport generates vast volumes of telemetry data, including speed, acceleration, temperatures, pressures, vibration, yaw and many other variables tracked at high frequencies. AI can be leveraged to detect hidden patterns in telemetry data [25], identifying correlations between driving style and performance or detecting anomalies [26] which can hint at incipient failures, enhancing the capability to improve performance while increasing both safety and reliability.

7) Driver coaching and simulations: High-performance simulation systems are progressively combined with artificial intelligence models to form adaptive training environments capable of dynamically responding to driver behavior. These AI components analyze detailed telemetry and control inputs to detect patterns associated with suboptimal driving techniques, such as inefficient braking, inconsistent throttle application, or poor racing line selection. The simulation can then automatically modify training scenarios to focus on these specific deficiencies, while delivering precise, quantitative feedback that supports continuous performance improvement and skill development [29], [25].

8) Predictive maintenance and reliability: Through the analysis of how various mechanical and thermal parameters of the car evolve over time, AI models can anticipate the probability of a fault before it effectively manifests itself, enabling an optimal strategy for component replacement planning, maximizing their life-span utilization within safe boundaries while also minimizing the risk of race abandonment due to mechanical failures [27], [6].

9) Cross-domain perspectives autonomous driving: While direct motorsport research is relatively sparse, a large volume of academic work, especially in the area of autonomous driving, focuses on the interaction between Artificial Intelligence and vehicle dynamics. Many studies showcase that modern AI-based control systems are no longer limited to high-level planning but rather act as decision makers having control of the vehicle's acceleration, braking and steering inputs [4], [28], [5], [55].

These papers describe a clear shift from purely physical controls such as Proportional-Integral-Derivative (PID), Linear Quadratic Regulator (LQR) or Model Predictive Control (MPC) towards a data-based approach, in which modern AI controllers learn driving models through supervised or reinforcement learning [4], [28], [56]. This direction may prove relevant for motorsport, where vehicles operate close to the limit of grip and stability — though whether controllers trained for road driving transfer to racing conditions is an open question rather than an established result. While in autonomous driving, controllers are calibrated for comfort, safety and reliability, in racing environments the same controllers are optimized to maximize grip and performance and minimize lap times, still considering reliability. Both approaches solve a similar problem: mapping the current state of big data to continuous control actions which respect the highly non-linear nature of vehicle dynamics.

Another area of interest is the integration of deep learning and reinforcement learning techniques into the main control loop. Pérez-Gil et al. [29] show that DQN and DDPG reinforcement algorithms may be used to control autonomous vehicles, providing steering and acceleration inputs with a precision comparable with that of classic LQR controllers. Similarly, hybrid approaches like Reda et al. [30] combine supervised learning with reinforcement learning to extract the best compromise between accuracy, input finesse and response time, essential components in high-performance driving.

Beyond pure tracking performance, more recent work has emphasized modeling driving style and explainability. Gao et al. [57] introduce a human-like neural network for longitudinal control that explicitly mimics driver behavior, and Li et al. [58] integrate explainability into a deep reinforcement learning controller using SHAP analysis. While comfort is less relevant in motorsport, these approaches could inform the understanding and shaping of driving style — a potential connection that would require dedicated study within a racing context to confirm, an aspect that is increasingly important when AI is used to support or emulate human drivers.

Another important link between autonomous driving and motorsport lies in mixed-autonomy and interaction modeling. Di and Shi [28] and Babaei et al. [55] highlight that modern AI-based vehicle controllers are often trained not only to follow a path, but to interact strategically with other road users. This is conceptually analogous to racing situations, where a driver's control inputs are strongly influenced by the behavior of competitors, slipstreaming, defensive driving, and overtaking maneuvers.

From a system-level perspective, surveys such as Kuutti et al.[4], Elallid et al.[5], and Babaei et al.[55] emphasize that AI-based vehicle control is typically embedded in a layered architecture that includes perception, prediction, planning, and control. Motorsport applications follow a similar structure, even if perception is less emphasized. The control layer, however, faces even stricter requirements, as racing vehicles operate at higher speeds, higher lateral accelerations, and much smaller margins for error.

