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A comprehensive review on humanoid robots: perspectives from academia and industry

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Abstract: Humanoid robotics represents a rapidly evolving research domain that integrates artificial intelligence and robotics. Despite significant advances, existing reviews have predominantly focused on narrow technical aspects and lack comprehensive analysis from academic and industrial perspectives. This paper presents a systematic dual-perspective survey, in which academic literature, commercial products, and industry reports are extensively analyzed. A comprehensive taxonomic framework and systematic review of key enabling technologies are established, including ontological structures, perception systems, locomotion control, intelligent decision-making algorithms, foundation model integration, and human–robot interaction (HRI) technologies. From academic and industrial perspectives, research progress across diverse applications is examined, and a detailed comparative analysis of commercial products from leading companies, including Tesla, Boston Dynamics, and UBTECH, is performed. Six major challenge categories are identified: hardware design limitations, control system complexities, perception constraints, HRI difficulties, application-specific requirements, and ethical considerations. In addition, the transformative impact and integration challenges of large language models are particularly discussed. Seven promising research directions are outlined, and a systematic academic–industrial gap analysis is conducted. Consequently, significant disparities and technology transfer bottlenecks are identified, and successful collaboration models are examined. This comprehensive survey provides the first systematic examination combining academic research insights with industrial development analysis. It thus offers valuable guidance for researchers, engineers, and policymakers working toward more capable, affordable, and socially integrated humanoid robots.

Key words: Humanoid robots; Dual-perspective analysis; Industrial applications; Technical challenges; Future directions

1 Introduction

Humanoid robotics, also known as anthropomorphic or human-like robots, represents a significant research branch within intelligent robotics that has witnessed unprecedented growth in recent years. In general, humanoid robots possess human-like forms and functions, including anthropomorphic limbs, movement, and operational skills, as well as perception, learning, and cognitive abilities. They can perform complex or specific human-like activities in various environments, embodying a high degree of integration between artificial intelligence (AI) and robotics technologies. Compared with other types of intelligent robots, humanoid robots exhibit stronger environmental adaptability, perform more diverse task operations, and establish more harmonious human–robot interaction (HRI); thus, they are recognized as comprehensive embodiments of robotic technologies.

The application domains of humanoid robots are expanding rapidly, with areas encompassing education, entertainment,

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service industries, healthcare, industrial production, disaster rescue, and military operations. With technological advancements driven by breakthroughs in AI, materials science, and manufacturing processes, humanoid robots are gradually transitioning from laboratory prototypes to practical assistants in human life and work. However, existing research and applications of humanoid robots, particularly those with high intelligence and commercial viability, face significant challenges that demand systematic analysis and strategic solutions. Recent advances in AI, particularly the emergence of large language models (LLMs) and foundation models, have provided new impetus for addressing these challenges and expanding the capabilities of humanoid robots. The integration of sophisticated natural language understanding with embodied intelligence represents a paradigm shift toward more intuitive HRI; however, it has introduced new technical and safety considerations that require systematic investigations.

Despite the growing interest in humanoid robotics, existing literature reviews exhibit several critical limitations that are addressed in this paper. Most previous surveys have focused narrowly on specific application domains or individual technological aspects, lacking the comprehensive perspective required to understand the current state and future trajectory of humanoid robotics. For instance, specialized reviews have examined humanoid robots in healthcare (Joseph et al., 2018; Lau et al., 2020), disaster response (Tsagarakis et al., 2017), or specific technical components such as robot heads (Li Y et al., 2024). In addition, early comprehensive works explored the potential applications of humanoid robots in home and factory environments (Kawamura et al., 1996). Other studies have provided foundational overviews of humanoid robot development from actuator perspectives (Saeedvand et al., 2019) and emphasized the robots' roles in specific fields such as healthcare and education (Denny et al., 2016). More recent comprehensive surveys have integrated AI technologies with robotics (Saeedvand et al., 2019) and provided systematic reviews of related technological progress (Fukuda et al., 2017; Stasse and Flayols, 2019; Tong et al., 2024). Although these studies provide valuable insights into particular aspects of humanoid robotics, they fail to capture the interdisciplinary nature and associated systemic challenges.

Furthermore, existing comprehensive surveys (Denny et al., 2016; Fukuda et al., 2017; Saeedvand et al., 2019; Stasse and Flayols, 2019; Tong et al., 2024; Cao, 2025) have predominantly adopted an academic perspective, emphasizing theoretical developments and research prototypes while insufficiently analyzing the industrial progress and commercial viability. This academic bias creates a significant gap in understanding the practical challenges, market dynamics, and real-world deployment considerations of humanoid robot systems that are crucial for the advancement of this field. The lack of systematic comparison between academic achievements and industrial products limits the ability to identify practical bottlenecks and guide future development strategies.

Another notable limitation in existing literature is the absence of a detailed comparative analysis of mainstream commercial products. Although academic papers may mention specific robots such as ASIMO, Atlas, or Optimus, they rarely provide systematic technical comparisons or market analysis that will inform both researchers and practitioners about the current state of technology transfer from laboratory to industry. This gap is particularly problematic due to rapid commercial developments in recent years, with companies such as Tesla, Boston Dynamics, and UBTECH making significant strides in humanoid robot development.

To address these limitations, we conducted a comprehensive survey by employing several innovative approaches and making contributions. First, we adopted a dual-perspective analytical framework that systematically examines humanoid robots from both academic research and industrial development viewpoints. Using this approach, humanoid robotics can be comprehensively understood based on the relationships, gaps, and synergies between theoretical advances and practical implementations. Second, we performed extensive comparative analyses of representative commercial products, including detailed technical specifications, performance benchmarks, and market positioning analyses, dimensions that existing studies have rarely explored. Third, we employed a systematic challenge–solution methodology in our survey to identify current limitations and proposed targeted improvement strategies along with promising research directions. Rather than simply cataloging existing studies, we analyzed the underlying causes of technical bottlenecks and provided actionable recommendations for overcoming them. Fourth, we established a comprehensive taxonomic framework for humanoid robots that encompasses multiple classification dimensions, thereby offering researchers and practitioners a structured approach to understanding the diverse landscape of humanoid robotics.

1.1 Literature search methodology

We conducted a systematic literature search across IEEE Xplore, ACM digital library, Springer, and ScienceDirect (January 2000–December 2024), with targeted retrieval from ICRA (IEEE International Conference on Robotics and Automation), RSS (Robotics: Science and Systems), and CoRL (Conference on Robot Learning) proceedings (2015–2024). The search terms combined "humanoid robot*" and "bipedal robot*" with technical descriptors (locomotion control, perception, HRI, and foundation models) and application domains using Boolean operators.

The inclusion criteria included peer-reviewed publications, full-body humanoids ($\geq$12 degrees of freedom (DOFs)), significant technical contributions, and articles written in English. The exclusion criteria included non-humanoid platforms, purely theoretical work, and duplicates. For the industrial analysis, we examined official specifications, white papers, patents, and industry reports (2020–2024) for 12 representative commercial products selected based on market impact and technical advancements. The final corpus comprises about 300 academic papers and a comprehensive industrial product analysis.

1.2 Contributions and paper organization

The primary contributions of this paper are summarized as follows:

1. Comprehensive dual-perspective analysis. For the first time, we systematically analyzed humanoid robots from both

academic and industrial perspectives, revealing critical insights into technology transfer challenges and commercial viability factors.

2. Extensive industrial product analysis. We conducted a detailed comparative analysis of representative commercial humanoid robots, including technical specifications, performance metrics, and market positioning, thereby filling a significant gap in existing literature.

3. Systematic challenge–solution framework. We identified and categorized six major challenge areas with targeted improvement strategies and seven promising research directions, providing a roadmap for future development.

4. Integrated technological assessment. We comprehensively analyzed key enabling technologies and their interdependencies, revealing system-level design considerations that are often overlooked in component-focused reviews.

The remainder of this paper is organized as follows. Section 2 reviews the classification, development history, and key technologies of humanoid robots. Section 3 discusses recent advances in humanoid robot technology from both academic and industrial perspectives, analyzing the gaps and collaborations between the two sides. Section 4 explores current challenges facing humanoid robot technology, while Section 5 outlines promising future research directions. Finally, Section 6 concludes the paper.

2 Definition and taxonomy

2.1 Definition

Intelligent robots are advanced automated machines that integrate AI, perception systems, decision algorithms, and action capabilities to perform complex tasks; they thus exhibit a certain level of autonomy in their environment.

Humanoid robotics is the most influential and attractive branch of research and application within intelligent robotics. Humanoid robots generally have a human-like appearance, including a head, torso, limbs, and other features, as well as perception, locomotion, learning, and cognitive capabilities comparable to those of humans. They can replace humans in performing certain complex or specialized human-like activities and are a highly integrated product of AI, biology, and robotics technology. Compared with other categories of intelligent robots, humanoid robots have several advantages; these include a more friendly HRI experience, stronger environmental adaptability, and self-sufficiency. These robots can be widely applied in various fields such as home life, education, industrial production, social services, and rescue operations.

2.2 Classification

As shown in Fig. 1, humanoid robots can be classified into different categories according to different standards: (1) functionality: research, industry, service, entertainment, and education; (2) application fields: medical, home, industry, military, and space exploration; (3) mobility: fixed-based, wheel-based, bipedal walking, and multi-legged or hybrid mobile; (4) interaction capabilities: basic interaction, advanced interaction, and social interaction; (5) operational complexity: simple operation and complex operation; (6) autonomy: remote-controlled, semi-autonomous, and fully autonomous; (7) size: adult-sized and child-sized; (8) development stage: prototype systems and commercial products.

2.3 History

As shown in Fig. 2, the origin of humanoid robots can be traced back to the era of Leonardo da Vinci in the 15th century. The development of modern humanoid robots began in the first half of the 20th century in the United States, with in-depth research emerging in the 1960s. Overall, the development of humanoid robots can be categorized into four stages: The first stage is the preliminary walking stage of full-sized humanoid robots, exemplified by the WABOT-1 robot developed by Waseda University in Japan. The second stage is the breakthrough stage in the capabilities of humanoid robots,

