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Emerging Trends in Realistic Robotic Simulations: A Comprehensive Systematic Literature Review

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ABSTRACT
Simulation plays a pivotal role in providing safely reproducible scenarios to evaluate the ever-advancing domain of computer science and robotics. It was an essential part of the pandemic when no access to physical spaces was available. The advent of AI-powered platforms in conjunction with enhanced graphics, physics and other sensory engines attracts a new breed of interdisciplinary researchers to enter the robotic field, most notably from computer science, engineering and social sciences. Integration of ROS as a uniform middleware to deploy achieved outcomes in real practice provides an opportunity to move one step closer to the sim-to-real experiences that enables researchers to test ideas beyond the close laboratory spaces. There is a lack of comprehensive evaluation of ROS-enabled simulators, and the integration of advanced AI techniques for realistic scenario replication. This paper addresses this challenge by evaluating ROS-enabled simulators in the design and implementation of AI techniques through an in-depth systematic literature review (SLR). This SLR is guided by the research and commercial market demands, employing Population, Intervention, Comparison, Outcome, and Context (PICOC) and Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) frameworks with a major focus on Wheeled Mobile Robots (WMRs). We also highlight the increasing importance of game engines like Unity and Unreal in future of robotic simulations, especially under modelling close to real experiences. By comparing simulation platform features and capabilities, this paper offers guidance to developers and researchers, enabling them to select the most suitable platform for their projects efficiently that contradicts the commonly in use "one size fits all" approach. Finally, based on the thorough insights from the review, we identify and suggest some key future research directions in AI-enhanced realistic robotic simulations.

INDEX TERMS Simulation, Artificial Intelligence, Robot Operating System, Wheeled Mobile Robot

I. INTRODUCTION
IN the interdisciplinary field of robotic simulations, the convergence of Artificial Intelligence (AI) techniques with mobile robots represents a frontier of research development. Despite the burgeoning interest in this nexus, there exists a discernible gap in the literature that comprehensively synergises AI advancements and mobile robot simulation, particularly within ROS-enabled environments. This survey is pivotal, as it endeavours to bridge this gap by offering an exhaustive overview of AI-driven methodologies tailored for mobile robots in such simulators, underscoring the importance of perception, path planning, and control mechanisms that ensure efficient navigation and operation across varied environments.

Overcoming the challenges associated with implementing and testing robots that integrate AI techniques, including ensuring safety, managing the cost of testing scenarios, improving training speed, and addressing scalability issues, is crucial for researchers [1]–[3]. By addressing these challenges through simulation, researchers can ensure the reliability and effectiveness of the robots they design. AI training with simulation has several advantages:

1) **Improved Safety:** Simulation provides a secure environment where AI algorithms can be developed without posing a threat to human life or material assets [4]. For example, training autonomous vehicles in a virtual environment allows developers to test various scenarios and edge cases without risking lives or property. Similarly, when robots need to operate in extreme conditions such as fire or earthquakes, simulations can be used to assess their performance without real danger [5]. AI models can be fine-tuned for increased safety

ahead of real-world deployment by detecting and mitigating potential hazards through simulation.

2) **Faster training:** The process of training AI models in real-world conditions can often be slow and inefficient due to factors such as the extensive time and cost required for data collection, as well as the complexities of equipment setup. Simulations present an effective solution to these constraints, enabling rapid iteration cycles and the possibility of parallel training sessions. This approach capitalises on the power of high-performance computing resources, allowing for a more efficient learning process for AI algorithms. Consequently, this results in the facilitation of more rapid experimentation and development, providing an overall acceleration in the pace of research and the application of AI models [4].

3) **Cost-effectiveness:** Implementing AI training purely in the physical world can be expensive, necessitating significant resources such as equipment, data gathering, and operational costs. By minimising or eliminating these costs, simulation provides a cost-effective alternative. Once a simulation environment has been established, it is simple to duplicate, allowing AI training to be carried out at scale without facing the additional expenses associated with the real-world deployment [4], [6].

4) **Scalability:** Simulation enables AI training to be scaled to address big and complicated scenarios. This scalability allows AI algorithms to be trained on a diverse range of scenarios and edge cases, which may be challenging or costly to replicate in the physical world. By exposing AI models to a variety of simulated situations, they can be trained to manage complex and rare events, thus enhancing their overall performance and resilience. [4], [6].

Given the outlined benefits, the application of simulation in AI training is of paramount importance. Sim-to-real transfer techniques are particularly significant as they involve the effective transfer of learned behaviours or control policies from simulated environments to the real world. However, even advanced sim-to-real transfer techniques cannot compensate if the simulation severely lacks realism [7]. This is especially important in AI applications where robots may need to operate in extreme conditions with dynamic uncertainties and disturbances. For instance, consider a scenario where a robot is aimed to be trained to ascend a cliff using reinforcement learning (RL). The accuracy of the details in the simulation directly affects the resilience of the trained RL controller. Without a precise and realistic simulation, it is impossible to ensure that the robot is adequately trained before deploying it in the real world.

AI techniques play a transformative role in enhancing the autonomy and efficiency of autonomous robotic systems. By emphasising the integration of sophisticated AI methodologies in simulation platforms, this review illuminates the path towards achieving higher degrees of realism and operational fidelity. By implementing various AI techniques, mobile robots can collect environmental data, enhance their autonomy, and successfully complete complex tasks. They can improve their performance in various control tasks such as path and motion planning, as well as perception tasks such as object detection, collision avoidance, mapping, and localisation [2], [8]–[37]. An extensive review of numerous simulation platforms reveals the diverse capabilities and features critical to AI-centric research for mobile robots. This analysis is instrumental for developers and researchers, guiding them in selecting the most appropriate platforms for their specific needs. By comparing platforms based on criteria such as fidelity, scalability, and support for AI integration, this survey offers invaluable insights into the evolving landscape of robotic simulation technologies.

Game engines like Unity and Unreal are similarly gaining prominence in the realm of robotic simulations [38], [39], heralded for their high fidelity and capacity to replicate complex environmental conditions accurately [40]. Portions of this review highlight the transformative impact of game engine technologies in simulating challenging scenarios, such as disaster response environments, where the precision and realism of simulations are paramount. The adaptability and advanced rendering capabilities of these engines position them as indispensable tools in the future of robotic simulation, enabling researchers to push the boundaries of what is possible in simulating AI-enhanced mobile robots under extreme conditions.

These game engines excel at simulating complex, dynamic environments with high degrees of realism, making them invaluable for robotic research [41]. Their ability to render intricate scenarios in real-time allows for the simulation of various conditions under which mobile robots must operate, ranging from urban landscapes to unstructured terrain, thus providing an essential tool for testing perception, navigation, and interaction systems without the physical constraints and risks associated with real-world testing. Moreover, the use of game engines in robotic simulation democratises access to advanced research tools. The availability of free or relatively inexpensive licenses for academic use opens up possibilities for institutions and researchers with limited resources, fostering innovation and collaboration across the field. This accessibility, combined with the engines' scalability and flexibility, empowers researchers to explore new frontiers in AI and robotics, from developing more sophisticated autonomous agents to testing novel algorithms in highly realistic virtual worlds.

Once researchers have validated their design concept through simulations, they face the task of implementing their ideas on a real robot. This implementation process involves the translation of algorithms, control systems, and perception techniques developed during the research phase into executable code that can

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be run on the hardware of the robot. ROS (Robot Operating System) serves as a framework that facilitates the testing and implementation of robots by providing a range of tools, libraries, and conventions. It facilitates the creation of sophisticated and reliable robot behaviours across different robotics platforms [42]. As an alternative approach to creating specialised robot software, ROS provides a set of standard operating system services that cover hardware abstraction, low-level device control, implementing commonly used features, inter-process message passing, and package management [43]. Execution of ROS processes is represented through a graph architecture, where nodes are responsible for exchanging messages to accomplish tasks such as sensor multiplexing, control, status monitoring, planning, and actuation. As a significant and open-source tool in the robotics domain, ROS is widely used by makers, researchers, and the industry. It seamlessly integrates with various simulators like Gazebo, Webots, MORSE, V-REP, and others, highlighting its adaptability and utility [44]. The integration of ROS with game engines introduces additional layers of realism and functionality. ROS bridges the gap between simulation and real-world applications by providing a standardised communication layer, allowing for seamless transition of code and concepts from a simulated environment to physical robots. This integration is pivotal for advancing research in autonomous systems, as it enables the simulation of complex interactions within a controlled environment while ensuring that the developed systems are directly applicable to real-world scenarios.

Mobile robotics is a rapidly evolving scientific field that has the potential to cooperate with humans or replace humans in many tasks. They can function in various environments, such as crowded warehouses, rugged terrain like Mars, and hazardous areas like earthquake disaster zones. When classifying mobile robots based on their movement systems, there are several broad categories: manipulators, land-based robots, airborne robots, waterborne robots, and others [45]. The unique environments and physics involved in each category require special considerations. For example, waterborne robots must account for fluid dynamics [46], buoyancy, water currents, and pressure differences [47], while airborne robots, including Uncrewed Aerial Vehicle (UAV), must consider air resistance, turbulence, and aerodynamics [48]. Additionally, these airborne robots encounter significant challenges in terms of safety, scalability, cost-efficiency, and ecological considerations during hardware testing phases [49]. Land-based robots, on the other hand, are affected by gravity, wheel friction, and terrain roughness [50]. Unlike their airborne and waterborne counterparts, which require consideration of fluid dynamics, buoyancy, and aerodynamics, land-based robots are primarily influenced by gravity, wheel friction, and terrain roughness, necessitating a different simulation approach. Within the land-based robot category, we propose four additional subcategories. This classification aids in refining the focus of our systematic literature review:

1) **Wheeled mobile robots (WMR):** These robots predominantly use wheels for locomotion, enabling them to traverse various terrains.