Taken together, these observations are best read as hypotheses worth investigating rather than as evidence of established transfer: the extent to which the parallels translate into practical, transferable applicability — given the fundamentally different objective functions and operating constraints of each domain — is examined critically in Section IV-A3.

10)Research coverage and identified gaps: Following the thematic frequency analysis described in Section II-F, the distribution of identified literature across core application areas reveals a highly uneven research landscape. Race strategy, autonomous racing, and vehicle performance optimization are relatively well-covered, while predictive maintenance, telemetry analysis, and computer vision applications remain largely unexplored.

Because motorsport in general and Formula 1 in particular is extremely secretive — as even small gains and insight into a competitor's research or data can lead to a major competitive advantage — there is a fairly small volume of publicly available research. The fact that teams closely guard their data means that the areas of research are limited both in terms of scope and precision. For instance, Formula One teams have access to telemetry with a frequency of 1 kHz, while public telemetry is sampled at around 3 Hz frequency. The combination of proprietary sensor data and closely guarded internal research leads to this area being a fairly under-researched domain. Predictive maintenance and reliability is an especially under-researched area, with most industry papers focusing on sensor data. Computer Vision is another technique that is not well researched or applied in motorsport, leaving a sizeable void in potential advancements.

IV. DISCUSSION

A. Summary of Evidence

This scoping review identified 50 sources addressing AI and ML applications in motorsport, spanning the period 2003–2026. While this body of literature confirms growing academic interest in the field, a critical examination reveals several fundamental weaknesses that limit the strength of the conclusions that can be drawn.

1) Methodological fragility of the evidence base: The most significant concern is the predominance of simulation-based research. As shown in Table IV, 20 of the 50 included sources rely exclusively on simulated or synthetic data, while only 5 have demonstrated deployment in actual competition environments. This raises a critical question: To what extent do simulation-validated AI models generalize to the extreme and unpredictable conditions of real racing? The sim-to-real transfer problem is well-documented in robotics and autonomous driving, yet very few motorsport studies explicitly address this gap, mainly due to the lack of access to data. Models trained on idealized simulator physics may fail to capture the non-linear tire behavior, aerodynamic turbulence from competitor vehicles, or track surface variability encountered in real races. The fact that only five studies — notably Kabzan et al. [37], Betz et al. [46], and Wurman et al. [31] — have demonstrated real-world or competition-level deployment underscores how far the field remains from practical maturity.

Furthermore, 8 of the 50 sources are conceptual papers or surveys that do not introduce new empirical evidence. While these contribute to structuring the field, their inclusion means that over 60% of the evidence base either lacks real-world validation or presents no original experimental results. This is a structural limitation of the current literature, not merely a gap to be filled.

2) Uneven thematic coverage and its implications: The distribution of research effort across application domains is very uneven: race strategy leads (n=14) with autonomous racing and vehicle performance fairly close behind (n=12 each), while predictive maintenance (n=2) and telemetry-based anomaly detection remain almost entirely unexplored. This imbalance does not necessarily reflect the relative importance of these domains in actual motorsport practice. Rather, it likely reflects data accessibility: race strategy benefits from publicly available telemetry APIs (e.g., FastF1) and well-defined optimization formulations, while predictive maintenance requires proprietary sensor data from components operating under extreme thermal and mechanical loads — data that teams have no incentive to share.

This creates a problematic feedback loop: the domains most critical to competitive performance are precisely those where public research is thinnest, because the data needed to study them is the most commercially sensitive. The current literature therefore provides a skewed picture of AI's role in motorsport, overrepresenting areas where data is accessible and underrepresenting those where AI arguably has the greatest untapped potential.

3) Questionable transferability from autonomous driving: A substantial portion of the included sources (10 of 50) originate from autonomous driving research rather than motorsport proper. While the review's eligibility criteria explicitly permit cross-domain work with clear transferability, the actual degree of this transferability warrants critical scrutiny. Autonomous driving controllers are optimized for safety, comfort, and regulatory compliance, whereas motorsport controllers must maximize performance at the physical limits of grip and stability. The objective functions, constraint sets, and operating envelopes are fundamentally different. For example, a reinforcement learning agent trained to maintain safe following distances on public roads [28] faces a qualitatively different problem from one that must optimize overtaking maneuvers at 300 km/h with millimeter-level precision.