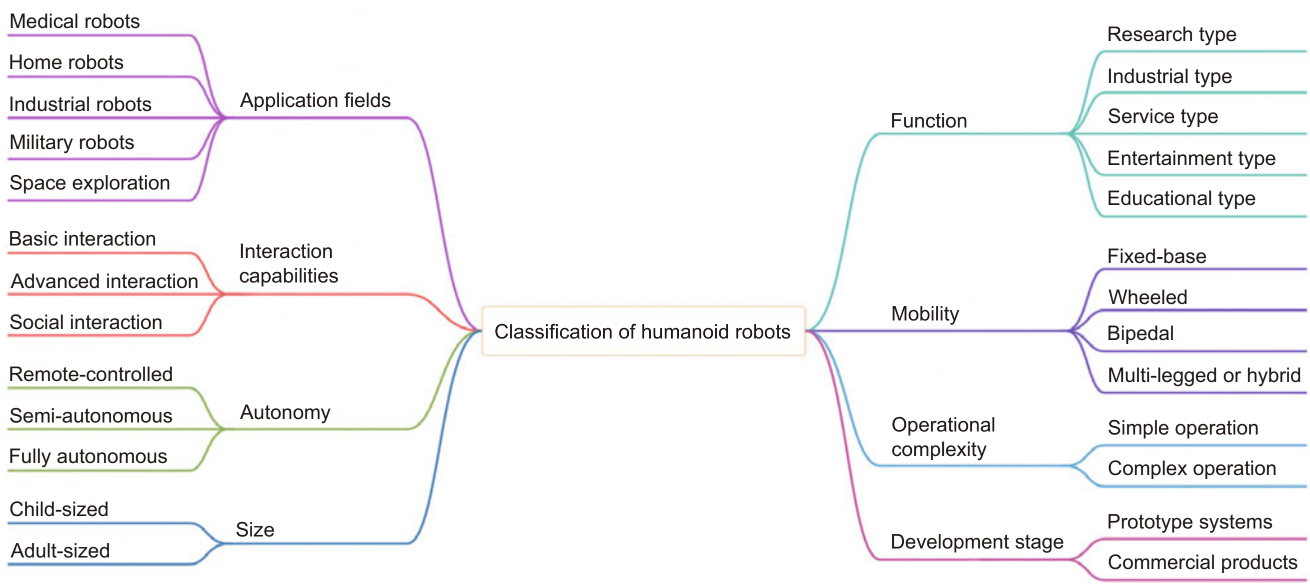

Fig. 1 Classification of humanoid robots

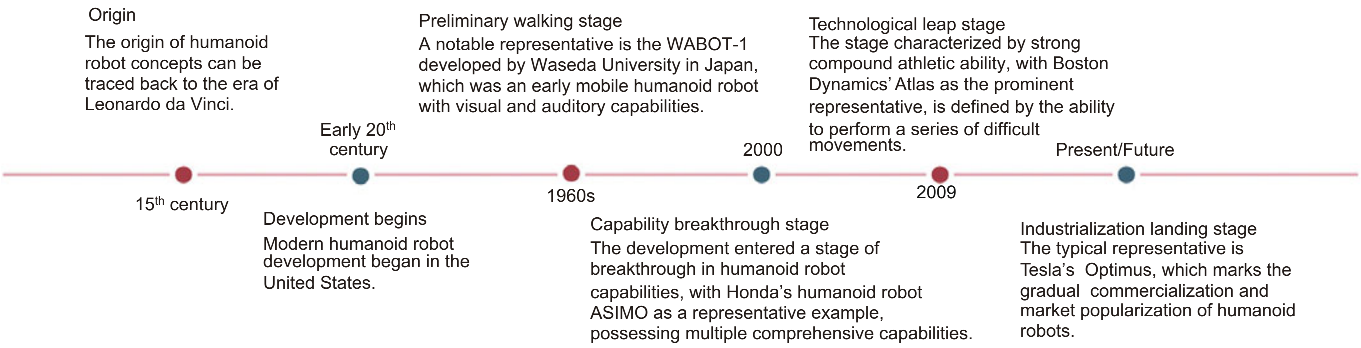

Fig. 2 Development timeline of humanoid robots

represented by ASIMO created by Honda. The third stage is the technological leap stage, characterized by strong composite motion capabilities, such as Atlas developed by Boston Dynamics. The fourth stage is the industrialization landing stage, illustrated by the Optimus robot developed by Tesla (Su, 2023).

WABOT-1, developed by Waseda University in 1973, was equipped with a limb control system, a visual system, and a speech interaction system. It marked the initial achievement of bipedal walking in a full-sized humanoid robot, and its main creator, Ichiro Kato, is known as the father of humanoid robots. Honda's ASIMO was first introduced in 2000 and has undergone several iterations since then. The latest generation possesses various integrated capabilities, including obstacle avoidance, predefined actions, and response to human voice and gestures. Boston Dynamics' Atlas was introduced in 2009; with years of optimizations, it can now perform various challenging movements, including jumping, rolling, running, and triple jumps in complex obstacle environments. Tesla's Optimus robot is currently one of the most representative achievements in humanoid robotics. It can precisely control its movements, navigate and remember paths, and perform end-to-end action control based on human motion demonstrations.

The field of humanoid robotics has progressed from development toward its high integration, environment perception, agile movement, precise manipulation, and industrial quantification.

2.4 Key technologies

Although the adopted technologies vary across humanoid robots and continuously evolve, many technologies have universal applicability. Herein, key technologies adopted by humanoid robots, including ontological structure, perception capabilities, locomotion capabilities, intelligent control, and decision-making, are discussed. The main functional modules include the perception module (similar to human sensory organs such as eyes, ears, nose, and skin used to perceive external environmental information), the body control module (similar to the human torso and limbs, enabling movement, body control, and energy provision), and the HRI module (similar to the human brain that implements functions such as speech recognition, image recognition, speech synthesis, intelligent learning, and decision-making), as shown in Fig. 3.

2.4.1 Ontological structure

Humanoid robots are complex systems with multiple human-like joints and redundant DoFs. Their body is the

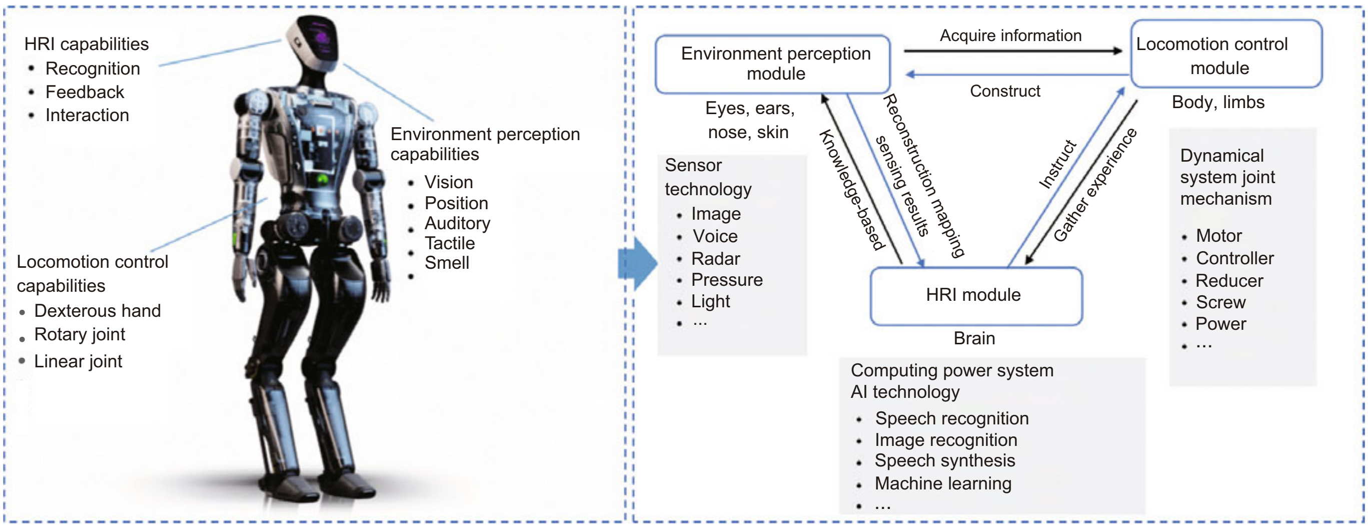

Fig. 3 Main functional modules and key technologies of humanoid robots

foundation for achieving high speed, dexterity, and explosive locomotion. The ontological structure of humanoid robots can generally be divided into three parts: actuators (including servo systems, gear reducers, and drive units); controllers (such as industrial control systems and AI-related systems); and sensors (including body perception sensors and machine vision).

2.4.2 Perception capabilities

Humanoid robots must perceive their environment like humans and autonomously adjust their behaviors based on environmental changes. To perform data collection and environmental cognition, these robots must be equipped with various types of sensors (such as vision, auditory, tactile, and light sensors). Multi-sensor information fusion technology combines complementary and redundant information across space and time, based on certain optimization criteria, to generate a consistent interpretation of the observed environment. By employing multi-sensor information fusion, humanoid robots can precisely detect environmental changes and perform effective movements and efficient operations.

2.4.3 Locomotion capabilities

Locomotion capabilities are crucial for humanoid robots to achieve human-like movements and perform dynamic tasks. To this end, technologies such as dynamic configuration modeling, high DOF locomotion planning, and unknown disturbance balance control are employed. The United States is at the forefront of humanoid robot locomotion control technology, offering technical support and talent reserves for the industrialization of humanoid robots. Boston Dynamics continuously improves the locomotion capabilities of humanoid robots by employing advanced mechanical designs and dynamic control systems. Its humanoid robot, Atlas, demonstrates exceptional locomotion, including dynamic walking, running, jumping, and complex acrobatics in challenging environments. Tesla leverages AI algorithms to enhance the locomotion adaptability of its humanoid robots. Optimus integrates advanced neural network-based motion planning and environmental perception systems, enabling adaptive locomotion in diverse scenarios. The integration of AI-driven locomotion planning with real-time environmental feedback represents a significant advancement in humanoid robot mobility.

2.4.4 Intelligent control systems

As electromechanical intelligent composites, humanoid robots aim to approach or even exceed human performance levels in task execution. This objective is primarily accomplished using sophisticated control systems comprising multiple layers of control algorithms and decision-making processes. Advanced control algorithms, including horizontal reaction control, zero moment point (ZMP) control, and adaptive walking control, are integrated with hardware components such as control systems, gear reducers, and motors. These integrated control architectures support intelligent behavior decision-making and enable real-time responses of humanoid robots to environmental changes. The complexity of control systems considerably increases as humanoid robots become increasingly sophisticated. This necessitates seamless integration across low-level motor control, mid-level motion planning, and high-level cognitive decision-making. Modern humanoid robots employ hierarchical control architectures that can process sensory information, plan appropriate actions, and execute complex behaviors while maintaining stability and safety during HRIs.

2.4.5 Foundation models and embodied intelligence

The integration of foundation models, particularly LLMs and multimodal models, is a transformative advancement in humanoid robotics; it enables more natural HRIs and enhanced autonomous decision-making capabilities. Recent developments in LLMs have shown remarkable capabilities in understanding natural language instructions and translating them into executable robot behaviors (Brohan et al., 2023). These models can process complex task descriptions and decompose them into step-by-step action sequences that can be executed by humanoid robots.

Vision–language models (VLMs) enable robots to understand and reason about visual information and textual instructions (Driess et al., 2023). These models process camera feeds, identify objects and scenes, and generate appropriate responses based on visual and linguistic contexts. Embodied AI systems that integrate abstract language concepts with physical-world constraints with robot capabilities are critical developments in this context (Ichter et al., 2022). Technologies such as robotic Transformers (RT-1, RT-2) demonstrate how Transformer architectures can be adapted to directly output robot actions while maintaining reasoning capabilities. These technologies thus bridge the gap between high-level language understanding and low-level motor control.

The integration of embodied AI, particularly in cross-embodiment learning and model efficiency, has witnessed rapid advancements during 2024–2025. OpenVLA achieved a 16.5% absolute performance improvement over RT-2-X (55 billion parameters) while using 7× fewer parameters (7 billion), after training on 970 000 robot demonstrations across 29 tasks and multiple embodiments (Kim MJ et al., 2024). This superior data efficiency, combined with a 20.4% performance gain over diffusion policy in multitask environments, demonstrates the effectiveness of vision–language–action integration for generalist manipulation.

The Open X-embodiment collaboration represents a paradigm shift in robotic learning datasets. It unites 293 authors from 34 institutions (22 academic and 12 industrial), creating over 1 million real robot trajectories spanning 22 platforms and 527 skills (Collaboration, 2024). The resulting RT-X models have achieved a 50% average success rate improvement compared with embodiment-specific methods. RT-2-X has achieved 3× generalization improvements, validating the cross-embodiment training hypothesis. This collaborative framework addresses the data scarcity problem that has historically constrained robotics research by establishing shared evaluation benchmarks and data formats. These innovations have accelerated technology transfer between academic and industrial domains.

Complementary advances in generalist robot policies further enhance robot deployment capabilities. Octo, trained on 800 000 trajectories from Open X-embodiment, demonstrates zero-shot control across nine robot platforms, while supporting efficient fine-tuning to new sensor configurations and action spaces (Octo Model Team et al., 2024). Octo has achieved performance parity with RT-2-X on WidowX tasks with considerably low computational requirements, indicating that efficient model architectures can match the performance of larger systems in specific domains. Recent efficiency optimizations via quantization and architectural improvements have reduced inference time and computational costs, making real-time humanoid robot deployment increasingly feasible (Kim MJ et al., 2024; Octo Model Team et al., 2024).

These breakthroughs collectively address critical deployment barriers: OpenVLA's parameter efficiency enables edge deployment, Open X-embodiment's scale provides robust generalization, and Octo's flexibility supports rapid adaptation to new platforms. However, challenges remain in grounding language understanding in physical world constraints, ensuring real-time performance in safety-critical applications and maintaining reliability across diverse operational conditions. Future research must balance foundation-model capabilities with the practical requirements of robust, safe, and efficient humanoid robot systems.