2) **Walking (or legged) mobile robots:** These robots are equipped with legs or walking mechanisms, providing them with the ability to navigate through challenging environments.

3) **Tracked slip/skid locomotion:** Some land-based robots employ tracks instead of wheels, enhancing their traction and manoeuvrability on various surfaces.

4) **Hybrid:** Certain land-based robots incorporate a mix of different locomotion systems to achieve versatile movement capabilities.

Our team spearheads a project, focusing on modelling multi-agent interactions in near-real environments, particularly during extreme events, to study uncertainty. This project has highlighted the need for a comprehensive understanding of the current state of simulation technologies, specifically those that can accurately replicate real-world conditions for WMRs. The use of WMRs offers numerous benefits to our lives, ranging from autonomous vehicles and warehouse operations to life-saving rescue missions. These systems can automate or aid in monotonous, dangerous, or difficult tasks. During the COVID-19 pandemic, wheeled robots have been used for critical functions, such as delivering food to quarantined individuals and disinfecting public areas. However, the deployment of this kind of robot also brings about new and unexpected challenges, especially when operating under extreme conditions such as earthquakes. Despite these challenges, WMRs can be instrumental in scenarios that demand risk reduction or potential life-saving interventions [2]. Their capability to traverse various terrains, from smooth flat surfaces to uneven landscapes, grants them a significant degree of adaptability. This makes WMRs particularly well-suited for a multitude of applications including, but not limited to, exploration missions, efficient logistics in warehouses, precise operations in agriculture, continuous surveillance in security-sensitive areas, and remote interventions in disaster-stricken zones. As such, the potential and versatility of WMRs underscore their increasing importance in our evolving technological landscape. Based on the discussion above, this paper focuses its analysis on WMRs, given their broad applicability and pivotal role in advancing mobile robotics.

Beyond the advantages provided by AI training with purely software simulation, another important topic in robotic development is the integration of Hardware-In-the-Loop (HIL) and Human-In-The-Loop (HITL) testing. Testing control strategies directly on real robots can often be time-consuming, expensive, and pose higher risks. HIL simulations can mitigate these challenges, replicating real-world conditions and offering more accurate results [51]. This method allows for earlier problem detection and resolution in the development process, consequently reducing testing costs. Additionally, HIL ensures the smooth integration of various hardware components. It helps developers confirm the proper functioning of control systems, actuators, and sensors before they are incorporated into the complete robot setup [52]. On the other hand, HITL introduces a human element into the development loop. Robots can quickly adapt to changing situations, correct errors, and perform better when given direct human input. Over time, the robot refines its behaviour to the point where human intervention becomes minimal [53]. This synergy between hardware, software, and human expertise accelerates the transition from simulations to real-world applications.

To simulate the dynamics of wheeled robots, various physics engines are typically employed, including ODE, DART, MuJoCo, Bullet, SimBody, PhysX, or RaiSim. These engines focus on solving problems related to rigid articulated bodies, collisions, and contacts [46]. In Table. 1, a comprehensive list of platforms that are widely used for the simulation of robots and can integrate with ROS has been compiled. The various simulation platforms are examined and compared based on several metrics, including the supported physics engine, programming languages, key features, and open-source availability. Among the most versatile platforms are Gazebo and CoppeliaSim (formerly V-REP), supporting multiple physics engines and programming languages such as Python and C++. Gazebo stands out for its realistic physics and graphics, extensibility through plugins, a large library of models and environments, as well as strong community support. CoppeliaSim (formerly V-REP) is notable for facilitating simulation of complex kinematics and dynamics, and offering extensive sensor and actuator support. Platforms like MuJoCo and Webots offer specific strengths, such as fast and accurate physics and reinforcement learning integration for MuJoCo, and a large library of robot models and web-based simulation for Webots. ARGoS is particularly tailored for large-scale multi-robot swarm simulation, while CARLA and USARSim excel in simulating realistic driving and urban environments. RaiSim and NVIDIA Isaac Sim offer high-fidelity physics and advanced features like GPU acceleration and deep learning support. Unity and Unreal Engine, while not traditionally considered robotic simulators, are acknowledged for their high-quality graphics and realistic environments. Overall, the choice of simulation platform would be dependent on specific project requirements, such as the type of robotics application, the required level of physical realism, programming language support, or specialised simulation capabilities.

Considering the described context, this study aims to provide answers or insights to the following research questions based on our review of the relevant works:

RQ1: What are the application areas facilitated by AI-driven methodologies in the domain of WMRs?

RQ2: What are the primary perception and control objectives of WMRs, and how does AI contribute to their achievement?

RQ3: Which ROS-enabled WMRs are employed in AI-driven perception and control research?

RQ4: What ROS-compatible simulation platforms are available for WMRs?

RQ5: How significant are HIL and HITL testing methodologies in the design process of WMRs?

Consequently, this systematic literature review addresses the following critical aspects:

1) An exploration of the diverse applications of WMRs, reflecting the increasing interest in this subject area and the substantial increase in research.

2) A detailed analysis of the main perception and control tasks of WMRs, outlining the various AI approaches employed and offering insights into the methodologies and techniques used.

3) Identification of the most commonly used WMRs, providing valuable reference information for the field.

4) A breakdown of simulation platforms enabled by ROS, highlighting the dominance of the Gazebo simulator and the emergence of game engines in robotic simulators.

5) An examination of Hardware-in-the-Loop (HIL) and Human-in-the-Loop (HITL) testing methodologies, underscoring their potential in the design process of WMRs.

This paper is organised into five sections: Section II outlines the method used for the literature review. Section III presents the findings derived from the review. Section IV answers the posed research questions and discusses the gaps found in current research. Finally, Section V presents our conclusions.

II. METHOD

This paper was conducted using the Systematic Literature Review (SLR) approach, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [54]. A SLR evaluates and analyses available research on a certain topic area or interest phenomenon. The SLR aims to provide a fair review of a research issue by employing a reliable and rigorous technique. The SLR guidelines are separated into three phases: planning the review, conducting the review, and reporting the review.

A. PLANNING THE REVIEW

The initial phase of the SLR involves planning the review, which includes determining and defining the review's execution process to ensure its validity [54] After formulating the research questions, the scope of the review was determined by employing the PICOC method introduced by Petticrew and Roberts [55]:

TABLE 1. Comparison of Simulation Platforms

Name	Physics Engine	Programming Language	Key Features	Open Source
Gazebo	ODE, Bullet, Simbody, DART	• Python • C++	• Realistic physics and graphics • Extensibility with plugins • Large library of models and environments • Community support and active development	Yes
MuJoCo	MuJoCo	• Python • MATLAB • C++	• Fast and accurate physics • Seamless Reinforcement Learning (RL) Integration • Flexible API for customization • Support for soft bodies and deformable objects	Yes
Webots	ODE	• Python • MATLAB • C++ • C • Java	• Large library of robot models and environments • Offers web-based simulation • User-friendly interface • Modular and user-extensible design	Yes
CoppeliaSim (V-REP)	Bullet, ODE, MuJoCo, Vortex Studio, Newton Dynamics	• Python • MATLAB • C++ • Lua	• Simulation of complex kinematics and dynamics • Fast algorithm development • Remote API and connectivity • Wide range of sensor and actuator support	Free and paid version
ARGoS	Bullet, ODE	• Python • C++ • Lua	• Large-scale multi-robot swarm simulation • Extensibility with plugins • Customizable robot models • Easy experiment and simulation setup	Yes
PyBullet	Bullet	• Python • MATLAB • C++ • Java	• Easy integration with machine learning libraries • High performance and efficiency • Diverse robotics and soft body simulation • Real-time physics debugging	Yes
CARLA	Unreal Engine 4 (PhysX), Project Chrono	• Python • C++	• Autonomous driving scenario definition and evaluation • OpenDRIVE road network generation • Dynamic and realistic traffic simulation • Comprehensive sensor suite	Yes
RaiSim	RaiSim	• Python • C++	• Advanced sensor simulation • High-fidelity physics • Modular and lightweight architecture • Efficient GPU acceleration	No
Project Chrono	Project Chrono	• Python • C++	• Multibody dynamics and granular simulation • High-performance parallel computing • Advanced vehicle dynamics • Realistic terrain and geological simulation	Yes
USARSim	Unreal Engine 2 (PhysX)	• Python • C++	• Realistic urban environment simulation • Wireless communication simulation • Sensor and actuator fault simulation • Extensible architecture	Yes
OpenRAVE	ODE, Bullet	• Python • MATLAB • C++	• Focus on motion planning and manipulation • Extensive kinematics and dynamics solvers • Robust collision detection and grasping support • Support for multi-robot simulations	Yes
AirSim	Unreal Engine 4 (PhysX)	• Python • MATLAB • C++	• Photorealistic graphics and environments • Dynamic weather and lighting conditions • Easy integration with Machine Learning libraries • Hardware-in-the-loop (HIL) simulations	Yes
SOFA	SOFA	• Python • C++ • XML	• Advanced multi-physics simulation • Modular and extensible architecture • Real-time interaction and haptics support • Parallel computing and GPU acceleration	Yes
NVIDIA Isaac Sim	PhysX 5	• Python • C++	• Physically accurate simulations • High-Quality Visuals and Rendering with NVIDIA RTX • Deep Learning and Reinforcement Learning Support • Integration with the NVIDIA Omniverse ecosystem	Yes
Unity	PhysX	• C#	• Real-Time Physics Simulation • High-Quality Graphics and Realistic Environments • Machine Learning Integration • Vast Asset Store and Community Support	Free and paid version
Unreal Engine	Unreal Engine (PhysX)	• C++ • Blueprints visual scripting	• High-fidelity visuals and realistic environments • Robust physics simulation • Large library of high-quality assets • Physically based materials and material editor	Free and paid version