Moreover, the layered perception–planning–control architecture common in autonomous driving [4], [5] does not map cleanly onto motorsport, where perception requirements are narrower (no pedestrian detection, fewer traffic scenarios) but control requirements are far more demanding (higher speeds, higher lateral accelerations, tighter margins). The inclusion of these cross-domain sources enriches the review's breadth but should not be mistaken for direct evidence of AI maturity within motorsport itself.

4) Evidence quality and publication bias: Of the 50 included sources, 30 are peer-reviewed journal articles and 11 are conference papers, representing the most robust evidence. However, 6 are theses or dissertations, and 3 are preprints without formal peer review. While the inclusion of grey literature is methodologically appropriate in a scoping review — ensuring comprehensive coverage of an emerging field — it introduces heterogeneity in scientific rigor. Critically, some of the more specific findings in underrepresented domains such as telemetry analysis and predictive maintenance rely disproportionately on this weaker evidence base.

There is also a likely publication bias at work: studies reporting positive results (successful AI models outperforming baselines) are far more likely to be published than those reporting negative results or failed implementations. The absence of failure reports in the literature should not be interpreted as evidence that AI methods reliably succeed in motorsport applications; rather, it reflects a systematic gap in reporting that obscures the true difficulty of deploying these methods in practice.

5) The temporal trajectory and its risks: The review identifies a clear temporal shift from physics-based approaches (pre-2010) through hybrid models (2010s) to deep learning and reinforcement learning (2020 onwards). While this mirrors broader trends in AI research, it also carries risks specific to motorsport. The increasing reliance on black-box deep learning models raises concerns about explainability and trust in high-stakes racing decisions. When an AI system recommends a pit-stop strategy or predicts tire failure, the engineering team needs to understand *why* — yet only two papers [58], [57] from the cross-domain autonomous driving literature explicitly address explainability. The rush toward more complex models without corresponding advances in interpretability may ultimately limit the adoption of AI in competitive motorsport, where engineers and race directors must be able to justify decisions under time pressure.

6) Deployment and systems constraints: A dimension almost entirely absent from the reviewed literature is the sys-

TABLE V. PROPOSED RESEARCH AGENDA FOR AI IN MOTORSPORT

Research direction	**Barrier**	**Proposed approach**	**Horizon / priority**
Open benchmarks and shared data standards	Telemetry and performance data are proprietary and closely guarded, with no common formats (Section IV-A2)	Public simulator datasets and a standardized open telemetry schema enabling reproducible, comparable studies	Near-term; high feasibility
Sim-to-real transfer	20 of 50 studies are validated only on simulated or synthetic data under idealized physics (Section IV-A1)	Domain randomization and transfer-learning pipelines; staged validation against real track telemetry	Near- to medium-term
Predictive maintenance for racing components	Component sensor data gathered under extreme thermal and mechanical loads is commercially sensitive (Section IV-A2)	Synthetic data and transfer learning from broader automotive predictive maintenance; physics-informed degradation models	Medium-term
Explainability and trust in decision support	Black-box deep models, while engineers must justify strategy calls under time pressure (Section IV-A5)	SHAP, attention, and interpretable-surrogate methods adapted to strategy and reliability models	Near-term
Transparent reporting of failures	Publication bias toward positive results; failed or abandoned deployments go unreported (Section IV-A4)	Negative-result and real deployment case studies; registered-report formats; shared failure taxonomies	Near-term; process change
Computer vision for race operations	Under-explored area with few annotated motorsport image and video datasets	Computer vision for pit-lane operations, driver assessment, and real-time monitoring, supported by annotated public benchmarks	Medium-term

tems engineering required to move AI from offline analysis onto a moving race car. Deployment imposes hard real-time constraints that simulation-validated studies rarely confront: strategic recommendations must be produced within the narrow windows that precede a pit-stop decision, while autonomous-racing perception and control must close their loops at high frequency even as the vehicle travels at racing speed. These computations run on constrained on-car hardware bounded by strict power, thermal, weight, and vibration budgets. For example. the full-stack Indy Autonomous Challenge systems of Betz et al. [3] and Raji et al. [45], execute on a single-GPU on-vehicle edge-AI computer mounted in a Dallara AV-21 operating at speeds approaching 270 km/h. Such budgets make model compression and quantization a practical precondition for deploying deep models at the edge, and they place a premium on deterministic, hard real-time execution and on functional-safety requirements (e.g., ISO 26262) that non-deterministic deep-learning components do not naturally satisfy. Tellingly, only the small set of competition-deployed autonomous-racing studies [37], [3], [45] engages with these concerns; the far larger body of strategy- and performance-oriented work is largely silent on them, leaving the practical question of real-time deployability underexamined.