2.4.6 HRI technologies

HRI technologies enable natural and intuitive communication between humans and humanoid robots via multimodal communication, emotional intelligence, and adaptive interaction mechanisms. Effective HRI requires integrating multiple communication channels, including verbal and nonverbal cues. Modern humanoid robots employ sophisticated speech recognition and synthesis systems, while gesture recognition systems enable them to understand human body language, hand gestures, and facial expressions (Breazeal, 2003).

Affective computing technologies enable robots to analyze facial expressions, vocal intonation, and contextual information to infer human emotional states (Bethel and Murphy, 2010). In addition, advanced systems incorporate social cognition capabilities that allow robots to understand human intentions and social dynamics, enabling contextually appropriate responses (Scassellati, 2002). Natural language processing systems enable robots to understand complex instructions, engage in multiturn conversations, and maintain contextual awareness throughout extended interactions (Thomaz and Breazeal, 2008). Modern HRI systems incorporate user modeling capabilities that enable robots to adapt their interaction style to individual users over time (Leite et al., 2013). They thus learn user preferences and communication patterns to provide personalized interactions.

3 State of the art in research

3.1 Academic perspectives

3.1.1 Literature analysis based on application fields

The integration of robotics and AI technologies has driven the development of humanoid robots. Today, humanoid robots are extensively applied in various fields such as social production, daily life, entertainment, service industry, healthcare, education, and disaster relief and rescue. These robots have considerably reduced the workload for humans in these domains while providing a wide range of extended services.

1. Daily life, entertainment, and services

Sawasaki et al. (2003) developed a remotely controlled humanoid domestic robot with an interactive interface. Bäck et al. (2012) investigated the feasibility of using humanoid robots as service assistants in nursing homes, using the NAO H25 humanoid robot to provide care for older adults. In the event of an abnormality, this robot issues an alarm and transmits real-time images while helping establish a voice connection between residents and remote caregivers. Bui et al. (2017) effectively integrated humanoid robots into ECHONET-based smart home environments to provide living support for the elderly and disabled individuals.

Entertainment applications have shown significant progress with robots such as SDR-3X (Ishida et al., 2001) and SDR-4X (Fujita et al., 2003), which incorporate real-time adaptive locomotion control, spatial perception, and multimodal HRI capabilities for dancing and singing performances. Kudoh et al. (2008) adopted the "learning from observation" paradigm for humanoid robots to learn classic Japanese folk dances.

In tourism management and services, humanoid robots enhance service efficiency and promote HRI. Osawa et al. (2017) introduced the world's first robot hotel, Henn na Hotel, where most operations are performed by robots. In addition, Yoganathan et al. (2021) designed a hotel check-in service robot, demonstrating the broad prospects of humanoid robots in the service industry.

2. Healthcare

Healthcare is a crucial domain for humanoid robot deployment, and related studies have focused on patient assistance (Zhang F and Demiris, 2022), caregiving scenarios (Nishiyama et al., 2003), and elderly care (Tanioka, 2019). Bhuvaneswari et al. (2013) developed a physiotherapeutic assistive trainer using the NAO humanoid robot. To address patient handling risks, Hu et al. (2011) developed a mobile robotic nursing assistant with intelligent navigation and omnidirectional driving capabilities.

3. Sports

Humanoid robots have demonstrated strong capabilities in sports applications, particularly in soccer competitions. Fan et al. (2019) reported a fully autonomous humanoid robot developed by the ZJUDancer team for RoboCup 2019, featuring 18 DOFs and advanced hardware–software integration. Various control methods have been employed to improve the performance of robots in soccer (Sulistijono et al., 2010; Allali et al., 2017, 2024). The HuroCup competition has expanded to include multiple events such as basketball, weightlifting, and marathon, addressing key research areas such as active balance and complex motion planning (Chou et al., 2011; Baltes et al., 2017; Zhang SQ et al., 2023).

4. Industrial and manufacturing

Humanoid robots have been employed in industrial applications to operate in challenging environments and perform complex tasks. Early developments include HRP-1 and HRP-1S robots that can operate industrial vehicles in harsh outdoor environments (Hasunuma et al., 2002, 2003; Yokoi et al., 2003).

Recently, humanoid robots have been employed for aircraft manufacturing (Kheddar et al., 2019) and large-scale assembly industries (Kaneko et al., 2019), emphasizing safety, shared workspace considerations, and advanced joint technologies for industrial applications. For heavy-duty manipulation tasks, Ohmura and Kuniyoshi (2007) developed a humanoid robot that could lift 30 kg objects using whole-body contact and tactile feedback, demonstrating the potential for employing humanoid robots for material handling applications.

5. Education

Educational applications leverage humanoid robots as interactive teaching platforms. Studies have focused on developing robots as teaching assistants (Chin et al., 2011), implementing natural language processing for student interaction (Budiharto et al., 2017), and creating specialized educational robots for sign language instruction (Meghdari et al., 2019). These applications emphasize the importance of HRI in educational contexts and the development of cost-effective solutions for diverse educational needs.

6. Rescue and high-risk environments

Humanoid robots show significant potential in disaster response and high-risk operations. Applications include search and rescue operations, post-disaster rapid deployment (Tsagarakis et al., 2017), and specialized tasks that require dexterous manipulation and robust locomotion (Wagoner et al., 2015; Negrello et al., 2016). In addition, military applications of humanoid robots focus on casualty extraction tasks (Choi et al., 2019), while space applications encompass extravehicular activities and planetary exploration (Diffler et al., 2003; Stoica and Keymeulen, 2006; Diftler et al., 2011). These applications emphasize the need for robots that can reliably operate in extreme conditions while maintaining human-like dexterity and decision-making capabilities.

7. Real-world deployment case studies

To illustrate practical implementation challenges, we present representative case studies from education and disaster response domains, highlighting achievements and limitations in the real-world deployments of humanoid robots.

(1) Education domain

NAO robot for autism spectrum disorder therapy. Multiple studies between 2020 and 2022 deployed NAO robots for social-skill training in children with autism spectrum disorder (ASD). Rakhymbayeva (2021) conducted a study including 11 children aged between 4 and 11 years over seven 15-min sessions. Although no statistically significant changes were observed in the overall engagement duration, children showed higher engagement in familiar tasks compared to novel activities. Alnajjar et al. (2021) demonstrated that NAO-assisted interventions could improve attention and emotional recognition in 11 children with ASD via autonomous robot–child interactions. However, Korneder et al. (2021) found that children generally required more prompts from robots than from human therapists to successfully complete joint attention tasks, indicating that robots function best as therapeutic supplements rather than replacements. Common implementation barriers included high costs ($15 000–20 000 per unit), weekly maintenance requirements, and the persistent need for guidance from human therapists in 80%–90% of effective interventions.

(2) Disaster response domain

Boston Dynamics Spot in COVID-19 hospital operations. During the COVID-19 pandemic, Boston Dynamics deployed its quadruped robot Spot at Brigham and Women's Hospital in Boston for contactless patient triage and monitoring vital signs (Boston Dynamics, 2020). Researchers from the Massachusetts Institute of Technology (MIT) and the hospital mounted thermal cameras and iPad interfaces on Spot, so that healthcare workers could remotely assess patients in outdoor triage tents (Huang HW et al., 2022). This system measured skin temperature, breathing rate, pulse rate, and blood oxygen saturation of patients from a distance of 2 meters. The hospital staff reported that one-sixth of their workforce had contracted COVID-19 before robot deployment; however, the initial deployment of Spot reduced healthcare workers' exposure during patient-intake shifts.

However, significant limitations emerged: thermal screening accuracy proved insufficient for reliable fever detection (±0.5 ℃ variance), requiring follow-up using conventional methods (Huang HW et al., 2022); navigation failures occurred in 20%–25% of attempts in cluttered indoor environments; approximately 30% of elderly patients reported discomfort with robot interactions (Boston Dynamics, 2020). The deployment cost of 74 500 per unit plus 25 000–35 000 for medical equipment integration proved prohibitive for most hospitals (Boston Dynamics, 2020). Post-pandemic, no hospitals continued regular robotic operations, and administrators cited unsustainable costs and strong patient preference for human care. This real-world deployment illustrated the "last-mile" challenge: although robots reduced exposure during initial screening, critical patient care required human presence, which limited the practical value proposition for routine clinical use.

3.1.2 Literature analysis based on key technologies

1. Ontological structure

(1) Actuators

The selection of actuators and reduction ratios is an important issue in the design of humanoid robots. These actuators must meet the following criteria: a high power-to-weight ratio, the capability to generate high torque at low speeds, small size, and the capability for reverse driving (Stasse and Flayols, 2019).

Electric actuators. Electric actuators are commonly used in humanoid robots, offering high control precision and reliability. These actuators use brushed or brushless direct current (DC) motors, each offering distinct advantages. Brushless DC motors provide higher power density and torque bandwidth, whereas brushed DC motors offer enhanced design flexibility and thermal performance under harsh conditions (Kanehira et al., 2002; Oh et al., 2006; Park et al., 2007; Gouaillier et al., 2009). Although alternating current (AC) motors require more complex control systems, they provide higher speed capabilities and are suitable for applications that require rapid footstep corrections (Kim JY et al., 2007).

Pneumatic actuators. Pneumatic actuators, particularly McKibben artificial muscles, offer bio-inspired characteristics with excellent power-to-weight ratios and natural compliance (van Ham et al., 2003; Hashimoto et al., 2006; Niiyama et al., 2007; Yoshikawa et al., 2011; Tondu, 2012). These actuators are particularly suitable for applications requiring dynamic movements and natural human-like motion patterns, as demonstrated in robots such as Mowgli (Niiyama et al., 2007), SAYA (Hashimoto et al., 2006), and Lucy (van Ham et al., 2003).

Hydraulic actuators. Hydraulic actuators provide extremely high power density and bandwidth, making them ideal for complex dynamic operations. Although these actuators have high noise and power requirements, many of these limitations have been addressed in recent developments in integrated electro-hydraulic actuators (Cheng G et al., 2007; Alfayad et al., 2011; Nelson et al., 2012; Atmeh et al., 2014). Atlas exemplifies the successful application of hydraulic actuators in achieving exceptional dynamic capabilities.

Advanced actuator technologies. Emerging actuator technologies include cable-driven systems that reduce inertia loads (Parmiggiani et al., 2012; Tian et al., 2017), variable stiffness actuators (VSAs) that enable compliance control (Tonietti et al., 2005; van Ham et al., 2007; Vanderborght et al., 2009; Jafari A et al., 2010; Kim BS and Song, 2010; Tsagarakis et al., 2011), and series elastic actuators (SEAs) that provide mechanical robustness and energy efficiency (Pratt et al., 2012; Hutter et al., 2012; Tsagarakis et al., 2013; Yu HY et al., 2015; Truong et al., 2020). These technologies address specific requirements for safe HRI and energy-efficient operation.

(2) Sensors

Sensors play a crucial role in robotic perception and interaction with the external world (Tong et al., 2024). Key sensor types include visual sensors (cameras and infrared), motion sensors (inertial measurement units (IMUs) and encoders), proximity sensors (ultrasonic and laser), and tactile sensors (pressure and force/torque).

Vision systems. Cameras provide essential visual information for navigation and object recognition. Monocular and stereo vision systems are employed for robotic perception, with recent developments incorporating advanced image processing capabilities (Michel et al., 2005; Cho et al., 2011; Saeedvand et al., 2018; Ficht et al., 2020). Laser sensors enhance environmental perception and obstacle detection, particularly for autonomous navigation (Tellez et al., 2008).

Motion and orientation sensing. IMUs combining accelerometers, gyroscopes, and magnetometers are fundamental for the balance control and locomotion of humanoid robots (Cho et al., 2011; Saeedvand et al., 2018; Ficht et al., 2020). These sensors provide crucial feedback for maintaining stability during dynamic movements and enable precise pose estimation.