- **Population (P):** ROS-enabled simulators for WMRs.
- **Intervention (I):** Utilising ROS-enabled simulators in conjunction with AI-based techniques.
- **Comparison (C):** Assessing and comparing various simulation platforms for AI-based perception and control of WMRs.
- **Outcome (O):** Identifying research gaps and trends in the field of ROS-enabled simulators for WMRs, with a specific focus on the utilisation of AI techniques for perception and control tasks.
- **Context (C):** Investigating WMRs across varied applications.

Based on the PICOC framework, the inclusion and exclusion criteria for selecting relevant papers that answer the research questions are defined as follows.

- **Inclusion Criteria:** Papers written in the English language AND papers that have been published within the last ten years AND papers published in peer-reviewed conference proceedings, journals, or technical reports AND papers that report the simulation of wheeled robots AND papers that utilise ROS AND Papers that implement AI techniques.
- **Exclusion Criteria:** Papers that focus solely on physical robot design and mechanical engineering OR papers on mobile robots using locomotion forms other than wheels OR papers on general AI or robotics theories not specific to WMRs OR papers focusing entirely on real-world testing and deployment of WMRs.

In order to define the scope of our SLR, we have identified four key domains that intersect to form the focus of our research, as illustrated in Figure 1. These domains are: ROS, AI, WMR and Simulation. Our review is specifically tailored to papers that discuss the application of AI-based methods for the perception and control of wheeled mobile robots operating within ROS-enabled simulators. While there are various platforms for robot control, types of robots, and simulation environments, our review narrows down the scope to this specific intersection to provide a comprehensive understanding of the advancements in AI-based perception and control mechanisms for wheeled mobile robots in ROS-enabled simulation environments.

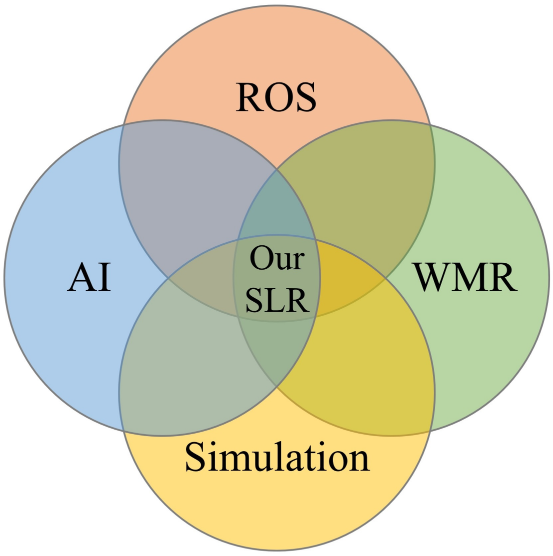

FIGURE 1. The Scope of Papers Included in the Systematic Literature Review: This Venn diagram illustrates the overlapping academic fields of Robot Operating System (ROS), Artificial Intelligence (AI), Wheeled Mobile Robots (WMR), and Simulation. Only papers that intersect across all these domains are considered for review.

B. SEARCH METHODOLOGY

When conducting a SLR, it is crucial for the appropriate databases relevant to the research topic to be carefully selected. In this paper, the IEEE Digital Library, ScienceDirect, SpringerLink, and the ACM Digital Library were utilised. The selection of these databases was based on their reputation and prominence in the research field.

To optimise the efficacy of our SLR, we devised a search strategy comprising five major thematic sections, each encompassing a range of specific search terms. The first section focuses on diverse categories of WMRs. The second section is about artificial intelligence techniques. The third section is relevant to perception and control methodologies. The fourth section is linked to simulation platforms. The final section emphasises the use of ROS in the research context. Within each major thematic section, search terms are interlinked using "OR" statements to ensure comprehensive coverage, whereas "AND" statements are used to connect the sections. This methodology enables the identification of papers that match at least one search term from each section, thereby fostering a structured and inclusive approach to sourcing pertinent studies for our SLR. The detailed list of search terms, reflective of this structured approach, is presented in Table 2

The wildcard character, denoted by the asterisk (*), is incorporated in the designated keyword search. The inclusion of this wildcard character enhances the search query's range and flexibility by allowing it to stand in for one or more characters. For instance, inputting "robot*" in the search box will yield results containing terms like "robot," "robotics," and "robots." It is worth noting that the ScienceDirect database imposes restrictions on the advanced search queries that can be used. Consequently, the following search string was used for that database instead: *(robot OR agent) AND (learning OR intelligence OR AI) AND (control OR perception) AND simulator AND ROS*.

C. LITERATURE SELECTION

The data compilation process in this research followed a phased approach guided by the PRISMA flow diagram [56], [57], as shown in Figure 2. This diagram provides a comprehensive overview of the SLR process and the actions taken at each stage.

TABLE 2. Logical grid of search terms

Domain	Search Term
Wheeled Mobile Robots	mobile robot* OR rover* OR omnidirectional mobile* OR unmanned robot* OR ground robot* OR wheeled robot* OR autonomous robot* OR mobile ground OR autonomous ground vehicle* OR multi-agent system OR mobile agent OR automated guided vehicle* OR unmanned ground vehicle*
Artificial Intelligence Techniques	artificial intelligence OR AI OR *reinforcement learning OR intelligent* OR machine learning
Perception and Control Methodologies	control OR path planning OR trajectory planning OR motion planning OR multi-objective optimisation OR object recognition OR perception OR localisation OR navigation OR SLAM OR obstacle avoidance OR object detection OR collision avoidance
Simulation Platforms	digital twin OR physics engine OR computer game OR game engine OR simulat* OR sim-to-real OR sim2real
Robot Operating System	robot operating system OR ROS

1) In the initial stage of identification, a search was conducted using the specified search string described in the previous subsection. A total of 2525 papers were initially identified. However, 65 papers were excluded due to duplicate reports or being part of conference proceedings that later resulted in full articles.

2) The next stage involved screening the remaining records based on their titles and abstracts, resulting in the exclusion of 2250 papers. The main reasons for exclusion were as follows: A) Papers related to non-wheeled ground (n=16), airborne (n=94), waterborne (n=53), and arm (n=93) robotics topics. B) Papers that did not utilise the ROS (Robot Operating System) platform (n=67). D) Papers that did not employ AI methods (n=87). F) Papers that did not utilise a simulator (n=161). E) Irrelevant papers or other miscellaneous reasons (n=1679).

3) In the subsequent stage, 210 papers were considered eligible for further assessment. However, five of these papers were excluded because the PDF files could not be found, and three were excluded because they were written in languages other than English.

4) In the last stage, the remaining reports were thoroughly assessed for eligibility, resulting in the exclusion of 19 additional papers. The main reason for exclusion at this stage was that after reviewing the content, it was discovered that some papers did not explicitly mention the specific methods for perception and control (n=11), and some papers claimed in their abstracts to utilise AI methods but upon closer examination, no such methods were found within the papers themselves (n=8). In the end, 186 papers were deemed suitable for the final stage of the review.

Figure 3 categorises the selected papers by their year of publication, spanning from 2012 to 2023. It is important to note that the data for 2023 includes only the publications from the first six months. The trend clearly indicates a marked increase in publications over recent years, underscoring the growing academic interest in this field. Within the collected works, there are 101 conference papers and 85 journal articles. The near-even split between conference papers and journal articles suggests a balance between the urgency to publish new findings and the need for thorough, peer-reviewed research in the field.

D. THREATS TO VALIDITY

A systematic review inherently offers the potential for an unbiased analysis, however, certain risks and challenges may influence the outcome and introduce bias into the synthesised conclusions. The following points enumerate some of these threats:

1) **Selection of digital libraries:** Despite our careful selection of widely recognised digital libraries, the confinement to a limited number may exclude relevant papers available elsewhere. An expansion to include additional libraries could enlarge the pool of articles, yet it simultaneously complicates the task of analysing all the results within a manageable timeframe.

2) **Difficulties in quality assessment:** The quality assessment phase presents several challenges that may impede the accurate answering of research questions. Such difficulties stem from multiple factors, including poor writing quality, inefficient presentation of information, issues with confidentiality, and the risk of subjective judgement. For example, a paper might discuss a specific perception method in the abstract but may not furnish sufficient detail in the main body of the text.

3) **Formulation of search terms:** Though preliminary tests were conducted to refine the search strategy, the task of defining the optimal search string remains intricate. Libraries like ScienceDirect may necessitate modifications to the search string, owing to inherent limitations. Such alterations, while sometimes essential, carry the risk of introducing irrelevant results into the review. This highlights the delicate balance required in generating search strings that are both inclusive and specific, a challenge that has implications for the reliability and validity of the entire review.