B. Limitations

Several limitations of this review must be acknowledged. Although consistency measures were applied (pilot-testing on a subset and post-hoc re-screening), the absence of independent dual screening means that subjective judgments — particularly regarding the “clear transferability” criterion for cross-domain autonomous driving sources — may have introduced bias that cannot be fully quantified.

The restriction to English-language publications likely excluded relevant work, particularly from research groups in Japan, China, and continental Europe where significant motorsport engineering activity exists. More fundamentally, the secretive nature of motorsport means that the publicly accessible literature almost certainly underrepresents the actual state of AI adoption. Formula 1 teams, for instance, employ dedicated AI and data science divisions whose work never enters the public domain. This review can therefore only map what is publicly documented, which may bear limited resemblance to the true state of the art within the industry.

The absence of formal critical appraisal — while consistent with scoping review methodology — means that simulation-based studies with idealized assumptions are given equal weight alongside experimentally validated work. Readers should, therefore, consult Table IV when evaluating the strength of evidence behind specific claims. Finally, the inclusion of Google Scholar as a database source, while increasing coverage, introduced grey literature whose quality could not be independently verified.

C. Conclusion

Although motorsport, and particularly Formula 1, is recognized as one of the most advanced and innovative domains of modern engineering, public research is limited due to the highly competitive and secretive character of the sport. Telemetry data, performance models and strategies are treated as highly confidential, limiting the quantity and depth of research papers. The lack of open data leads to a significant gap between the potential of AI usage in motorsport and the level at which it is documented in scientific literature. Many of the advanced AI use cases — real-time strategy optimization, tyre behaviour modeling, or the integration of decision support systems — although developed and used internally by teams, do not appear in academic publications, with existing literature often focusing on a partial image of the actual state of the technology based on limited case studies, simulations, or synthetic data.

Rather than pursuing only incremental improvements to AI techniques, future work should target the structural weaknesses identified in the Discussion. Table V translates these into a concrete research agenda: for each gap it states the underlying barrier, a proposed approach, and an indicative time horizon.

Across these directions, the common prerequisite is data access. Open benchmarks and shared telemetry standards are therefore the highest-priority and most feasible near-term step, since meaningful progress on sim-to-real validation, predictive maintenance, and explainability all depends on a richer, openly available evidence base. Establishing that shared foundation would be the single most effective way to convert motorsport AI from a fragmented set of case studies into a cumulative research field.

FUNDING

The publication of this research was supported by the University of Oradea.

REFERENCES

[1] A. Remonda, S. Krebs, E. E. Veas, G. Luzhnica, and R. Kern, "Formula RL: deep reinforcement learning for autonomous racing using telemetry data," *CoRR*, vol. abs/2104.11106, 2021. [Online]. Available: https://arxiv.org/abs/2104.11106

[2] F. Hojaji, A. J. Toth, J. M. Joyce, and M. J. Campbell, "Ai-enabled prediction of sim racing performance using telemetry data," *Computers in Human Behavior Reports*, vol. 14, p. 100414, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2451958824000472

[3] J. Betz, H. Zheng, A. Liniger, U. Rosolia, P. Karle, M. Behl, V. Krovi, and R. Mangharam, "Autonomous vehicles on the edge: A survey on autonomous vehicle racing," *IEEE Open Journal of Intelligent Transportation Systems*, vol. 3, p. 458–488, 2022. [Online]. Available: http://dx.doi.org/10.1109/ojits.2022.3181510

[4] S. Kuutti, R. Bowden, Y. Jin, P. Barber, and S. Fallah, "A survey of deep learning applications to autonomous vehicle control," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, pp. 712–733, 2019.