Tactile and force sensing. Tactile sensors enhance object manipulation capabilities of humanoid robots by providing detailed information about the object (Schmidt et al., 2006; Schmitz et al., 2010a; Chang et al., 2019; Ramalingame et al., 2019; Bao et al., 2023; Guo et al., 2023). Force/torque sensors placed at joints and end-effectors enable precise HRI control and improve safety during human–robot collaboration (Kajita et al., 2005; Tellez et al., 2008; Tsagarakis et al., 2013).

(3) Processing unit

Modern humanoid robots increasingly adopt miniaturized personal computer (PC) solutions, advanced reduced instruction set computing (RISC) machine (ARM)-based boards, and specialized processors (Al-Busaidi, 2012; Lapeyre et al., 2014; Almubarak and Tadesse, 2017; Ficht et al., 2018; Fan et al., 2019; Allali et al., 2024). The selection of an appropriate solution depends on the computational requirements and power constraints of specific applications.

(4) Power supply

Most humanoid robots are powered by portable rechargeable batteries, primarily lithium-ion (Li-ion) and lithium polymer (Li-Po) batteries (Hirose and Ogawa, 2007; Metta et al., 2010; Kajita et al., 2011; Allgeuer et al., 2015; Ficht et al., 2018). Li-Po batteries are preferred for their high energy density, lightweight characteristics, and rapid charging capabilities.

(5) Comparative analysis of typical research cases

Table 1 provides a detailed comparison of various humanoid robots, revealing the diversity in design and functionality among different research organizations. In terms of height, robots such as LOLA, WALK-MAN, and HRP-5P reach 180 cm, 191.5 cm, and 183 cm, respectively, close to the height of an adult human. These robots are highly suitable for scenarios that require high interactivity or complex environmental operations. In contrast, smaller robots such as NAO and DARwIn-OP have heights of only 57 cm and 45.5 cm, respectively; these robots are lightweight and agile, making them highly suitable for education, entertainment, and domestic applications. Robots have different weights, ranging from 2.8 kg for DARwIn-OP to 132 kg for WALK-MAN. This difference reflects the various purposes and load-bearing requirements in robot design. For instance, heavy-duty robots such as Atlas and DRC-HUBO+ demonstrate tremendous potential in fields such as rescue and industrial manufacturing owing to their strong load-carrying capacity and stability. In addition, their DOFs range from 20 to 67, indicating their wide range of motion complexity. A higher DOF indicates that the robot can perform more precise and complex actions. Furthermore, most robots employ lightweight yet robust materials such as aluminum and magnesium alloys, which enhance their overall performance and durability. Some robots, such as igus and Surena-Mini, use three-dimensional (3D) printing technology to reduce costs and accelerate prototyping. In terms of actuators, most humanoid robots use electrical drive systems owing to their efficiency, low noise, and ease of control. However, robots such as Atlas and CB use hydraulic drive systems, which are renowned for their exceptional locomotion capabilities. In terms of sensor and processing unit configurations, modern humanoid robots are becoming increasingly intelligent and autonomous. These robots are equipped with various sensors to achieve comprehensive environment perception and response. Powerful processing units, such as Intel Core processors, endow humanoid robots with efficient data processing capabilities and real-time decision-making abilities. These comparative results reveal the evolution of humanoid robot technology over time and reflect the influence of different application scenarios on robot design and functional requirements.

2. Intelligent control

(1) Classification of control methods

Traditional control methods. ZMP-based methods form the foundation of humanoid robot control (Yamaguchi et al., 1999; Sugihara et al., 2002). These methods are effective for basic locomotion; however, they face limitations in walking speed and environmental adaptability.

Table 1 Comparison of typical product parameters in the ontology structure

Robot	Year	Height (cm)	Weight (kg)	Material	Actuator	Sensor	Processing unit	Power	DOF	Organization
SDR-3X (Ishida et al., 2001)	2001	50	5	–	Electrical	Camera, IMU, infrared, microphone	64 bit MIPS RISC (×2)	–	26	Sony, Japan
ASIMO (Sakagami et al., 2002)	2002	120	52	Magnesium alloy	Electrical	Camera, force, IMU	Mobile Pentium III-M 1.2 GHz	Ni-MH (38.4 V, 10 Ah)	26	Honda, Japan
Albert HUBO (Oh et al., 2006)	2005	137	57	Metal, Frubber	Electrical	Force/torque, IMU	PCM-3370	Li-Po (24 V)	66	KAIST, Republic of Korea
CB (Cheng G et al., 2007)	2006	157.5	92	–	Electrical	Camera, IMU, force/torque, microphone	On-board PC104-plus CPU stack with an Intel 1.4 GHz Pentium-M	–	50	ATR, Japan
H7 (Nishiwaki et al., 2007)	2006	146.8	57	–	Hydraulic	Camera, tactile, force, IMU	Dual Pentium III 1.4 GHz	Lead-acid (12 V, 2.0 Ah), Ni-MH (48 V, 6 Ah)	50	AIST, Japan
Reem-B (Tellez et al., 2008)	2008	147	60	Aluminum	Electrical	Camera, laser, ultrasonic, force/torque, infrared, IMU, microphone	AMD Geode 500 MHz, Intel Core 2 Duo 1.66 GHz	Ni-MH (45 V)	40	PAL Robotics, Spain
HRP-4C (Kajita et al., 2011)	2009	158	43	Metal, silicone, plastic	Electrical	Force, posture, IMU	Intel Pentium M 1.6 GHz	Ni-MH	42	AIST, Japan
LOLA (Buschmann et al., 2009)	2009	180	55	–	Electrical	Camera, IMU, force/torque	Intel Core Duo 2.33 GHz	–	25	TUM, Germany
NAO (Gouaillier et al., 2009)	2009	57	4.5	ABS	Electrical	Camera, IMU, MRE, infrared, ultrasonic, etc.	x86 AMD GEODE 500 MHz CPU, 256 MB SDRAM, 1 GB Flash memory	Li-ion	25	Aldebaran, France

To be continued

Table 1 continued

Robot	Year	Height (cm)	Weight (kg)	Material	Actuator	Sensor	Processing unit	Power	DOF	Organization
DARwIn-OP (Ha et al., 2011)	2011	45.5	2.8	–	Electrical	Camera, IMU, microphone, force	ATOM Z530 1.6 GHz, 1 GB DDR2, 4 GB Flash disk	Li-Po (11.1 V)	20	University of Tokyo, Japan
COMAN (Tsagarakis et al., 2013)	2013	94.5	31.2	Aluminum, titanium	Electrical, SEA	Force/torque, IMU, etc.	Dual core Pentium PC104 2.5 GHz	Li-Po	25	IIT, Italy
BHR-5 (Yu ZG et al., 2014)	2014	162	65	Aluminum, plastic	Electrical	Camera, IMU, force/torque	–	Li-Po	30	BIT, China
Poppy (Lapeyre et al., 2014)	2014	84	3.5	PLA/ABS	Electrical	Camera, force, IMU	Raspberry Pi	–	25	Flowers Lab, France
igus (Allgeuer et al., 2015)	2015	90	6.6	Tribo-polymer	Electrical	Camera, encoders, IMU	Intel i7-5500U 2.4 GHz, 4 GB DDR3, 120 GB SSD	Li-Po (14.8 V, 3.8 Ah)	20	University of Bonn, Germany
Pepper (Gardecki and Podpora, 2017)	2015	121	27.8	ABS-PC	Electrical	Camera, IMU, laser, infrared, ultrasonic, MRE, microphone	ATOM E3845 1.9 GHz Quad core	Li-ion (30 Ah)	20	SoftBank, Japan
Atlas (Atmeh et al., 2014)	2014	150	80	Aluminum, titanium	Hydraulic	Camera, LiDAR, etc.	–	–	28	Boston Dynamics, USA
WALK-MAN (Negrello et al., 2016)	2016	191.5	132	–	Electrical, SEA	Camera, torque, temperature, position, force, IMU, MRE, lasers, microphone	Pentium i7 Quad core	–	67	IIT, Italy
Surena-Mini (Nikkhah et al., 2017)	2017	53.4	3.3	PLA	Electrical	Tactile, infrared, force, IMU, etc.	Intel Core m5-6Y57 VPro 1.1 GHz	Li-Po (14.8 V, 2.3 Ah)	23	University of Tehran, Iran

To be continued

Table 1 continued

Robot	Year	Height (cm)	Weight (kg)	Material	Actuator	Sensor	Processing unit	Power	DOF	Organization
DRC-HUBO+ (Jung et al., 2018)	2018	170	80	–	Electrical	Camera, force/torque, IMU, FOG, optical flow, LiDAR	Intel NUC Kit D54250WYK, i5-4250U 1.30 GHz (×2)	Ni-ion (4 V, 11.4 Ah)	32	KAIST, Republic of Korea
NimbRo-OP2X (Ficht et al., 2018)	2018	135	19	Carbon fiber, plastic	Electrical	Camera, encoders, IMU, torque	Intel Core i7-8700T, 2.7–4.0 GHz, GTX 1050 Ti	Li-Po (14.8 V, 8.0 Ah)	30	University of Bonn, Germany
ARC (Saeedvand et al., 2018)	2018	54	2.9	PLA/ABS	Electrical	Camera, IMU, compass	Intel Core i5 6260 U, 8 GB DDR4, 120 GB SSD	–	20	University of Tabriz, Iran
HRP-5P (Kaneko et al., 2019)	2019	183	101	–	Electrical	Camera, IMU, force/torque, LiDAR	Intel Core i7-5557U 3.1 GHz, Intel Core i7-7567 3.5 GHz	–	37	AIST, Japan
ROBOTIS OP3 (Vasilyev et al., 2019)	2019	51	3.5	Metal	Electrical	Camera, IMU, infrared, microphone	Intel Core i3 Dual core, 8 GB DDR4, 128 GB M.2SSD, ARM Cortex-M7	Li-Po (11.1 V, 1.8 Ah)	20	ROBOTIS, Republic of Korea
iCub (Parmiggiani et al., 2012)	2012	104.6	33	Aluminum alloy, etc.	Electrical	IMU, force/torque, tactile, encoders, etc.	CPU Intel i7 7600, 4 GB RAM, 32 GB SSD	Battery (36 V, 9 Ah)	53	IIT, Italy
MIT robot (Chignoli et al., 2021)	2021	70	21	–	Electrical	Tactile, etc.	–	Battery (60 V, 3 Ah)	16	MIT, USA
Sigmaban (Allali et al., 2024)	2023	70	5.5	Aluminum, TPU	Electrical	Camera, IMU, pressure	Intel Core i5 AMD 1.2 GHz Micro-6700T, STM32 72 MHz	–	20	University of Bordeaux, France

MIPS: microprocessor without interlocked pipeline stages; ABS: acrylonitrile butadiene styrene; ABS-PC: ABS-polycarbonate; TPU: thermoplastic polyurethane; LiDAR: light detection and ranging; SSD: solid state drive; DDR: double data rate; RAM: random access memory; CPU: central processing unit; MRE: magnetic rotary encoder; FOG: fiber-optic gyro. "–" indicates data not available. KAIST: Korea Advanced Institute of Science and Technology; ATR: Advanced Telecommunications Research Institute International; AIST: National Institute of Advanced Industrial Science and Technology; TUM: Technische Universität München; IIT: Istituto Italiano di Tecnologia; BIT: Beijing Institute of Technology

Optimization-based control methods. Advanced optimization techniques, including particle swarm optimization and model predictive control, enable more sophisticated motion planning and control of humanoid robots (Huan and Anh, 2015; Huan et al., 2018; Tao et al., 2021; Choe et al., 2023). These methods address complex multi-constraint optimization problems inherent in humanoid locomotion.

Bio-inspired control methods. Bio-inspired approaches, including cerebellum-based control and central pattern generators (CPGs), enhance adaptability and robustness (Itoh et al., 2004; Ijspeert, 2008; Or, 2010; Capolei et al., 2019; Tolu et al., 2020; Yao et al., 2022; Zhang JH et al., 2023). These methods provide natural motion patterns and improved disturbance rejection capabilities.