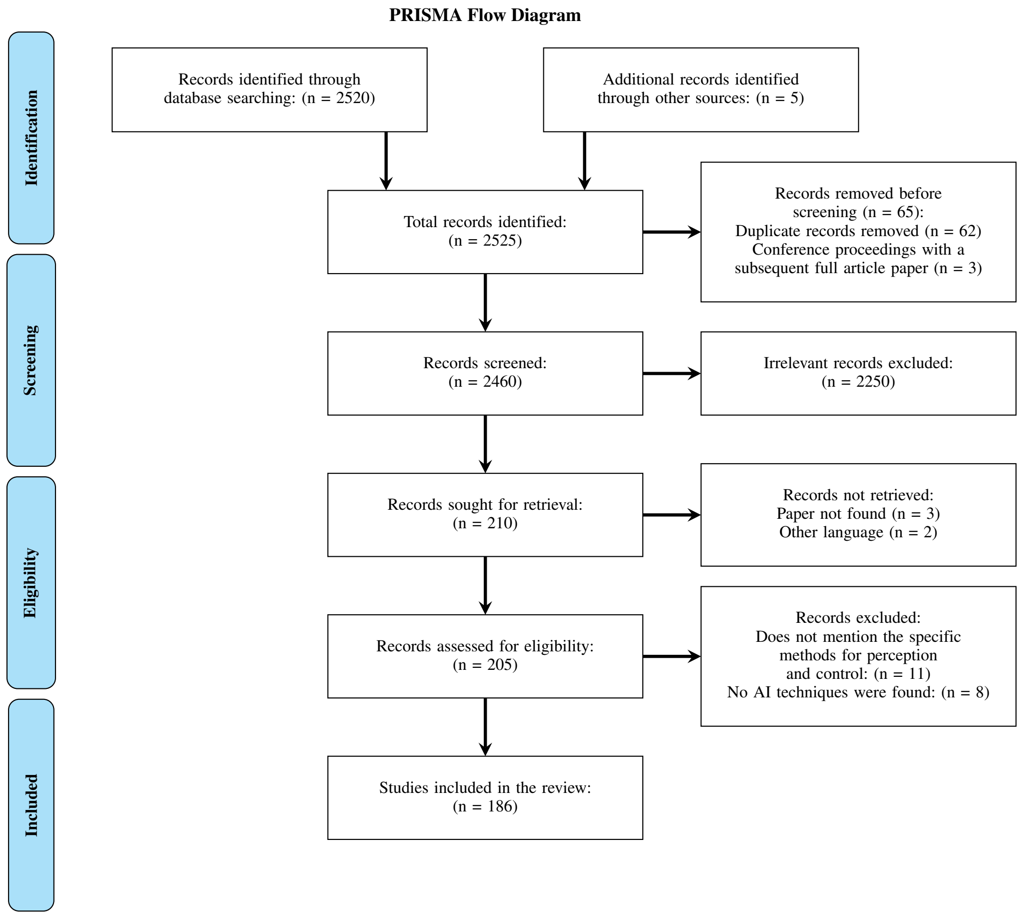

FIGURE 2. **PRISMA Flow Diagram illustrating the four key stages of literature selection for this systematic review: Identification, Screening, Eligibility, and Inclusion. The diagram details the initial number of records, exclusions at each stage, and the final count of papers included in the review, offering a transparent view of the methodology employed.**

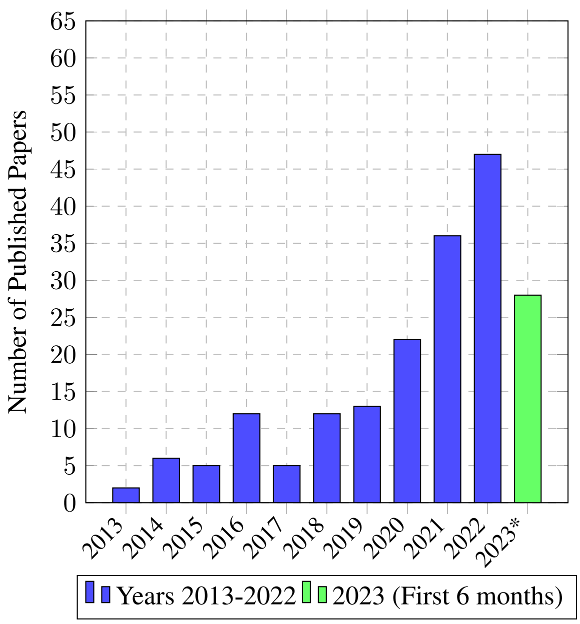

FIGURE 3. **Number of Published Papers by Year: This figure displays the trend in the number of published papers related to ROS-Enabled Simulators for AI-Enhanced Wheeled Mobile Robots from the year 2013 to 2023. The y-axis represents the total count of papers, while the x-axis marks the publication years. For the year 2023, the green bar represents actual data from the first six months.**

III. FINDINGS

In this section, the results of our comprehensive research are presented. We organise and discuss all findings gathered from our database searches in relation to our specific research objectives.

A. APPLICATION AREAS OF AI-BASED TECHNIQUES IN WMR PERCEPTION AND CONTROL

This section provides an overview of the diverse domains in which AI techniques are utilised to augment the control and perception capabilities of WMRs. Based on the literature reviewed, encompassing a total of 97 papers, the application areas for AI-enhanced WMRs controlled with the Robot Operating System (ROS) can be divided into thirteen distinct categories, as outlined in Table 3. Among the identified applications, "Research" emerged as the predominant category, encompassing 35% (34 out of 97) of the literature. Such predominance is anticipated, given that this category encapsulates papers emphasising broad-spectrum algorithmic development and techniques with generalised applications, though not necessarily tethered to a specific use-case within those studies. Beyond research, the "Automotive" sector constituted 20.6% (20 out of 97) of the citations, trailed by

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"Healthcare" at 13.4% (13 out of 97).

The significant representation of the Research category underscores the ongoing exploration and innovation within AI methodologies, demonstrating the field's dynamic nature and its potential for wide-ranging applications. The prominence of Automotive and Healthcare sectors highlights the critical impact of AI in enhancing safety, efficiency, and accessibility, addressing some of the most pressing challenges in these areas. These statistics not only reflect the current state of research but also hint at the evolving trends in the application of AI technologies in WMRs, suggesting a broadening scope that may encompass even more diverse fields in the future.

B. AI APPROACHES ADOPTED IN WMRS

The purpose of this section is to provide a systematic classification of AI techniques employed in research focusing on ROS-enabled WMRs. Our aim is to highlight the advancements and applications of AI methods in the development of perception and control systems for these robots. Based on our comprehensive literature review, the research is categorised into three distinct areas :

1) **Perception and Safety:** This domain emphasises the robot's capability to interpret its environment, recognise objects, and ensure safety. These functionalities are important for real-time decision-making and circumventing obstacles or hazards.

2) **Path Planning:** research in this category focuses on empowering robots to devise efficient and safe trajectories, factoring in dynamic environments and unforeseen challenges.

3) **Control Mechanisms:** This area is dedicated to the algorithms and techniques that regulate the robot's movements, ensuring stability, precision, and responsiveness.

To provide a clearer understanding of the interplay between these areas, Figure 4 offers a graphical illustration. Moreover, to provide more detail on the AI techniques and their applications, Table 4 presents a breakdown of each category, detailing the specific AI techniques and their associated literature references.

The perception domain primarily leans on AI algorithms that harness data from sensors such as cameras, depth sensors, and Light Detection and Ranging (LiDAR) to empower the robots with environmental comprehension. Some of the primary tasks within this domain include object detection, obstacle awareness and gesture recognition. By relying on visual inputs from cameras, these functionalities enable robots to interact effectively with their environments. Convolutional Neural Networks (CNN) serve as the backbone for these tasks within modern robotics, with the You Only Look Once (YOLO) suite of algorithms emerging as particularly dominant [31], [62], [103]. The YOLO algorithms' efficiency in facilitating real-time processing has made them popular in robotic applications.

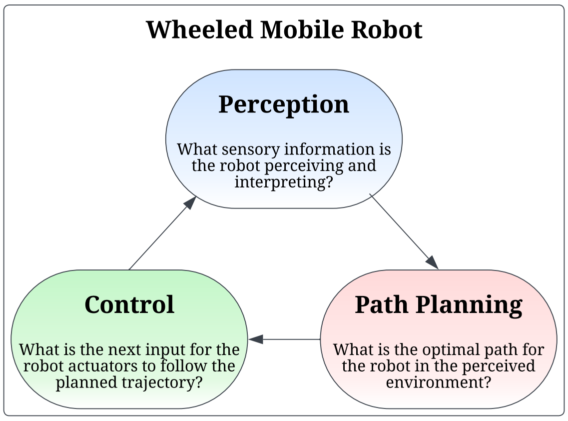

FIGURE 4. Conceptual Framework for AI-Driven Decision-making in ROS-Enabled WMRs. The diagram illustrates the interconnected nature of sensory interpretation, trajectory optimisation, and actuator control, emphasising their cyclical relationship in the functioning of an autonomous WMR.