[5] B. B. Elallid, N. Benamar, A. S. Hafid, T. Rachidi, and N. Mrani, "A comprehensive survey on the application of deep and reinforcement learning approaches in autonomous driving," *Journal of King Saud University – Computer and Information Sciences*, vol. 34, pp. 7366–7390, 2022.

[6] F. Arena, M. Collotta, L. Luca, M. Ruggieri, and F. Termine, "Predictive maintenance in the automotive sector: A literature review," *Mathematical and Computational Applications*, vol. 27, no. 1, p. 2, 2022.

[7] H. Arksey and L. O'Malley, "Scoping studies: Towards a methodological framework," *International Journal of Social Research Methodology - INT J SOC RES METHODOL*, vol. 8, pp. 19–32, 02 2005.

[8] D. Levac, H. Colquhoun, and K. O'Brien, "Scoping studies: Advancing the methodology," *Implementation science : IS*, vol. 5, p. 69, 09 2010.

[9] A. C. Tricco, E. Lillie, W. Zarin, K. K. O'Brien, H. Colquhoun, D. Levac, D. Moher, M. D. Peters, T. Horsley, L. Weeks, S. Hempel, E. A. Akl, C. Chang, J. McGowan, L. Stewart, L. Hartling, A. Aldcroft, M. G. Wilson, C. Garritty, S. Lewin, C. M. Godfrey, M. T. Macdonald, E. V. Langlois, K. Soares-Weiser, J. Moriarty, T. Clifford, O. Tunçalp, and S. E. Straus, "PRISMA extension for scoping reviews (PRISMA-ScR): Checklist and explanation," *Annals of Internal Medicine*, vol. 169, no. 7, pp. 467–473, 2018.

[10] K. ISHII, T. NISHIDA, K. TOSHIMA, M. NEGORO, M. YOSHIDA, and Y. MARUYAMA, "Development of electronic control system for formula one," 2010.

[11] I. Besselink, T. Veldhuizen, and H. Nijmeijer, "Improving yaw dynamics by feedforward rear wheel steering," in *2008 IEEE Intelligent Vehicles Symposium*, 2008, pp. 246–250.

[12] H. Richardson, "Modelling the evolution of tyre performance in a motorsport application-analysis of effects on vehicle performance in a real-time simulation environment," 2017.

[13] D. Piccinotti, "Open loop planning for formula 1 race strategy identification," 2019.

[14] R. Vesel, "Racing line optimization @ race optimal," *SIGEVOlution*, vol. 7, no. 2–3, p. 12–20, Aug. 2015. [Online]. Available: https://doi.org/10.1145/2815474.2815476

[15] M. Stoll, R. Krüger, T. Ertl, and A. Bruhn, "Racecar tracking and its visualization using sparse data," in *Proc. Workshop on Sports Data Visualization*, 2013.

[16] J. Cressell and I. Tornberg, "A combination of object recognition and localisation for an autonomous racecar," Master's thesis, 2018.

[17] C. L. W. Choo, "Real-time decision making in motorsports: analytics for improving professional car race strategy," Ph.D. dissertation, Massachusetts Institute of Technology, 2015.

[18] S. Diasinos, T. Barber, and G. Doig, "Numerical analysis of the effect of the change in the ride height on the aerodynamic front wing–wheel interactions of a racing car," *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, vol. 231, no. 7, pp. 900–914, 2017.

[19] X. Zhang and J. Zerihan, "Aerodynamics of a double-element wing in ground effect," *AIAA journal*, vol. 41, no. 6, pp. 1007–1016, 2003.

[20] L. Akin, "Data-driven vehicle performance optimization for formula student racing," Ph.D. dissertation, Politecnico di Torino, 2024.

[21] A. Sasikumar, A. A. Leema, and P. Balakrishnan, "Data-driven pit stop decision support for formula 1 using deep learning models," *Frontiers in Artificial Intelligence*, vol. Volume 8 - 2025, 2025. [Online]. Available: https://www.frontiersin.org/journals/artificial-intelligence/articles/10.3389/frai.2025.1673148

[22] A. M. Rao, "Predictive model for pitstop strategy in formula 1 using ensemble learning," Ph.D. dissertation, Dublin, National College of Ireland, 2025.