Learning-based control methods. Machine learning approaches, particularly reinforcement learning and imitation learning, enable autonomous skill acquisition and adaptation (Schaal, 1999; Wang SY et al., 2012; Taylor et al., 2021; Ding et al., 2023). Recent advances in deep reinforcement learning and inverse reinforcement learning have demonstrated significant potential for robotic manipulation tasks, while emphasizing the importance of trustworthy and interpretable AI systems (Ozalp et al., 2024). These methods enable discovering effective control solutions without extensive modeling.

(2) Learning capabilities

Learning capabilities in humanoid robots refer to their ability to continuously adapt and improve performance via ongoing experience during real-world deployment.

Unlike pretrained control methods, these learning capabilities enable robots to update their neural networks and refine their behaviors while actively performing tasks in dynamic environments.

Online learning and adaptation. Online learning algorithms enable humanoid robots to continuously update their knowledge base and control strategies during operation. These systems enable robots to adapt to new environments, user preferences, and unexpected situations without requiring offline retraining. For example, robots can learn user-specific interaction patterns and gradually improve their service quality via repeated interactions (Taylor et al., 2021).

Continual learning without catastrophic forgetting. A critical challenge with deployed humanoid robots is maintaining previously learned skills while acquiring new ones. Continual learning frameworks prevent catastrophic forgetting by selectively updating network parameters while preserving essential knowledge. This capability is particularly important for service robots that must retain their core functionalities while adapting to new tasks or environments (Hua et al., 2021).

Real-time network updating. Modern humanoid robots update their control networks in real time by employing techniques such as elastic weight consolidation and progressive neural networks. These methods enable robots to incorporate new sensory experiences and user feedback directly into their decision-making processes, resulting in progressive performance improvements during deployment (Peng et al., 2018).

Adaptive skill acquisition. Humanoid robots can acquire new motor skills via observation and practice during their operational lifetime. Meta-learning approaches enable robots to quickly adapt to new tasks by leveraging previously learned motor primitives and control strategies. This capability enables robots to expand their skill repertoire without extensive reprogramming (He ZP et al., 2021).

Experience-based performance optimization. By continuously interacting with their environment, humanoid robots can optimize their performance metrics such as energy efficiency, task completion time, and safety margins. Experience buffers store successful interaction patterns, which are used to refine future behaviors; this results in increasingly sophisticated and efficient operation of robots over time (Delhaisse et al., 2017).

(3) Locomotion control

Locomotion control enables humanoid robots to coordinate leg movements to achieve omnidirectional walking at various speeds and terrains. As humanoid robots are highly nonlinear and inherently unstable systems with many DOFs, they need to adapt to environmental uncertainty and respond correctly to environmental changes; this makes bipedal motion control a major challenge (Wang SY et al., 2012).

Traditional locomotion methods. Methods based on ZMP and the inverted pendulum principle are widely used to generate walking patterns and ensure dynamic stability of humanoid robots during locomotion (Kajita et al., 2003; Jánoš et al., 2022). However, Vasilyev et al. (2019) proposed a different approach by designing a walking algorithm based on quasi-static stability, which improved walking stability of humanoid robots but at the expense of dynamic performance. Buschmann et al. (2009) employed an impedance control method combining hybrid position/force control in the task space with internal joint position control loops to achieve fast and agile walking while ensuring stability.

Advanced control strategies. Kim JY et al. (2005) achieved dynamic walking on the KHR-2 robot using predefined walking patterns and online controllers with sensor feedback. Kaymak et al. (2023) proposed a framework combining deep reinforcement learning, multi-sensor data fusion, and posture balance to endow humanoid robots with enhanced walking stability. García et al. (2021) focused on nonlinear model predictive control methods and proposed a new control strategy based on centroidal dynamics to improve control efficiency by simplifying line-feet contact modeling.

Robust locomotion in complex environments. To address the challenges of achieving agility in electrically driven humanoid robots, Bergonzani et al. (2023) proposed a locomotion planning and whole-body control method based on ZMP that enabled fast stepping and long-distance walking. Liu CJ et al. (2020) presented an online footstep placement compensator using orbital energy conservation and a discrete control Lyapunov function to maintain system stability. In addition, Kuindersma et al. (2016) developed a comprehensive locomotion control system that integrated state estimation, walking controllers, and optimization techniques for enabling Atlas to achieve reliable dynamic walking in complex environments.

Learning-based locomotion. Yang et al. (2020) presented a framework combining imitation learning and deep reinforcement learning to help humanoid robots learn more natural and dynamic gait behaviors. Radosavovic et al. (2024) introduced reinforcement learning-based locomotion control strategies that dynamically predicted and adjusted actions using historical data; consequently, the humanoid robot could stably walk on various outdoor terrains with remarkable robustness.

Multicontact and advanced planning. Ichter and Pavone (2019) proposed a latent sampling-based motion planning method to provide efficient solutions for high-dimensional systems and enable visual space-based locomotion planning. Murooka et al. (2022) presented a novel online centroidal trajectory generation method supporting low computational costs while combining preview control and force distribution for stable walking and multicontact motions.

(4) Balance and stability control

Balance and stability control is one of the major challenges in simulating human locomotion with humanoid robots. To address this challenge, traditional approaches and modern learning-based methods have been developed.

Optimization-based balance control. Elhosseini et al. (2019) proposed a variant of the whale optimization algorithm (WOA) to determine optimal hip joint parameter settings for improving the dynamic stability of humanoid robots. In addition, Liu CJ et al. (2021) designed a foot position compensator based on policy gradient reinforcement learning to help humanoid robots maintain balance during continuous walking. Xie et al. (2021) proposed a framework to control physical interaction between humanoid robots and the ground by optimizing ground reaction forces, the center of pressure, and joint torques.

Disturbance rejection and recovery. Maintaining stability under external forces is crucial for the practical application of humanoid robots. Pratt et al. (2006) proposed a strategy based on computing the capture point and capture region, enabling humanoid robots to respond to large external pushes by stepping into the capture region. Kim MJ et al. (2023) presented a robust balance control framework combining model predictive control with stepping controllers to endow humanoid robots with strong walking stability under external disturbances.

Inverted pendulum models. The inverted pendulum model serves as a foundation for balance control in humanoid robots. Kim JH and Oh (2004) proposed a simple inverted pendulum model with compliant joints and a damping controller for enhancing the locomotion stability of robots using comprehensive sensing systems. Huang Q et al. (2022) introduced a "resistant compliance" control strategy that enabled robots to actively reject external disturbances by combining virtual mass models with linear inverted pendulum models to handle external forces and uneven terrains.

Advanced balance control methods. To address the limitations of traditional low-dimensional model-based methods, Koolen (2020) proposed a new approach based on nonlinear variable-height inverted pendulum models. In addition, Meng et al. (2023) introduced an online running-gait generator based on variable-height inverted pendulum models and generated complete running motions with smooth state transitions. Choe et al. (2023) proposed a control method based on a real-time nonlinear model predictive control, enabling humanoid robots to quickly react to imbalances by employing ankle, hip, and gait adjustment strategies.

Learning-based balance control. Reinforcement learning has shown significant promise in balance control. Tran et al. (2020) proposed a method combining self-organizing maps and Q-learning algorithms for fall detection and push recovery. Aslan et al. (2023, 2024) developed push recovery controllers using the deep Q-network and the double deep Q-network architectures; they demonstrated that deep reinforcement learning methods can outperform traditional proportional–integral–derivative (PID) and model predictive control approaches in humanoid balance tasks.

(5) Behavior control

Behavior control comprises autonomous, semi-autonomous, and remote control methods, covering basic actions, complex tasks, and affective computing. Existing studies have primarily focused on path planning, footstep planning, and navigation for autonomous systems.

Basic task execution. Humanoid robots can perform various basic tasks through precise control, including object manipulation (Zhang SG et al., 2023), kicking and shooting (Jafari M et al., 2019), stair climbing (Fu and Chen, 2008; Caron et al., 2019), non-prehensile object transportation (Selvaggio et al., 2023), and movement imitation (Cheng XX et al., 2024). These capabilities form the foundation for more complex robot behaviors.

Navigation and path planning. Navigation technology faces key challenges such as localization (Hornung et al., 2010; Saeedvand et al., 2018), obstacle avoidance (Rossini et al., 2023), path planning (Gutmann et al., 2005b), and footstep planning (Kuffner JJ et al., 2001; Kuffner J et al., 2003). Duguleana and Mogan (2016) applied Q-learning and neural network planners to generate collision-free trajectories in uncertain workspaces with static and dynamic obstacles. In addition, Kumar et al. (2019) proposed a controller based on artificial potential fields for path planning in unknown environments. Vikas and Parhi (2023) combined linear regression with a gravity search algorithm and chaos theory to achieve optimal path planning in static and dynamic terrains.

Advanced path planning. Vikas et al. (2023) proposed efficient path-planning methods combining a memory-based improved gravitational search algorithm with differentially perturbed velocity methods for complex environments. They successfully solved navigation issues for multiple humanoid robots using Petri nets to achieve coordinated operation.

Footstep planning. Footstep planning must account for balance, ground conditions, obstacles, and dynamic characteristics. Chestnutt et al. (2005) developed a footstep planner for Honda ASIMO using an A* search algorithm with state-relevant actions. Kim JH et al. (2023) proposed a real-time footstep planning framework employing two-layer feasibility checks to avoid collisions. In addition, Liu H et al. (2012) proposed a hierarchical rapidly exploring random tree (RRT) for complex environments, and Perrin et al. (2012) employed swept volume approximations for collision-free footstep planning.

Advanced footstep planning. To address the limitations of sampling-based algorithms, Mishra et al. (2022) proposed a footstep planning method based on generative adversarial networks (GANs) for automatic collision-free trajectory generation. Gao ZF et al. (2024) proposed a greedy heuristic optimization method combined with quadratic programming for global optimal footstep planning.

Affective computing. Affective computing involves recognizing facial expressions and body language. Liu XF et al. (2023) proposed a lightweight deep neural network for real-time facial feature detection and mirroring behavior of humanoid robots. Li THS et al. (2019) developed an emotion recognition system based on convolutional neural networks and long short-term memory for real-time emotion recognition. For gesture recognition, Barros et al. (2014) proposed a real-time human gesture recognition model based on deep neural networks, and Ajili et al. (2017) developed a gesture recognition system based on hidden Markov models.

(6) Perception and interaction

Perception. Perception technology enables humanoid robots to perceive and understand their environment like humans; it involves information acquisition, interpretation, and interaction with their surroundings.

Visual perception. Visual perception forms the foundation of HRI systems; this technology uses cameras, LiDAR, and infrared sensors for object perception (Andrychowicz et al., 2020), navigation (Lobos-Tsunekawa et al., 2018), and obstacle avoidance (Gutmann et al., 2005a). Monocular vision systems provide single-viewpoint information and require algorithms to infer 3D scene structure (Lee D and Nakamura, 2007). Stereo vision systems capture multiple perspectives using multiple cameras, thereby enabling 3D scene information acquisition (Sabe et al., 2004). Owing to LiDAR's superior range and accuracy, Bertrand et al. (2020) used it as a primary visual perception sensor for detecting walkable areas and obstacles. Donca et al. (2022) designed a depth-based perception system using red/green/blue-depth (RGB-D) cameras and LiDAR for obstacle detection, mapping, and localization.

Tactile perception. Tactile perception considerably enhances humanoid robot dexterity by detecting the properties of objects such as surface roughness, texture, and weight (Dahiya et al., 2010). Goger et al. (2009) proposed a highly integrated tactile sensing system that enabled responsive grasping based on tactile data. Schmitz et al. (2010b) presented improved tactile sensors with 12 height-sensitive measurement areas for accurate pressure distribution measurement. Burns et al. (2022) developed a full-hand tactile sensor that closely mimicked human hand tactile functionality for object recognition via touch.

Auditory perception. Microphones serve as core sensors for speech recognition, sound interaction, and environmental awareness. Dávila-Chacón et al. (2014) equipped robots with microphones to simulate human binaural hearing and developed neural-network-based sound source localization systems. In addition, Juang and Zhao (2020) proposed continuous speech recognition using hidden Markov models for intelligent communication with NAO robots. Boztas (2023) used four microphones and deep neural networks for estimating the position of sound sources.