Object tracking, another core task within the perception domain, can also take advantage of YOLO algorithms when paired with other methods like Kernel-based Correlation Filters (KCF) [104]. However, the landscape here is more varied, with other algorithms such as Continuous Adaptive Mean Shift (CAMShift) [93] and Actor-Critic Reinforcement Learning [140] being actively employed. Additionally, there is an increasing emphasis on risk assessment in the literature, highlighting the efforts directed at algorithms that can evaluate and prevent potential hazards in a robot's operational environment.

Another very prominent perception task is Simultaneous Location And Mapping (SLAM), which focuses on the robot's ability to simultaneously create a map of an environment while also estimating its own position within that environment. Given the real-time requirements of robotics, streamlined and efficient methodologies are essential. To this end, techniques like Rao-Blackwellized Particle Filters (RBPF) [58], Extended Kalman Filters (EKF) [116], and Iterative Closest Point (ICP) [132] have become go-to choices for SLAM implementations. For a comparative insight into SLAM algorithms, [58] offers an instrumental study, assessing the computational efficiency of four widely adopted algorithms (Gmapping, Hector SLAM, Karto SLAM, and RTAB) on an autonomous vehicle. It should be noted that GMapping is a highly efficient Rao-Blackwellized particle filter designed for learning grid maps from laser range data [177].

Path planning is an essential component of robotic navigation that bridges the gap between perception and control mechanisms. This domain delves into strategising routes a robot should undertake, considering both the environmental constraints and the robot's objectives. It is a discipline that oscillates between pure algorithmic approaches and adaptive learning-based methodologies.

For known environments where the terrain and

TABLE 3. Application Areas of AI-based WMRs

Application	Items
Automotive	• Self-parking applications under SAE (Society of Automotive Engineers)-Level 3 of vehicle automation [58] • Advanced driving assistant system (ADAS) + neuroscience for enhanced vehicle control [59] • Path planning application in unknown and complex environments [2] • Autonomous driving applications [21], [33], [37], [60]–[66] • Intelligent Transportation Systems (ITS) [67] • Gesture recognition for human-vehicle interaction [68] • All-terrain vehicle (ATV) with autonomous navigation and teleoperation [69] • Robust localisation of Autonomous Cars [70] • Socially aware robot navigation [34], [71], [72]
Research	• Digital twin models in Cyber-Physical Manufacturing Systems (CPMS) [73], [74] • Analog Twin (AT) Framework for Human and AI Supervisory Control [75] • Experimentation in a remote laboratory setting [76] • Multi-robot localization and mapping [23], [77], [78] • Learning from observation [25] • Mobile manipulator positioning for object pick-up [26] • Navigation and obstacle avoidance [35], [36], [79]–[85] • Autonomous exploration in indoor environments [30], [86]–[88] • Immersive telepresence [89] • The specific application was not mentioned [27]–[29], [32], [53], [90]–[95]
Healthcare	• Autonomous Wheelchair [24], [96]–[98] • Rescue and healthcare services in disaster scenarios [99] • Monitoring and visualisation of ROS data in healthcare [100] • Assistance for elderly people in healthcare settings [101] • Human-vehicle interaction in healthcare [68], [102] • Long-term care facilities (LTCFs) [31], [103] • Autonomous pedestrian following (following medical staff) [104] • Medication delivery and vital signs monitoring [105]
Warehouse and logistics	• Warehouse management in retail and manufacturing [106] • Fleet management and luggage transport robots [107] • Manufacturing logistics based on the Open Platform for Innovations in Logistics (OPIL) [108] • Intralogistics applications such as commissioning [109] • Autonomous pedestrian following (following workers in a warehouse and delivery personnel in logistics) [104] • sustainable operation of multiple Self-Guided Vehicles (SGVs) in a dynamic manufacturing environment [110] • Navigation in congested environments [111]
Manufacturing	• Remote inspection of industrial plants [112] • Asymmetric threat protection [113]
Agriculture	• Protecting agricultural fields [114] • Cooperative localization in agriculture [115] • Autonomous navigation in vineyards for pruning and harvesting [116] • Autonomous maize sowing in agricultural fields [117]
Rescue and disaster response	• Urban search and rescue (USAR) [118]–[121] • Assisting in disaster scenarios through various tasks [5] • Multi-robot patrolling [122] • Autonomous pedestrian following (following security personnel in a patrol) [104]
Extreme environments	• Planetary exploration [123], [124] • Navigating hazardous environments [125] • Inspecting confined spaces (subterranean gold mines, dam galleries, and pipes) [126], [127]
Military	• Environmental exploration and destruction in uncertain environments [22]
Education	• Education and industrial applications [74] • Manufacturing education [128]
Entertainment	• Entertainment applications [129]
Building and construction	• Robotized facility inspection in construction and building maintenance [130]
Household	• Lawn mowing in irregular environments. [131]

obstacles are static, deterministic algorithms such as Dijkstra's algorithm [119], [120], [151] and A* [71], [156]–[158] are often employed. Their reliability and predictability make them suitable for tasks where deviations from a set path can be costly. However, in unpredictable or dynamically changing environments, robots need to be more adaptable. The combination of reinforcement learning and planning techniques has demonstrated potential. Methods such as Deep Deterministic Policy Gradient (DDPG) [15], [146], Asynchronous Advantage Actor Critic (A3C) [148], SARSA (State-Action-Reward-State-Action) [152], and Socially Attentive Reinforcement Learning star (SARL*) [150] allow robots to learn and adjust their paths based on interactions with their surroundings.

Collision avoidance is a critical sub-domain within path planning. The balance between swift navigation and safety is crucial. Techniques like Fuzzy inference [13], [98], Dynamic-Window Approach (DWA) [76], [159], and some RL approaches [99] have come to the forefront in this regard. They ensure that while a robot remains agile in its movements, it doesn't endanger its integrity or that of its environment.

TABLE 4. AI Techniques

Category	AI Techniques
Perception and Safety	
1 - Simultaneous Localization and Mapping (SLAM)	RBPF[1] [58], EKF[2] [116], ICP[3] + SVM[4] [132], 2D multi-SLAM [77], GMapping [87], [88], [105], FNN[5] [27], Visual-SLAM + RTAB-Map[6] [126], RTAB-Map [94], Cartographer [65], Monocular SLAM + RL [36], KimeraMulti [133]
2 - Object Detection	YOLOv4[7] [62], [103], YOLOv3 [31], [59], [62], YOLOv2 [134], PointNet [135], CNN[8] [21], [23], [136], SVM [137], MobileNet [138], YOLOv2 + JPDA[9] + IMM[10] [139]
3 - Object Tracking	CAMShift[11] [93], HOG[12] + SVM [129], Actor-Critic RL [140], YOLOv3-Tiny + KCF[13] [104]
4 - Instance Segmentation	Mask R-CNN [30]
5 - Gesture Recognition	YOLOv5 + k-means clustering + attention mechanism [68], OpenPose [28]
6 - Out-Of-Distribution Detection	VAE[14] [32]
7 - Obstacle Awareness and Risk Assessment	YOLOv5 [60], Spiking Neural Network [141], A* or Dijkstra's algorithm + costmaps [125], Neural Network [34]
8 - Sensor Fusion	DQL[15] [142]
9 - Target Search	Vacancy chain + DQL [22]
10 - Point Cloud Completion	GRNet[16] [30]
Path Planning	
1 - Path Planning in Unknown Environments	SARSA[17] + RRT[18] [2], RRT [17], [143], [144], DDPG[19] [15], [145], [146], GFE[20] [147], A3C[21] [148], Dyna-Q algorithm [11], [149], SARL*[22] [150], ROAMFREE [69], Two-stage stochastic programming [81], TEB[23] + A* [95], [127]
2 - Global Path Planning	IDE[24] [16], Dijkstra's algorithm [119], [120], [151], SARSA [152], DQL [8], [153], [154], Evolutionary algorithm [5], [33], [35], Hierarchical-DDPG [155], A* algorithm [71], [127], [156]–[158], ARA*[25] [84], Theta* + DWA[26] [89], G-RRT*[27] [83]
3 - Collision Avoidance	DRL[28] [99], RRT [144], Fuzzy inference [13], [98], DWA [76], [159], [160], Particle Filter [161], AMARL[29] [162], VFH+[30] [76], SND[31] [76], A-FGM[32] [85], CNN [163], [164]
4 - Navigation	CNN + MGRL[33] [165], RL + APPL[34] [53], DWA [166], BDI[35] [79], [123], ANN[36] + DPP[37] [24], B-spline curves [82], Petri Nets [111], PID[38] controller + RANSAC[39] [117], DRL [37], PaCcET[40] [72], AMCL[41] [167]–[172],
Control Mechanisms	
1 - Motion Control	RBFNN[42] [115], ANN [173], Fuzzy inference [174], DDPG [51], Kalman Filters [86], B-RV[43] [131], TD3[44] [26], Evolutionary algorithm [35]
2 - Teleoperation	LSTM[45] [102]
3 - Collaborative Control	ACT-R[46] [97], DTW[47] [29], SMM[48] [124]
4 - Voice Commands Control	NLP[49] [28], [175], [176]