[23] M. Rondelli, "The future of formula 1 racing: Neural networks to predict tyre strategy," 2022.

[24] T. Shakila and K. Baalaji, "Optimizing tyre and brake performance in formula 1 using big data analytics: A survey on predictive models and strategies," in *2025 International Conference on Emerging Trends in Industry 4.0 Technologies (ICETI4T)*. IEEE, 2025, pp. 1–6.

[25] A. Avignone, S. Chiusano, and L. Peroni, "Mine4race: A user-friendly toolset for enhancing racing telemetry analysis and visualization," *Results in Engineering*, p. 108865, 2025.

[26] S. BASILE, "Anomaly detection in motogp telemetry data," 2024.

[27] A. Theissler, J. Pérez-Velázquez, M. Kettelgerdes, and G. Elger, "Predictive maintenance enabled by machine learning: Use cases and challenges in the automotive industry," *Reliability Engineering & System Safety*, vol. 215, p. 107864, 2021.

[28] X. Di and R. Shi, "A survey on autonomous vehicle control in the era of mixed-autonomy: From physics-based to AI-guided driving policy learning," *Transportation Research Part C: Emerging Technologies*, vol. 125, p. 103008, 2021.

[29] Ó. Pérez-Gil, R. Barea, E. López-Guillén, L. M. Bergasa, C. Gómez-Huélamo, R. Gutiérrez, and A. Diaz-Diaz, "Deep reinforcement learning based control for autonomous vehicles in CARLA," *Multimedia Tools and Applications*, vol. 81, pp. 3553–3576, 2022.

[30] A. Reda, R. Benotsmane, A. Bouzid, and J. Vásárhelyi, "A hybrid machine learning-based control strategy for autonomous driving optimization," *Acta Polytechnica Hungarica*, 2023.

[31] P. R. Wurman, S. Barrett, K. Kawamoto *et al.*, "Outracing champion gran turismo drivers with deep reinforcement learning," *Nature*, vol. 602, pp. 223–228, 2022.

[32] F. Fuchs, Y. Song, E. Kaufmann, D. Scaramuzza, and P. Dürr, "Super-human performance in gran turismo sport using deep reinforcement learning," *IEEE Robotics and Automation Letters*, vol. 4, pp. 4257–4264, 2020.

[33] X. Liu and A. Fotouhi, "Formula-E race strategy development using artificial neural networks and Monte Carlo tree search," *Neural Computing and Applications*, vol. 32, pp. 15 191–15 207, 2020.

[34] S. Garlick and A. Bradley, "Real-time optimal trajectory planning for autonomous vehicles and lap time simulation using machine learning," *Vehicle System Dynamics*, vol. 60, no. 12, pp. 4269–4289, 2021.

[35] M. Boettinger and D. Klotz, "Mastering Nordschleife – a comprehensive race simulation for AI strategy decision-making in motorsports," *arXiv preprint arXiv:2306.16088*, 2023.

[36] F. Hojaji, A. J. Toth, and M. J. Campbell, "A machine learning approach for modeling and analyzing of driver performance in simulated racing," in *Artificial Intelligence and Cognitive Science (AICS 2022)*, ser. Communications in Computer and Information Science, vol. 1662. Springer, 2022.

[37] J. Kabzan, L. Hewing, A. Liniger, and M. N. Zeilinger, "Learning-based model predictive control for autonomous racing," *IEEE Robotics and Automation Letters*, vol. 4, pp. 3363–3370, 2019.

[38] P. R. Wurman *et al.*, "Challenges and opportunities of applying reinforcement learning to autonomous racing," *IEEE Intelligent Systems*, 2022.

[39] A. Heilmeier, A. Thomaser, M. Graf, and J. Betz, "Virtual strategy engineer: Using artificial neural networks for making race strategy decisions in circuit motorsport," *Applied Sciences*, vol. 10, no. 21, p. 7805, 2020.

[40] A. Boiarov *et al.*, "RaceLens: A machine intelligence-based application for racing photo analysis," in *IEEE 28th Pacific Rim International Symposium on Dependable Computing (PRDC)*, 2023.

[41] S. S. Veerasagar, R. Coelho, and L. K. Chandrashekar, "Optimum racing: A F1 strategy predictor using reinforcement learning," *International Journal for Research in Applied Science and Engineering Technology*, vol. 13, no. 4, 2025.