Multi-sensor fusion. Multi-sensor fusion enables comprehensive environmental information acquisition, improving perception capabilities and decision-making accuracy (Luo et al., 2024). Gao S et al. (2022) proposed tactile and vision fusion-based object recognition methods. He B et al. (2022) combined bio-inspired vision and tactile perception for 3D object reconstruction and pose estimation. In addition, Lee CH et al. (2007) proposed multi-sensor fusion methods based on ultrasonic sensors, IMU, and control commands for indoor navigation.

HRI. HRI is a challenging and promising research field aimed at enhancing the naturalness, efficiency, and intelligence of interactions with humanoid robots.

Safety and control architecture. Safety and reliability are primary considerations when deploying humanoid robots in human environments; these factors are achieved via mechanical design, actuation, control methods, and fault handling (de Santis et al., 2008). Control methods and architectures determine whether robots can adapt flexibly to different tasks and environments (Leylavi Shoushtari et al., 2016). Huang HH et al. (2021) proposed a control strategy based on broad fuzzy neural networks for establishing optimal robot–environment interaction via adaptive impedance learning.

Multimodal communication. HRI generally involves gesture recognition (Yoon et al., 2019; Qi et al., 2024), speech recognition (Stiefelhagen et al., 2007), facial expression interpretation (Yoon et al., 2019; Qi et al., 2024), and emotion recognition (Li THS et al., 2019; Spezialetti et al., 2020). The Intuitive Robots Lab (IRL) robot exemplifies comprehensive HRI capabilities, including omnidirectional mobility, compliant arms, sound source localization, and emotional expression (Ferland et al., 2013). The WE-4RII robot (Miwa et al., 2004) demonstrates advanced multimodal interaction via visual, auditory, tactile, temperature, and olfactory perception capabilities.

Advanced interaction technologies. Multimodal HRI enables more natural and robust HRI by integrating information from different modalities (Tsiourti et al., 2019; Wang T et al., 2024). Recent advances have focused on creating seamless interaction experiences by employing advanced AI technologies, natural language processing, and emotional intelligence systems.

To provide a systematic overview of the diverse technologies discussed thus far, the key technological components in humanoid robot control and perception systems are summarized in Table 2 and categorized into seven major areas: ontological structures (actuators), perception systems (vision and tactile), control methodologies (traditional, optimization-based, and learning-based approaches), and locomotion control. For each category, primary methods, representative studies, and their respective advantages and limitations are identified. This structured summary facilitates a clearer understanding of the current technological landscape and helps identify the strengths and weaknesses of different technologies.

As shown in Table 2, the technological development of humanoid robotics has evolved from traditional model-based approaches toward learning-based adaptive systems. Although conventional control methods such as ZMP and inverted pendulum models offer stability and reliability, they lack the flexibility required for deployment in complex, unstructured environments. In contrast, learning-based approaches provide superior adaptability and generalization capabilities but at the cost of substantial data requirements and computational resources. The diversity in actuator technologies reflects the ongoing trade-offs among precision, power density, cost, and weight. Similarly, perception systems must balance information richness and computational efficiency. This multifaceted technological landscape highlights the need for hybrid approaches that combine the strengths of multiple methodologies to achieve robust, efficient, and adaptive humanoid robots.

Table 2 Summary of key technologies for humanoid robot control and perception

Technology category	Key method	Advantage	Limitation
Ontological structure actuators	Electric, pneumatic, hydraulic, SEAs, VSAs	High precision control, various power densities available, compliant interaction capabilities	High cost, weight and size trade-offs, maintenance complexity
Perception vision	Monocular cameras, stereo vision, LiDAR, RGB-D sensors	Rich environmental information, real-time processing, multi-scale perception	High computational cost, lighting sensitivity, occlusion issues
Perception tactile	Capacitive sensors, resistive sensors, optical tactile sensors	Direct contact feedback, force/pressure measurement, safe interaction	Limited coverage area, calibration requirements, durability concerns
Control: traditional	ZMP, inverted pendulum model, preview control	Stable and predictable, well-established theory, easy implementation	Limited adaptability to terrain, conservative motion, fixed assumptions
Control: optimization	Particle swarm optimization, model predictive control, quadratic programming	Handles complex constraints, optimal trajectory generation, real-time capable	Computational complexity, local minima issues, parameter tuning
Control: learning-based	Reinforcement learning, imitation learning, transfer learning, deep neural networks	Adaptive to environments, generalizable across tasks, data-driven approach	Large data requirements, training time, black-box nature, safety concerns
Locomotion	CPGs, dynamic walking, balance control, whole-body motion planning	Natural and efficient motion, energy optimization, robust to disturbances	Robustness challenges, terrain adaptability, real-time computation

To provide a systematic visualization of these technological relationships, a hierarchical framework organizing the key technologies into four integrated layers is shown in Fig. 4. This architecture illustrates how lower-level hardware components, such as actuators, sensors, and power systems, support higher-level cognitive and interactive capabilities. It thus emphasizes the interdependencies essential for achieving comprehensive humanoid robot functionality.

3.2 Industrial perspectives

Humanoid robots have garnered extensive attention from governments and enterprises. According to the 2024 White Paper on the Humanoid Robot Industry Chain, the humanoid robot market was predicted to achieve a high growth rate of over 50% by 2035. In addition, the global market size is projected to reach hundreds of billions of dollars, with demand potentially reaching tens of millions of units under optimistic scenarios.

Slowing population growth and aging trends have created development opportunities for humanoid robots because the substitution of machines for humans has become a long-term necessary driver of economic growth. In the industry chain of humanoid robots, upstream includes the hardware market, midstream includes research and production, and downstream includes application scenarios. The main production enterprises in humanoid robots include Tesla, Boston Dynamics, UBTECH, and Xiaomi.

As comprehensively analyzed in Section 3.1, the development of technologies in humanoid robots comprises multiple interconnected layers: (1) hardware foundation layer, including ontological structures (actuators, sensors, processing units, and power systems); (2) perception and cognition layer, integrating vision, tactile, and auditory perception with foundation models for intelligent decision-making; (3) control and locomotion layer, encompassing traditional model-based control, optimization methods, and learning-based approaches for

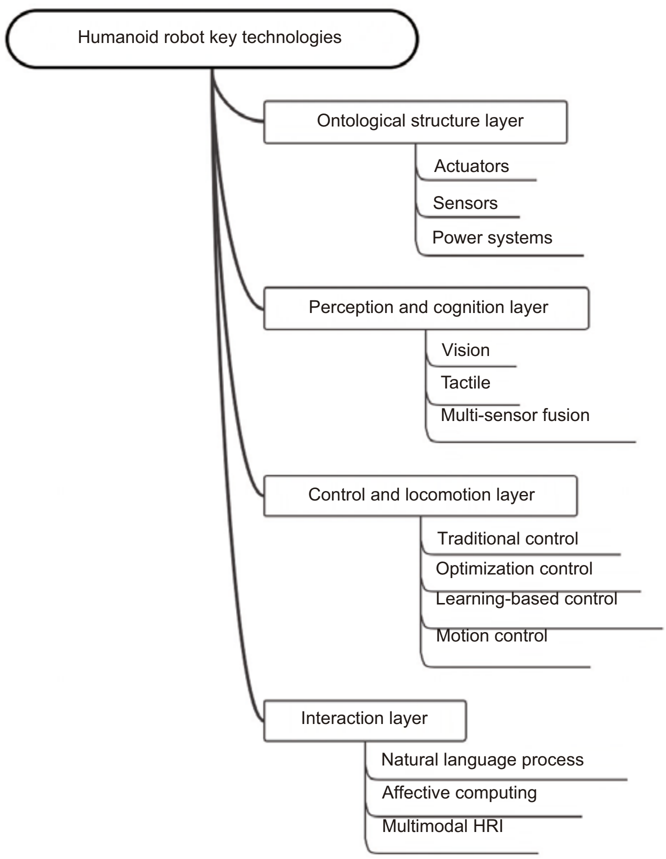

Fig. 4 Hierarchical framework of key technologies for humanoid robots

stable bipedal locomotion; (4) interaction layer, enabling natural HRI via multimodal communication. These technological components, systematically summarized in Table 3, form the foundation for the industrial products shown in Fig. 5, demonstrating the progression from academic research to commercial applications.

3.2.1 Representative products of humanoid robots

1. Tesla's Optimus

Tesla Optimus, launched in October 2022, is 173 cm tall and weighs 57 kg. It has 40 DOFs and can walk at 8 km/h while lifting 20 kg objects. It leverages Tesla's automotive expertise by integrating the full self-driving system, neural networks, and Dojo D1 supercomputer chips; it thus provides 9 peta floating-point operations per second (PFLOPS) of computing power. Positioned for manufacturing, logistics, and service industries, Optimus marks the strategic entry of the automotive industry into humanoid robotics, with planned limited production starting in 2025.

2. Agility Robotics' Digit

Developed by Agility Robotics after their 2015 ATRIAS robot (Hubicki et al., 2016), Digit is 175 cm tall and weighs 65 kg; it can lift 16 kg objects. This human-centered robot is specifically designed for warehousing and logistics applications, demonstrating high flexibility and autonomy. Digit has been tested in Amazon logistics warehouses for picking, moving, and lifting operations, representing a focused approach to commercial deployment in specific industrial sectors.

3. Boston Dynamics' Atlas

Atlas, a full-sized hydraulic humanoid robot, is 150 cm tall and weighs 89 kg; it has 28 DOFs and a walking speed of 5.4 km/h. Its distinctive hydraulic system provides exceptional dynamic capabilities, enabling Atlas to achieve complex acrobatic movements such as split-legged jumps, 360° rotations, handstands, and backflips. Atlas uses advanced control algorithms for environmental planning and 3D printing technology for hydraulic component integration. It thus establishes the benchmark for dynamic humanoid robot performance in challenging environments.

4. Xiaomi's CyberOne

CyberOne, launched in August 2022, is 177 cm tall and weighs 52 kg; it has 21 DOFs and achieves walking speeds up to 7.2 km/h. This robot highlights Xiaomi's integration of consumer electronics expertise with robotics, featuring the Mi-Sense depth vision module and advanced AI interaction algorithms. CyberOne can recognize human emotions and distinguish 85 environmental semantic cues and 45 human emotional states, positioning Xiaomi as a major consumer electronics player that has entered the humanoid robotics market.

5. UBTECH's Walker Series

The evolution of UBTECH's Walker series from Walker (2018) to Walker X (2021) and Walker S1 (2024) has demonstrated progressive commercial development. Walker X is 130 cm tall and weighs 63 kg; it has 41 DOFs, featuring enhanced perception systems and navigation capabilities. Walker S1 has achieved notable commercial success with over 500 units ordered by automotive factories, including BYD and Dongfeng Liuqi for material handling and quality inspection. This demand has represented its successful transition from prototype to industrial application.

6. AGIBOT's RAISE A1

RAISE A1, released in August 2023, is 175 cm tall and weighs 55 kg; it has 49 DOFs and a walking speed of 7 km/h. Its core innovation is the embodied intelligence brain architecture with WorkGPT multimodal large model integration; it enables sophisticated task understanding and environmental perception. The PowerFlow joint motor provides a peak torque of 350 N·m while weighing only 1.6 kg. Its 12-DOF dexterous hand demonstrates advanced manipulation capabilities. AGIBOT exceeded production expectations in 2024, shipping nearly 700 units and contributing to open-source development with the introduction of the AGIBOT World dataset.

7. Unitree's H1

H1, released in 2023, stands 180 cm tall and weighs 47 kg; it has 19 DOFs and demonstrates exceptional speed capabilities up to 3.3 m/s with potential to exceed 5 m/s. This robot is equipped with proprietary M107 joint motors and advanced sensor systems, including 3D LiDAR and depth cameras, achieving a lightweight design and high-speed performance. H1 targets industrial manufacturing, service applications, and research platforms, where rapid movement and agility are prioritized.