[1] RBPF: Rao-Blackwellized particle filter
[2] EKF: Extended Kalman Filter
[3] ICP: Iterative Closest Point
[4] SVM: Support Vector Machine
[5] FNN: Fuzzy Neural Network
[6] RTAB-Map: Real-Time Appearance-Based Mapping
[7] YOLO: You Only Look Once
[8] CNN: Convolutional Neural Network
[9] JPDA: Joint Probabilistic Data Association
[10] IMM: Interactive Multiple Model
[11] CAMShift: Continuous Adaptive Mean Shift
[12] HOG: Histogram Of Gradient
[13] KCF: Kernelized Correlation Filters
[14] VAE: Variational AutoEncoder
[15] DQL: Deep Q-Learning
[16] GRNet: Gridding Residual Network
[17] SARSA: State-Action-Reward-State-Action
[18] RRT: Rapidly exploring Random Tree
[19] DDPG: Deep Deterministic Policy Gradient
[20] GFE: Greedy Frontier Exploration
[21] A3C: Asynchronous Advantage Actor-Critic
[22] SARL*: Socially Attentive Reinforcement Learning star
[23] TEB: Timed Elastic Band
[24] IDE: Improved Differential Evolution
[25] ARA*: Anytime Repairing A*
[26] DWA: Dynamic-Window Approach
[27] G-RRT*: Goal-oriented Rapidly Exploring Random Tree
[28] DRL: Deep Reinforcement Learning
[29] AMARL: Assured Multi-Agent Reinforcement Learning
[30] VFH+: Vector Field Histogram Plus
[31] SND: Smoothed Normalized Distance
[32] A-FGM: Adaptive Follow the Gap Method
[33] MGRL: Multi-Goal Reinforcement Learning
[34] APPL: Adaptive Planner Parameter Learning
[35] BDI: Belief, Desires and Intentions
[36] ANN: Artificial Neural Network
[37] DPP: Dynamic Policy Programming
[38] PID: Proportional Integral Derivative
[39] RANSAC: Random Sample Consensus
[40] PaCcET: Pareto Concavity Elimination Transformation
[41] AMCL: Adaptive Monte Carlo Localisation
[42] RBFNN: Radial Basis Function Neural Networks
[43] B-RV: Boustrophedon motions and Rapid Voronoi diagram
[44] TD3: Twin-Delayed Deep Deterministic policy gradient
[45] LSTM: Long Short-Term Memory
[46] ACT-R: Adaptive Control of Thought-Rational
[47] DTW: Dynamic Time Warping
[48] SMM: Shared Mental Model
[49] NLP: Natural Language Processing

Navigation serves as an integral component, bridging path planning and control mechanisms by combining varied techniques to ensure robust movement within diverse environments. There are hybrid approaches to navigation, such as the combination of Convolutional Deep Neural Networks (CDNN) and Multi-Goal Reinforcement Learning (MGRL) [165], and the synergy between Artificial Neural Networks (ANN) and Dynamic Policy Programming (DPP) [24]. Algorithms like the Dynamic-Window Approach (DWA) [166] and Deep Reinforcement Learning (DRL) [37] further enhance the robot's adaptability and responsiveness to dynamic scenarios. Incorporating the Belief, Desires and Intentions (BDI) model [79], [123], robots can process and react to their environments in more sophisticated and nuanced ways. Adaptive Monte Carlo Localization (AMCL) also plays a critical role in precise location estimation, vital for effective navigation and path planning [167]–[172]. Furthermore, strategies using B-spline curves [82], Petri Nets [111], and the use of PID controllers in conjunction with the RANSAC method [117] highlight the diverse range of tools available to address the complex challenges of robotic navigation.

Control mechanisms serve as the critical interface between a robot's planned trajectory formed through the understanding of its environment and its subsequent actions. These systems leverage AI techniques to ensure that a robot's movements are precise, fluid, and aligned with its perceived surroundings and intentions. In the motion control sector, traditional approaches like Fuzzy inference systems [174] coexist with more modern methodologies, such as Deep Deterministic Policy Gradient (DDPG) [51] and Radial Basis Function Neural Networks (RBFNN) [115]. These approaches aim to provide both deterministic and adaptive strategies, catering to scenarios that require fixed trajectories and those that demand on-the-fly adjustments.

Teleoperation represents the attempts to improve distant control, often in situations where human intervention is hazardous, with Long Short-Term Memory (LSTM) networks [102] being the prevalent choice. Collaborative control, on the other hand, captures the spirit of modern robotics, emphasising cooperative behaviour, often between multiple robots or between humans and robots. Techniques such as the Adaptive Control of Thought-Rational (ACT-R) [97], Dynamic Time Warping (DTW) [29], and Shared Mental Model (SMM) [124] echo the focus on synchronous operations and shared responsibilities.

Voice command control, powered primarily by Natural Language Processing (NLP) [28], [175], [176], encapsulates the convergence of robotics with everyday human life. As robots become more integrated into daily routines, the need for intuitive interfaces becomes paramount. Voice commands offer a user-friendly way for individuals to interact with robots, transforming them into dynamic assistants that understand and respond to human speech.

In summary, a robot's intelligence relies on perception and path planning, but control mechanisms are necessary to translate that intelligence into meaningful actions in the real world.

C. ROS-ENABLED WMRS EMPLOYED IN RESEARCH

In Table 5, the WMRs referenced in the reviewed literature are categorised and summarised into three principal categories: Mobile Robots, Self-driving Cars, and Wheelchairs. Mobile Robots dominate the literature, representing 83% (107 out of 129) of the reviewed papers, highlighting their significant role in current research. In contrast, Self-driving Cars and Wheelchairs account for 13% (17 out of 129) and 4.6% (6 out of 129) of the literature, respectively.

Within the Mobile Robots category, the *TurtleBot* series is notably the most frequently mentioned, 20% (26 out of 129), contributing to a significant portion of mobile robot-related references. The *Husky* and *Jackal* robots from *Clearpath Robotics* also stand out, collectively comprising 8.5% (11 out of 130) of the mobile robot-related literature. The *Pioneer 3-DX* follows with 3.8% (5 out of 129) representation. This indicates a preference for certain models within the Mobile Robots category, unlike in the Self-driving Cars and Wheelchairs categories, where a diverse range of robot models is utilised, including custom-built options.

It is also critical to note that approximately 24% (31 out of 129) of the reviewed papers were nonspecific about the robot type utilised, referencing general categories such as UGV (Unmanned Ground Vehicle), autonomous car, or robotic wheelchair without providing detailed information on the exact model or brand. This highlights a trend in the literature where the focus is more on the application or technology rather than on specific hardware details.

D. SIMULATORS UTILISED FOR WMRS

In this section, a review is presented of simulators that are used for AI-based perception and control of WMRs. The results of the review are summarised in Table 6. For clarity, in this table, we have only included the literature that explicitly mentions the simulator employed.

From the reviewed papers, Gazebo stands out as the most commonly used standalone simulator, accounting for 80% (101 out of 136)of the references. It is frequently paired with RViz for visualisation, highlighting the effectiveness of this combination for robotic algorithm development and testing. The usefulness of pairing Gazebo with other platforms such as NVIDIA Isaac Sim [109] is also reported in the papers.

Another emerging trend is the use of the Unity game engine as a 3D simulator, likely driven by its recent official support for ROS and its AI capabilities [198]. Unreal Engine is another game engine that is gaining traction in the field of robotics simulation, especially

TABLE 5. Types of WMRs Employed in Research

Category	Examples
Mobile Robots	PeopleBot [42], [91] Pioneer 3-DX [19], [36], [42], [72], [119] Clearpath Robotics Husky [28], [75], [85], [116], [174], [175], [178] Clearpath Robotics Jackal [18], [28], [53], [94] Willow Garage TurtleBot series [2], [8], [9], [12], [25], [30], [35], [70], [81], [88], [100], [105], [143], [144], [147], [148], [150], [158], [178]–[185] Willow Garage PR2 [87], [124] Roomba vacuum cleaner [86], [172] Eddie [186] Rob@work 3 [187] KUKA YouBot [138], [142] Arlobot [134] PlatypOUs [137] Ceres (Volksbot platform) [188] TiaGo [178] Justina [176] MR500 from Robot++ [121] Dabo (Segway RMP200 platform) [161] Robotnik Guardian [132] RoboSally [189] Aether [103] ARGONAUTS [112] NASA Curiosity rover [123] S1R [76] Neobotix MPO-700 [125] JNPF-4WD [27] EspeleoRobo (SpeleoRobot) [126] Kian-I [82] Aether [31] Duckietown DB18 [190] Servosila "Engineer" [120] EKLAVYA 7.0 [127] Polaris Ranger ATV [84] Erle-Rover [35] Custom robots (GripperBot, CamBot, Armbot) [29] Customised Yamaha Grizzly 700 ATV [69] Custom Tekniker robot (Segway + KUKA iiwa) [26] Unspecified UGV [13], [14], [16], [20], [22], [23], [34], [71], [74], [77]–[80], [83], [89], [95], [109], [111], [113], [117], [122], [130], [131], [140], [152], [161], [162], [191]–[193]
Self-driving Cars	iCab [151] MSU EvoRally [194] CaRINA [156] F1TENTH [51] Mahindra e2o electric car [65] Berkeley Autonomous Race Car (BARC) [195] AutoRally (1:5-scale autonomous vehicle) [33] Unspecified race car [64], [173] Unspecified car [21], [37], [52], [60], [63], [68], [153], [196]
Wheelchairs	P3AT robot [97] ATEKS [197] Electric/Smart wheelchair (EWC/SWC) [96] Unspecified robotic wheelchair [24], [98], [166]

for its realistic visualisations. Notably, it forms the basis for ROS-compatible simulation platforms like Microsoft's AirSim and the CARLA platform, which stands out as the most prominent platform specialised in autonomous vehicles from the literature reviewed.