[42] L. Paparusso, M. Riani, F. Ruggeri, and F. Braghin, "Competitors-aware stochastic lap strategy optimisation for race hybrid vehicles," *IEEE Transactions on Vehicular Technology*, vol. 71, no. 9, 2022.

[43] A. Remonda, E. Veas, and G. Luzhnica, "Comparing driving behavior of humans and autonomous driving in a professional racing simulator," *PLoS ONE*, vol. 16, no. 2, p. e0245320, 2021.

[44] R. K. Kavitha *et al.*, "Formula one: Racing intelligence in the age of AI," in *2025 3rd International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA)*, 2025.

[45] A. Raji, A. Liniger, A. Giove, A. Toschi, N. Musiu, D. Morra, M. Verucchi, D. Caporale, and M. Bertogna, "Motion planning and control for multi vehicle autonomous racing at high speeds," in *IEEE 25th International Conference on Intelligent Transportation Systems (ITSC)*, 2022.

[46] J. Betz, T. Betz, F. Fent *et al.*, "TUM autonomous motorsport: An autonomous racing software for the Indy Autonomous Challenge," *Journal of Field Robotics*, 2022.

[47] F. Hojaji, A. J. Toth, J. M. Joyce, and M. J. Campbell, "An AI approach for analyzing driving behaviour in simulated racing using telemetry data," in *Games and Learning Alliance (GALA), 12th International Conference*. Springer, 2023.

[48] A. Jiménez Elbal, A. Zarzuelo Conde, and E. Siampis, "Simultaneous optimisation of vehicle design and control for improving vehicle performance and energy efficiency using an open source minimum lap time simulation framework," *World Electric Vehicle Journal*, vol. 15, no. 8, p. 366, 2024.

[49] F. Bonini, A. Rivola, and A. Martini, "Braking torque estimation through machine learning algorithms," in *Theoretical and Applied Mechanics (AIMETA 2022)*, ser. Materials Research Proceedings, vol. 26. Millersville, PA, USA: Materials Research Forum LLC, 2023, pp. 213–218.

[50] F. Bonini, A. Rivola, M. Troncossi, and A. Martini, "Multi-sensor estimation algorithm for the friction coefficient and the braking torque of carbon braking systems for racing motorcycles," *Mechanical Systems and Signal Processing*, vol. 244, p. 113803, 2026.

[51] A. Jain and M. Morari, "Computing the racing line using Bayesian optimization," in *2020 59th IEEE Conference on Decision and Control (CDC)*. Jeju, Korea (South): IEEE, 2020, pp. 6192–6197.

[52] W. de Vries, E. van den Eshof, J. van Kampen, and M. Salazar, "Competitor-aware race management for electric endurance racing," in *2026 IEEE International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2026, accepted, in press.

[53] J. van Kampen, T. Herrmann, T. Hofman, and M. Salazar, "Optimal endurance race strategies for a fully electric race car under thermal constraints," *IEEE Transactions on Control Systems Technology*, vol. 32, no. 3, pp. 818–833, 2024.

[54] (2016) A brief history of computing in formula 1. [Online]. Available: https://www.mclaren.com/racing/team/a-brief-history-of-computing-in-f1-1052199/

[55] P. Babaei, N. Riahinia, and A. Azimi, "Towards a data-driven digital twin AI-based architecture for self-driving vehicles," *IET Intelligent Transport Systems*, 2025.

[56] R. De Almeida, "Literature research on machine learning applied to autonomous vehicle driving: A review," in *VI Seven International Multidisciplinary Congress*, 2024.

[57] Z. Gao, T. Yu, F. Gao, R. Zhao, and T. Sun, "Human-like mechanism deep learning model for longitudinal motion control of autonomous vehicles," *Engineering Applications of Artificial Intelligence*, vol. 133, p. 108060, 2024.

[58] M. Li, Z. Cui, Y. Wang, Y. Huang, and H. Chen, "An explainable Q-learning method for longitudinal control of autonomous vehicles," *IEEE Transactions on Intelligent Transportation Systems*, vol. 26, pp. 4214–4218, 2025.