8. Fourier Intelligence's GR-1

GR-1 is 165 cm tall and weighs 55 kg; it has 54 DOFs and a walking speed of 5 km/h. Its highly biomimetic design incorporates 32 self-developed Fourier smart actuators (FSAs) and adaptive balance algorithms for stable operation in disruptive environments. Notable for its open-source approach, GR-1 provides application code, software development

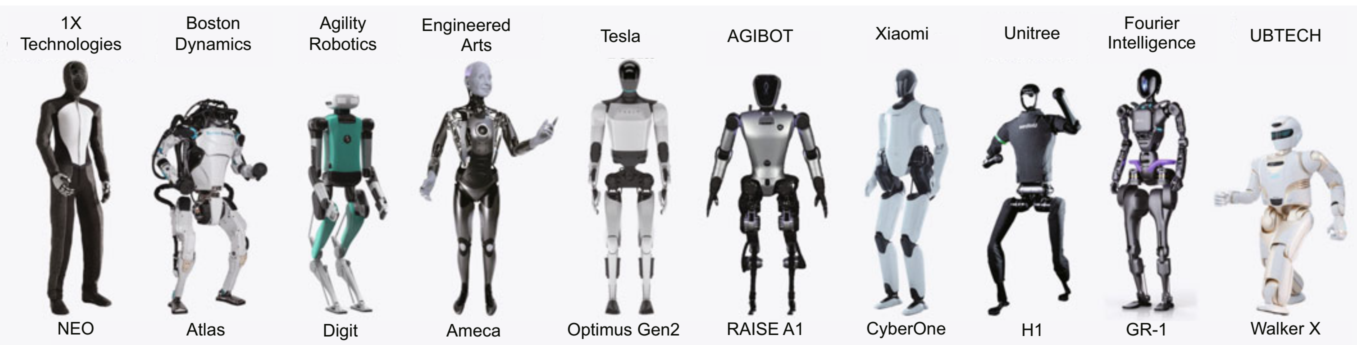

Fig. 5 Representative products of humanoid robots

Table 3 Performance comparison of different products

Robot	Height (cm)	Weight (kg)	Speed	Payload (kg)	Related function	DOF	Organization	Application domain
Optimus	172	56	8 km/h	20	It adopts the same chips as Tesla vehicles, a consistent and powerful computer vision system, and the full self-driving computer and neural network technologies related to Autopilot, which are derived from Tesla cars.	40	Tesla, USA	Manufacturing, logistics, service
Optimus Gen2	–	–	–	–	The neck gains two additional DOFs, enhancing head flexibility and motion balance. Fingertip sensors on each finger improve coordination and tool use. Feet with toe-linked torque sensors mimic the human foot structure, boosting stability and agility.	42	Tesla, USA	Manufacturing, logistics, home service
Digit	175	65	–	15.88	It can stand up and lift boxes from the ground, move around in outdoor and human environments, and map its surroundings. It has been tested in Amazon logistics warehouses to assist with picking, moving, and lifting boxes, with plans to expand its applications to scenarios such as cargo handling and delivery.	16	Agility Robotics, USA	Warehouse logistics, package handling, delivery
Atlas	150	89	5.4 km/h	–	It demonstrates exceptional agility, performing complex moves like split jumps, 360° spins, and handstands. An offline trajectory library and an MPC-based controller enable optimal motion planning and control.	20	Boston Dynamics, USA	Disaster response, industrial inspection, research
CyberOne	177	52	3.6 km/h	–	It possesses keen vision and can perform 3D reconstruction of the real world. The depth accuracy within 8 meters can reach 1%. The whole-body control algorithm can effectively coordinate 21 DOFs in its joints. It can perceive human emotions and distinguish 85 semantic categories and 45 human emotional states.	21	Xiaomi, China	Smart home, exhibition, entertainment
Walker	145	77	–	1.5	It achieves stable walking and balance through gait planning, and adapts to complex terrains. With real-time interaction and compliant control, it improves navigation accuracy and interaction safety, supporting multimodal HRI, which is widely used in smart homes.	36	UBTECH, China	Smart home services, elderly care, education
Walker X	130	63	3 km/h	10	Dynamic foot-leg control enables self-balancing and disturbance rejection. Its upgraded four-eye vision system and dual RGB-D sensors enhance object recognition and manipulation. With U-SLAM navigation and deep learning-based perception, it delivers accurate environment understanding and refined home services. It supports multimodal emotional interaction and human-like empathy.	41	UBTECH, China	Smart home, elderly care, healthcare

To be continued

Table 3 continued

Robot	Height (cm)	Weight (kg)	Speed	Payload (kg)	Related function	DOF	Organization	Application domain
RAISE A1	175	55	7 km/h	5	It comprises the cloud superbrain, main brain, cerebellum, and brainstem, handling tasks ranging from high-level planning to low-level control. Powered by the self-developed multimodal model WorkGPT, it understands user intentions, perceives the environment, and manages tasks. Equipped with a high-DOF dexterous hand and vision-based fingertip sensors, it supports multimodal perception, few-shot learning, and robust HRI. The PowerFlow joints and wheel-foot bipedal legs allow flexible terrain adaptation.	49+	AGIBOT, China	Manufacturing, logistics, education, interactive service, smart butlers, avatars
H1	180	47	3.3 m/s	–	It possesses the highest level of power performance globally, excelling in speed, strength, maneuverability, and agility. It has a stable gait and highly flexible motion capabilities for autonomous walking and running in complex terrains and environments. It can acquire real-time, high-precision spatial data, enabling panoramic scanning. Equipped with Unitree M107 joint motors, it exhibits exceptional power performance and endurance capabilities.	18+	Unitree, China	Research platform, industrial applications, inspection
GR-1	165	55	5 km/h	–	With a biomimetic body and humanoid motion control, it uses adaptive balance algorithms to handle complex disturbances and maintain stability. Self-developed FSAs ensure precise execution of complex tasks. Integrated GPT-based multimodal models enable natural speech and visual interaction.	54	Fourier Intelligence, China	Manufacturing, reception, security, healthcare, education, home services
NEO	165	30	4 km/h	20	It can walk, jog, and climb stairs. It can move like a human being, perceive the surrounding environment, and interact with the surroundings, enabling it to perform various intricate activities. The unique gearless design significantly reduces the overall weight and enhances agility. As a versatile humanoid robot, it is capable of not only handling industrial tasks such as logistics, manufacturing, and operating machinery, but also providing diverse services in daily life.	–	1X Technologies, Norway	Industrial manufacturing, logistics, home service
Ameca Gen2	187	49	Unable to walk	–	It has a high level of facial fidelity, with rich expressions and a good HRI experience. It achieves intelligent facial and expression recognition, as well as multi-person voice recognition.	61	Engineered Arts, UK	Exhibition, entertainment, customer service, research

To be continued

Table 3 continued

Robot	Height (cm)	Weight (kg)	Speed	Payload (kg)	Related function	DOF	Organization	Application domain
Unitree G1	127	35	2.0 m/s	2	It features a cost-optimized design with quasi-direct-drive actuators, achieving commercial viability at $16 000. Through rapid iteration, it demonstrates the democratization of humanoid technology and supports basic mobility and manipulation tasks.	43	Unitree, China	Service robotics, research platform, education
GR-2	175	63	1.5 m/s	5	It is equipped with advanced modular FSAs delivering 300 N·m peak torque. Its biomimetic design is optimized for rehabilitation scenarios, while integrated force feedback control ensures safe patient interaction.	53	Fourier Intelligence, China	Rehabilitation, healthcare, industrial assistance
RAISE A2	170	55	1.2 m/s	5 (per arm)	It features a dual-arm manipulation system with a 5 kg payload per arm, offering enhanced dexterity for industrial tasks. Integrated vision-based control enables precision in assembly operations.	49	AGIBOT, China	Manufacturing assembly, logistics, quality inspection
SE01	170	55	1.3 m/s	3	Its proprietary embodied foundation model integration enables natural language task planning, while the multimodal perception system combines vision and tactile sensing.	42	EngineAI, China	Service industry, interactive retail, smart facilities
CL-1	150	65	1.8 m/s	–	Its state-of-the-art bipedal locomotion algorithms achieve stable outdoor navigation. The point-foot design allows for agile movement, demonstrating robust performance on uneven terrains.	43	LimX Dynamics, China	Research platform, logistics, outdoor operations
H2	180	80	5.0 m/s	30	Its high-performance version features enhanced load capacity and a long-endurance battery system (4+ hours). It is designed for industrial material handling and logistics applications.	25	Unitree, China	Industrial logistics, material handling, warehousing
T1	172	52	1.5 m/s	3	It uses proprietary quasi-direct-drive actuator technology, optimized for warehouse logistics with collision-safe design. It performs real-time path planning for dynamic environments.	38	Booster Robotics, China	Warehouse logistics, inventory management, sorting
Walker S	170	77	–	10	The industrial-grade version is designed for automotive manufacturing. It offers enhanced manipulation precision for assembly tasks and is certified for collaborative operation on production lines.	41	UBTECH, China	Automotive manufacturing, assembly lines, quality control

"–" indicates data not available. GPT: generative pre-trained Transformer; MPC: model predictive control kit (SDK), and pre-programmed access to LLMs, thereby facilitating global developer collaboration. GR-1 was produced on a limited scale in 2024, focusing on industrial and service scenarios while promoting embodied intelligence development.

9. 1X Technologies' NEO

NEO represents an innovative design philosophy with its 165 cm height, 30 kg weight, and unique gearless motor technology that considerably reduces weight and enhances agility. This robot features an anatomical, muscle-like structure, abandoning traditional rigid hydraulic systems and enabling natural human-like movements such as walking, jogging, and stair climbing with a 20 kg payload capacity. NEO's versatile design targets industrial applications (logistics and manufacturing) and domestic services (cleaning and household organization).

10. Engineered Arts' Ameca

Ameca is 187 cm tall and weighs 49 kg; it has impressive 61 DOFs, enabling fluid and lifelike movements; however, it currently lacks walking capabilities. This UK-developed robot excels in facial expression fidelity and HRI, featuring advanced facial recognition, emotion analysis, and LLM integration. Ameca serves as a specialized platform for developing advanced interaction behaviors and represents the entertainment and companionship segment of humanoid robotics, with potential for future mobility enhancement.

3.2.2 Performance comparison of different products

Table 3 lists the standardized quantitative metrics used for objective cross-platform comparison: (1) mobility metrics include walking speed and terrain adaptability; (2) manipulation metrics capture payload capacity in kilograms (kg) and DOFs; (3) technology readiness level (TRL) is implicitly reflected via organizational maturity and application deployment status—commercial products from established manufacturers (Tesla and Boston Dynamics) represent a TRL of 7–9 with market deployment, whereas emerging platforms (Unitree G1 and LimX CL-1) with a TRL of 6–7 demonstrate technical feasibility with limited production. This systematic framework facilitates rigorous comparison while acknowledging that some industrial specifications remain proprietary.

The analysis of application domains reveals strategic market segmentation in the humanoid robotics industry. Manufacturing and logistics dominate commercial deployments (Optimus, Digit, RAISE A1/A2, NEO, Booster T1, and Walker S), reflecting near-term revenue opportunities in structured industrial environments. In addition, smart home and elderly care represent high-growth consumer markets (Walker series and CyberOne), requiring safe HRI and adaptive behavior. Research platforms, such as Atlas, H1, and CL-1, prioritize advancing technical boundaries over immediate commercialization, focusing on breakthroughs in locomotion algorithms and whole-body control. In contrast, healthcare robots like GR-1 and GR-2 emphasize precision force control and biomimetic compliance. Moreover, exhibition and entertainment robots (Ameca Gen2 and CyberOne) emphasize expressive HRI for public engagement. This clear delineation demonstrates how design philosophies, from Tesla's automotive technology integration to Fourier's rehabilitation-optimized actuators, directly align technical specifications with the requirements of the target market.