CoppeliaSim (formerly V-REP) was the second most popular specialised robotic simulator in the literature, accounting for 5.8% (8 out of 136) of the references, which shows that it remains a valuable tool for some specific studies but is far less prevalent than Grazebo. Furthermore, the occasional use of other robotic simulators, such as Webots and Bullet, highlights the diverse array of tools available to researchers.

It is important to underscore that many researchers integrate these simulators with additional software tools, such as the RViz visualiser or MATLAB, to further enhance their simulation capabilities, reflecting the available adaptability for addressing the specific needs of individual studies.

E. HIL AND HITL TESTING FOR WMRS

The study of HIL and HITL in the context of WMRs is an emerging and dynamic field. The current literature offers some insights but also leaves room for exploration. In the case of HIL, a limited number of publications have experimented with AI-enhanced ROS-enabled WMRs [51], [52], [65], [113]. These studies are primarily focused on critical applications, such as

TABLE 6. ROS-Enabled Simulators for WMR

Simulator Type	Reference Numbers
Gazebo Simulators	
Gazebo only	[13], [15], [18], [22], [28], [30], [33], [35], [36], [53], [78], [84]–[88], [90], [92]–[96], [98], [102], [104]–[107], [111], [112], [115], [116], [123], [125], [131], [137], [140], [143], [144], [147], [150], [151], [155], [156], [158], [159], [162], [166], [178], [181], [188], [192], [193], [195], [197], [199]–[202]
Gazebo + RViz	[1], [10], [16], [23], [58], [65], [83], [120], [127], [135], [138], [157], [174], [175], [181], [186], [203]
Gazebo + RViz + MoveIt	[135], [204]
Gazebo + MATLAB	[11]
Gazebo + Stage	[2], [19], [91], [122], [165]
Gazebo + USARSim	[97]
Gazebo + NVIDIA Isaac Sim	[109]
Gazebo + React.js	[100]
Gazebo + Pedsim	[99]
Gazebo + MAVS	[191]
Gazebo + AIMSUN-ROS co-simulation platform	[205]
Gazebo + NoStop	[113]
Gazebo + Unity	[29]
Unity Simulators	
Unity only	[31], [68], [89], [94], [103], [124], [206], [207]
Unity + MATLAB	[208]
Unity + Vuforia + MATLAB	[51]
Unity + MoveIt!	[26]
Unity + SEAN	[34]
3DCoAutoSim (Unity + SUMO)	[67]
Other Simulators/Software	
AirSim (Unreal Engine)	[79]
CoppeliaSim (formerly V-REP)	[20], [69], [117], [126], [142], [172], [209], [210]
PathBench (Panda 3D + ROS)	[17]
Webots	[76], [136]
CARLA (Unreal Engine)	[3], [21], [52], [60], [62], [196]
CARLA (Unreal Engine) + Autoware	[63]
OPIL (Open Platform for Innovations in Logistics)	[173]
Choreonoid (ROS–TMS)	[101]
Bullet	[74]
Duckietown Gym	[32]
RViz only	[81], [176], [189]
RViz + MATLAB	[139]
RViz + Software-in-loop (SIL)	[64]
MATLAB + Simulink	[27]
WiseMove and WiseSim	[37]
Stage (2D)	[72]

autonomous driving [51], [52], [65], and asymmetric threat protection [113]. This limited focus raises questions concerning the scalability and diversity of HIL testing, prompting the need for further exploration and experimentation across various domains and applications.

On the other hand, HITL has found a somewhat broader application, although it still presents limited engagement [24], [28], [29], [34], [53], [89], [98], [102], [103], [112], [119], [124], [176]. Most of these studies interpret HITL as a human control mechanism rather than a human-mediated testing method [28], [89], [98], [102], [112], [119], [176]. Other HITL applications are concerned with human collaboration with robots [29], [124] and social interactions [103]. Only a few pioneering works are leveraging HITL in the robot development process, such as [24], where a robot system learns from user demonstrations and [34] where human feedback trains autonomous methods for unsafe action prediction. Another notable mention is [53], emphasising how human interaction can lead to rapid robot adaptation, eventually eliminating the need for human intervention.

IV. DISCUSSION

In this section, we will answer the research questions as initially posed, based on the information extracted through our literature review.

A. RQ1: WHAT ARE THE APPLICATION AREAS FACILITATED BY AI-DRIVEN METHODOLOGIES IN THE DOMAIN OF WMRS?

Table 3 showcases the diverse application areas of AI-based WMRs. The predominance of "Research" applications is indicative of the critical role that academic inquiry plays in technological progression. For instance, research on digital twin models in Cyber-Physical Manufacturing Systems (CPMS) [73], [74] presents opportunities for real-time monitoring and control, laying the groundwork for its applications in sectors like manufacturing and logistics. Similarly, the academic focus on learning from observation [25] has specific implications for fields that require a high level of adaptability and operational scope. For instance, in a factory setting, robots enabled with learning-from-observation capabilities can watch skilled human operators or other robots to learn new tasks without the need for extensive reprogramming. This not only reduces the time needed for robot training but also enables more flexible robotic systems that can adapt to new tasks on the fly. Furthermore, studies focusing on multi-robot localization and mapping [23], [77], [78] are essential in addressing the challenges related to navigation and obstacle avoidance in multi-agent environments, which have broader implications in fields such as disaster response and agriculture. Importantly, academic research often acts as a testing ground for novel algorithms and techniques. Research outcomes not only validate these methods but also reveal limitations and suggest areas for future investigation. For instance, autonomous exploration in indoor environments [30], [86]–[88] may expose challenges related to sensory data processing or energy efficiency, thereby directing subsequent research or application-focused initiatives.

The strong representation of the "Automotive" and "Healthcare" sectors in the applications of AI-driven WMRs underlines the intersection between technology and societal needs. In the automotive realm, the push towards autonomous driving and complex path planning [2], [58], [60], [62], [65] epitomises the evolution of mobility, redefining our transportation paradigms. Meanwhile, the healthcare sector's diversification into autonomous wheelchairs, automation inside long-term care facilities, and medication delivery [24], [31], [96]–[98], [103], [105] underscores a compassionate application of technology aimed at enhancing human lives. The versatility of WMRs in sectors like "Warehouse and Logistics," "Agriculture," and "Rescue and Disaster Response" showcases the adaptability of AI methodologies. The application of AI in navigation, harvesting, and disaster management [106], [107], [115], [118]–[120] illuminates a technological response to complex real-world challenges. Additionally, the emergence of WMRs in unconventional sectors like "Entertainment" and "Household" [129], [131] offers a glimpse into the future where the boundary between conventional industrial applications and everyday life becomes increasingly blurred.

B. RQ2: WHAT ARE THE PRIMARY PERCEPTION AND CONTROL OBJECTIVES OF WMRS, AND HOW DOES AI CONTRIBUTE TO THEIR ACHIEVEMENT?

The extensive categorisation of AI techniques depicted in Table 4 underscores the multifaceted role of artificial intelligence in shaping modern robotics, particularly in the fields of perception and safety, path planning and control mechanisms. Within the Perception and Safety category, the integration of SLAM algorithms and object detection techniques like YOLO reflects a trend toward real-time processing and adaptability, emphasising the growing demand for responsive and autonomous systems [62], [87], [88], [103], [105]. Meanwhile, the use of algorithms such as RRT, DDPG, and DQL in Path Planning [2], [15], [153] highlights the push towards exploration in unknown or dynamic environments, fostering flexibility and versatility. In terms of Control Mechanisms, the application of LSTM, TD3, and Kalman filters [26], [86], [102] demonstrates a broader shift toward collaborative and adaptive control, reflecting the increasing complexity of tasks that robots are expected to undertake.

However, these advancements also present complexities beyond technical proficiency. One key issue is that of interoperability, as there remains a lack of standard protocols that enable seamless integration between different AI systems and robotic platforms. This raises questions about the potential inefficiencies and risks associated with a fragmented landscape of proprietary systems. Another critical factor is the standardisation of AI methodologies in WMRs [211]. While the development of uniform frameworks could streamline the integration and facilitate broader applications, it could also stifle innovation by creating barriers for emerging, non-standardised solutions. Lastly, there is an ethical dimension that cannot be overlooked, especially when dealing with highly autonomous systems. The deployment of WMRs in fields such as healthcare and public service raises critical questions about safety, privacy, and decision-making. For example, the level of machine autonomy in medical settings must be carefully balanced against patient safety, requiring stringent ethical guidelines [212]. Future research might, therefore, explore these challenges more rigorously, potentially by creating uniform frameworks or investigating the socio-ethical implications of deploying highly autonomous robotic systems in various domains.

By synthesising these findings, it becomes clear that AI's contributions to robotics are both transformative and multi-dimensional, setting a path for continual innovation while also opening avenues for critical examination and enquiry.

C. RQ3: WHICH ROS-ENABLED WMRS ARE EMPLOYED IN AI-DRIVEN PERCEPTION AND CONTROL RESEARCH?

The categorisation of WMRs into "Mobile Robots", "Self-driving Cars", and "Wheelchairs", as detailed in Table 5, presents several insights into the current state and direction of AI-driven perception and control research. The significance of the "Mobile Robot" category, particularly the TurtleBot series [2], [8], [9], [12], [25], [30], [81], [88], [100], [105], [143], [144], [147], [148], [150], [158], [178]–[181], indicates a strong focus on exploration and automation in unstructured environments. This trend may reflect the broader scientific interest in space exploration, disaster recovery, and autonomous navigation. On the other hand, the diversity within the "Self-driving Cars" and "Wheelchairs" categories suggests a more application-specific research focus. Innovations in self-driving cars [156], [194] may be driven by the automotive industry's push towards autonomy, while advancements in robotic wheelchairs [97], [197] likely reflect the growing need for assistive technologies in healthcare and ageing populations. The role of assistive robotics in healthcare, exemplified by platforms like Assistive Gym [213], demonstrates the adaptability and precision required for these applications, necessitating a deep understanding of both robotic taxonomy and the specific requirements of healthcare scenarios [214]. The disparate emphasis between categories illustrates the multi-dimensional nature of WMRs research, highlighting both the convergence on widely accepted platforms and the constant exploration of new terrains and functionalities. This difference gives insight into the challenges of harmonising standards with innovation in a rapidly evolving field.

D. RQ4: WHAT ROS-COMPATIBLE SIMULATION PLATFORMS ARE AVAILABLE FOR WMRS?

Our systematic review on ROS-enabled simulators for WMRs offers clear trends regarding simulation platform preferences and utilisation within the community. According to current academic literature, Gazebo has become the primary simulator, accounting for 70.5% of references in Table 6. This dominance can be attributed to its open-source nature, continuous community support, and modularity, as evidenced by its frequent pairing with RViz. Although Gazebo currently dominates, the data shows a noticeable increase in the use of game engines such as Unity [31], [68], [89], [94], [103], [124], [206] and Unreal Engine [3], [21], [52], [60], [62], [63], [79], [196]. The reason for the popularity of these engines is that they are capable of producing high-quality, real-time graphics rendering and contain easy-to-use machine learning tools. Unreal Engine serves as the foundation for leading autonomous vehicle simulators CARLA and AirSim, while Unity's latest official ROS support is likely to speed up its adoption even more.

A notable observation is the discrepancy between the list of available simulators in Table 1 and those frequently cited in Table 6. Many capable platforms, such as Webots and MuJoCo, are utilised less for WMRs compared to Gazebo. This disparity underscores the importance of factors beyond mere availability in determining simulator selection, such as physics engine and model format support, ease of use, integrative capabilities and community support [215]. As the robotics community progresses, their preferred tools will also advance. The steady rise of game engines, owing to their unmatched visualisation and emerging ROS support, suggests a potentially transformative shift in the near future. Future research might delve deeper into the factors influencing these choices to provide clearer guidance for both current researchers and newcomers to the field.

E. RQ5: HOW SIGNIFICANT ARE HIL AND HITL TESTING METHODOLOGIES IN THE DESIGN PROCESS OF WMRS?

The utilization of HIL and HITL testing methodologies in the design process of WMRs appears promising but is notably limited in current practice. Although HIL offers valuable advantages such as early problem detection and cost reduction, its application has been confined to a narrow range of critical domains, such as autonomous driving and threat protection [51], [52], [65], [113]. Similarly, while HITL could allow rapid adaptation, effective robot training and performance enhancement [24], [34], [53], the literature mainly interprets it as a human control mechanism rather than a testing method [28], [89], [98], [102], [112], [119], [176]. This scarcity of diverse applications in the reviewed literature may signal a discrepancy between the theoretical significance of HIL and HITL and their practical adoption. It raises important questions about the challenges, perceptions, or misconceptions that may be hindering wider experimentation and integration of these methodologies. Thus, while the benefits of HIL and HITL are evident, their actual impact on the design process of WMRs appears constrained, warranting further investigation and critical reflection on the underlying barriers to their more popular use.

V. CONCLUSION

In this comprehensive systematic literature review, we explored ROS-enabled simulators used for AI-enhanced WMRs. To ensure a robust methodology, our research was conducted by following the *PICOC* framework and employing the *PRISMA* diagram to categorise and analyse the selected papers. The investigation was guided by five research questions and addressed the following points:

1) **WMR Applications:** The various applications of WMRs across industries were examined, identifying the state-of-the-art advancements reported in 186 relevant papers. The growing interest in this subject area is evident from the significant increase in the number of papers published in recent years, as shown in our analysis.
2) **Perception and Control Tasks:** The main perception and control tasks for ROS-enabled WMRs are summarised. We explored the various AI approaches employed to accomplish these tasks, providing a detailed view of the methodologies and techniques used. This specification offers a clear understanding of the current landscape and serves as a foundational reference for future innovations and developments in the field.
3) **Widely Used Robots:** Widely used WMR models were identified in this study, providing a valuable reference for researchers and practitioners.

4) **ROS-enabled Simulation Platforms:** Our findings provide insight into ROS-enabled simulation platforms commonly used for designing AI-enhanced WMRs. Notably, we observed Gazebo's dominance as a simulator and the emergence of the Unity and Unreal Engine game engines for the purpose of robotic simulation.
5) **Significance of HIL and HITL testing:** Our survey of HIL and HITL testing methodologies highlighted their underutilisation but high potential in the design process of WMRs.

The distinct contribution of this review lies in its concentrated exploration of ROS-enabled simulators specific to AI-enhanced WMRs, a subject that has not been comprehensively addressed in the existing literature. This specialised emphasis offers fresh insights into the field, enhancing comprehension of the interplay between ROS-enabled environments and sophisticated AI techniques in WMRs, and consequently enriching the discourse with insights into how these technologies synergise to advance robotic capabilities. Our meticulous approach in dissecting and categorising the current state of research in this domain not only fills a critical gap in the academic literature but also paves the way for future explorations.

Future work

Based on the comprehensive insights gained from our review, we propose the following directions for future research in the domain of ROS-enabled simulators and AI-enhanced WMRs:

- **Advancing High-Fidelity Simulations:** Investigate the potential of advanced simulation platforms like Unity and Unreal Engine for their high-fidelity graphics capabilities. Future studies should explore how these platforms can enhance tasks requiring detailed visual data and assess their applicability in more complex simulation scenarios.
- **Enhancing Human-Robot Interaction:** Investigate the development of simulators that can effectively mimic human-robot interactions across various contexts, such as healthcare and public service. Emphasis should be on simulating diverse human behaviors and environments to enhance the adaptability and safety of WMRs in scenarios such as patient care, customer service and personal assistance.
- **Ethical Considerations in Autonomous System Deployment:** Address the ethical challenges associated with deploying highly autonomous WMRs, particularly in sensitive sectors like automotive, military and healthcare. Future studies should aim to develop ethical guidelines and safety protocols that balance the benefits of autonomy with the need for human oversight and safety.
- **Exploring Novel AI Techniques for WMRs:** Investigate emerging AI methodologies and their application in enhancing the perception and control capabilities of WMRs. Future research should delve into the potential of cutting-edge AI techniques to solve existing challenges and open up new possibilities in robotic navigation and task execution.
- **Standardisation and Interoperability in AI-driven WMRs:** Examine the need for standard protocols and frameworks to facilitate seamless integration between different AI systems and robotic platforms. Future research should focus on developing universal standards that can accommodate a diverse range of AI methodologies and robotic models, enhancing the interoperability within the field.
- **Advancing Collaborative Multi-Robot Systems:** Explore the development and coordination of multi-agent WMR systems for scenarios requiring teamwork, such as search and rescue or industrial tasks. Focus on enhancing communication, coordination, and collaborative task execution, integrating advanced AI to facilitate adaptive decision-making in these collaborative environments.
- **Enhancing WMR Adaptability in Unstructured Environments:** Investigate the development of WMRs for operation in unconventional and challenging environments, such as disaster zones and extraterrestrial missions. Emphasise improving robustness and adaptability to diverse conditions, including extreme weather and varied terrain, by integrating advanced sensory systems like LiDAR, SONAR, and thermal imaging. Focus on enhancing the reliability of AI systems in these dynamic settings to ensure effective operation and decision-making.
- **Expanding the Use of HIL and HITL in Robotics:** Explore the broader application of HIL and HITL methodologies in the development and testing of robotic systems. Future research should aim to understand how these approaches can improve the performance and efficiency of WMRs, particularly in complex control and environmental interaction scenarios.

This study's thorough examination of ROS-enabled simulators in AI-enhanced WMRs has far-reaching implications for the future of robotic research and application. By providing a thorough examination of current practices and emerging trends, our review lays the groundwork for significant advancements in the field. The insights garnered from this research could catalyse the development of more sophisticated control algorithms and perception models, thereby enhancing the autonomy and efficiency of WMRs. Additionally, the identification of gaps and underexplored areas presents opportunities for innovative research, potentially leading to breakthroughs in how WMRs interact with and navigate their environments. Furthermore, this research could inspire the development of more comprehensive, standardised, and interoperable ROS-based platforms. As the integration of ROS and AI continues to evolve, we anticipate a notable shift in the capabilities of robotic systems, opening new possibilities for their application in complex, real-world scenarios. This could result in transformative changes not only in robotic technology but also in how these systems are implemented across various sectors, from automotive to healthcare, logistics and beyond.

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