The rapid proliferation of humanoid platforms from Chinese and international startups was observed in 2024–2025, exemplifying three critical industry trends: (1) aggressive cost reduction—Unitree G1's \$16 000 price point represents a 89% decrease versus earlier commercial platforms, which often exceeded \$150 000, achieved via supply chain integration and modular quasi-direct-drive actuators; (2) accelerated iteration cycles—companies released multiple variants (Unitree G1/H2, Fourier GR-1/2, and RAISE A1/A2) within 6–12 month intervals, contrasting with traditional 3–5 year development cycles; (3) application-specific specialization—the emergence of domain-optimized designs for rehabilitation (GR-2 with 300 N·m torque FSA), warehouse logistics (Booster T1 with collision-safe design), and manufacturing assembly (RAISE A2 with dual 5 kg payload arms). Collectively, these emerging platforms secured over \$2 billion in funding in 2024, accelerating technology transfer from laboratory prototypes to commercial deployment and validating multiple parallel business models across diverse market segments.

3.3 Academic–industrial gap analysis and collaboration

The development of humanoid robots demands synergistic collaboration between academic institutions and industrial entities, with each bringing distinct advantages and unique challenges. Understanding these complementary strengths and addressing the gaps between academic research and industrial implementation is crucial for advancing the field of humanoid robots toward practical applications.

3.3.1 Comparative advantages and specializations

Academic institutions excel in fundamental research and theoretical breakthroughs, demonstrating specific strengths in developing novel algorithms, conducting long-term research with higher risk tolerance, and pursuing innovative approaches without immediate commercial pressure (Chesbrough, 2003). Universities foster interdisciplinary collaboration, bringing together experts from robotics, AI, cognitive science, and biomechanics to address complex theoretical challenges. In addition, the open publication model enables the rapid dissemination of research findings and global knowledge sharing. Notable academic contributions include dynamic walking algorithms developed by MIT, computer vision advances by Carnegie Mellon, and HRI frameworks developed by various universities.

The analysis of the Open X-embodiment collaboration reveals distinct resource allocation patterns: academic institutions primarily contribute to algorithmic innovations (RT-X models and novel training methods), whereas industrial partners (Google DeepMind and Boston Dynamics) provide large-scale data collection infrastructure (Collaboration, 2024). Academic projects tend to prioritize algorithm development, whereas industrial programs allocate more resources to manufacturing engineering and supply chain development. Analysis of major robotics conferences and patent records suggests that academic institutions contribute the majority of research publications while holding a smaller share of robotics patents, reflecting different knowledge dissemination strategies.

Industrial entities have demonstrated complementary strengths in system integration, manufacturing, and market-driven development. Companies also have substantial financial resources for large-scale research and development (R&D) projects and excel at transforming research prototypes into manufacturable products (Scassellati, 2002). In addition, industrial research addresses practical constraints, including cost optimization, reliability engineering, power consumption, and safety certification. Leading examples of such industrial contributions include Boston Dynamics' expertise in dynamic control and mechanical design, Tesla's integration of AI and manufacturing capabilities, and Honda's sustained ASIMO development; all these companies have combined theoretical research with practical implementation.

The investment in global humanoid robotics demonstrates industrial commitment: funding increased from approximately \$500 million (2020) to over \$6 billion (2024) based on disclosed rounds. Major players such as Tesla (estimated over \$1 billion annual Optimus investment), Figure AI (\$675 million Series B, February 2024), 1X Technologies (\$100 million Series B), and Chinese manufacturers (UBTECH and Xiaomi) collectively invested over \$2 billion. Current production costs range from \$150 000 to \$500 000 per unit at small scales (100–500 units/year), with actuators representing 55%–60% of the total cost. Industry projections indicate potential reduction in cost up to \$20 000–\$30 000 at scales, exceeding 100 000 units annually (Tesla, 2024; Goldman Sachs, 2024).

Table 4 summarizes key differences across multiple critical dimensions to systematically compare the distinct approaches and priorities of academic research and industrial development. This comparison reveals fundamental variations in the objectives, resource allocation, timelines, and success metrics of different approaches that shape the development trajectories and technology transfer challenges discussed below.

The academic–industrial gap manifests considerably in TRLs (TRLs 3–4 vs. 8–9), resource allocation patterns (70%–80% vs. 40%–50% on algorithms), and time horizons (2–4 years vs. 5–10 years). These disparities underscore the need for bridging mechanisms that can accelerate technology transfer while adhering to the distinct value propositions of each sector.

The radar chart shown in Fig. 6 clearly illustrates the complementary strengths of academic and industrial approaches. Academic institutions have demonstrated superior performance in algorithm innovation (resource allocation of 70%–80%), risk tolerance, and open collaboration, whereas industrial entities have excelled in hardware investment, extended testing protocols (mean time between failure (MTBF) exceeding 10 000 hours), and technology maturity (TRLs 8–9). This visualization underscores that neither approach alone is sufficient; successful humanoid robot development requires bridging these gaps via strategic academic–industrial partnerships.

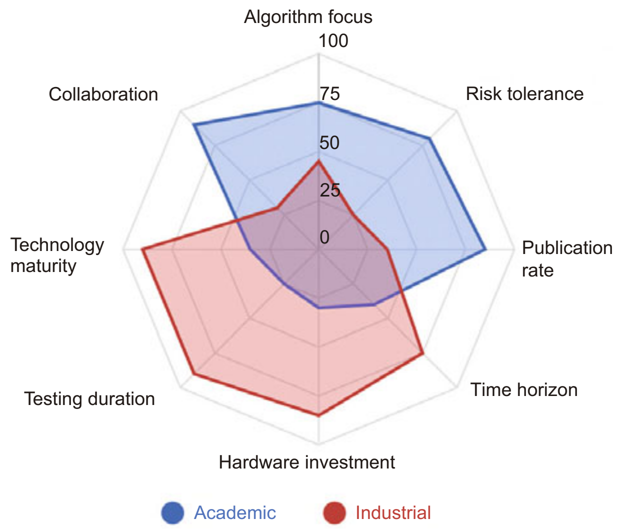

Fig. 6 Comparison of academic and industrial contributions

3.3.2 Technology transfer challenges and barriers

The transition from academic research to industrial application faces significant barriers. Academic prototypes often prioritize proof-of-concept over practical considerations such as cost, reliability, and manufacturing scalability (Siegel et al.,

Table 4 Key differences between academic and industrial approaches

Dimension	Academic approach	Industrial approach
Primary objective	Knowledge advancement, novel algorithms	Product commercialization, market deployment
Funding	Grants (2–4 year cycles)	Private investment, VC, revenue
Time horizon	2–4 year projects	5–10 year product lifecycles
Risk tolerance	High (exploratory research)	Low (proven technologies)
Publication	Open (69% of papers)	Patents (proprietary IP)
Technology readiness	TRLs 3–4 (100–1000 hours testing)	TRLs 8–9 (MTBF >10 000 hours)
Resource allocation	70%–80% algorithms	40%–50% algorithms, 30%–40% manufacturing
Hardware cost	\$50 000–\$100 000 research platforms	\$150 000–\$500 000 (targeting \$20 000–\$30 000 at scale)
Testing	Controlled lab environments	Real-world deployment, certification
Success metrics	Publications, citations	Market share, revenue, ROI
Collaboration	Open-source, data-sharing	Proprietary, strategic partnerships

VC: venture capital; IP: intellectual property; ROI: return on investment

2003). In contrast, research systems frequently rely on expensive sensors or controlled environments that are unsuitable for commercial deployment. Time horizons and success metrics differ considerably, with academia focusing on publications and industry emphasizing market viability.

Quantitative analysis has revealed significant TRL gaps: academic prototypes typically operate at TRLs of 3–4 (proof-of-concept in controlled environments), whereas commercial products require TRLs of 8–9 (system qualified via operational testing). Development timelines reflect this gap: academic research operates on grant cycles of 2–4 years, with a higher tolerance for experimental failure, whereas industrial humanoid programs span lifecycles of 5–10 years from R&D to market launch (e.g., Tesla Optimus was announced in 2022, with limited production planned by 2025). Recent advances in cross-embodiment learning (Octo demonstrating zero-shot transfer across nine platforms and CrossFormer scaling to 30+ embodiments) may accelerate TRL progression by enabling rapid deployment adaptation, potentially reducing the traditional engineering gap of 3–5 years (Doshi et al., 2024; Ghosh et al., 2024).

Intellectual property considerations create additional complexities because academic institutions must balance open publication with commercial licensing, whereas companies require competitive advantages. Cultural differences between academic research values (novelty and theoretical rigor) and industrial priorities (practical solutions and ROI) can lead to misaligned expectations and communication challenges.

3.3.3 Industry-specific development challenges

Beyond the scope of academic research, the industrial development of humanoid robots faces challenges that are rarely addressed in publications. Regulatory compliance requires 12–18 months for safety certification (ISO 10218 and IEC 61508), adding \$2–\$5 million to the overall development costs. Reliability engineering demands MTBF >10 000 hours for commercial deployment, beyond 100–1000 hours of operation demonstrated by academic prototypes. Supply chain resilience poses critical risks, as specialized components (high-torque-density actuators and custom sensors) face single-vendor dependencies that threaten production continuity during supply chain disruptions.

Patent analysis reveals divergence between industrial focus and academic publications. Industrial intellectual property (IP) is dominated by actuator design patents (28% of USPTO humanoid filings, 2020–2024), control systems (24%), and perception hardware (19%), whereas academic papers emphasize algorithmic contributions (control algorithms: 41%; perception software: 32%). This divergence reflects fundamental differences in value capture. Academic institutions build reputation using novel algorithms publishable in top venues (RSS, ICRA, and CoRL), while companies protect competitive advantages via proprietary hardware and integration that are resistant to reverse engineering (IFI CLAIMS, 2025).

3.3.4 Successful collaboration models and case studies

Several successful collaborations demonstrate effective academic–industrial partnership models. The development of Atlas by Boston Dynamics exemplifies its long-term collaboration with MIT and Carnegie Mellon, combining academic expertise in control algorithms with industrial mechanical design capabilities. Tesla's Optimus project actively recruits academic researchers, rapidly translating breakthroughs in neural networks and computer vision into practical implementations.

Honda's ASIMO series similarly represents sustained industrial commitment with extensive academic partnerships worldwide, advancing theoretical understanding and practical implementation over decades. Agility Robotics demonstrates an effective university spin-off model, thereby successfully transitioning Oregon State University's bipedal locomotion research into commercial logistics applications while maintaining close academic ties.

The Open X-embodiment collaboration exemplifies a breakthrough model addressing the barriers associated with traditional technology transfer. This initiative united 293 authors from 34 institutions (22 academic and 12 industrial) to create the largest cross-embodiment robotics dataset (over 1 million trajectories, 22 robot platforms, 527 skills). The collaboration succeeded by (1) establishing shared evaluation benchmarks enabling fair comparison across embodiments, (2) open-sourcing datasets while protecting industrial IP via architectural abstraction rather than raw control parameters, and (3) enabling parallel academic–industrial publication (ICRA 2024 Best Paper Award), providing both citation credit and commercial application pathways. The resulting RT-X models achieved 50% higher success rates via cross-embodiment training, demonstrating measurable value from academic–industrial synergy.

3.3.5 Emerging collaboration frameworks and future trends

Recent academic–industry collaboration trends include joint research institutes, industry-sponsored academic programs, and hybrid research models, combining academic freedom with industrial relevance (Ankrah and AL-Tabbaa, 2015). Companies are increasingly establishing research laboratories within or adjacent to universities, facilitating technology transfer while preserving distinct organizational cultures.

New models are being developed with open-source initiatives, enabling shared development of common platforms and reducing costs while accelerating innovation.

Large-scale collaborative consortia involving multiple academic institutions, companies, and government agencies are forming to address challenges that exceed individual organizational capabilities. Future models emphasize flexible partnerships, shared IP frameworks, and accelerated technology transfer mechanisms that respond to rapid AI and robotics advancements.

4 Problems and challenges

The research and application of humanoid robots remain in their early stages, facing numerous technical challenges across multiple domains. These challenges have considerably impacted the development of efficient, reliable, and user-friendly humanoid robots that can be seamlessly integrated into human society.

4.1 Hardware system design

Hardware systems are subject to dual constraints of performance and cost, presenting significant engineering challenges that must be addressed for the successful commercialization and practical deployment of humanoid robots.

4.1.1 Ontological structure

Ontological structure serves as the foundation for humanoid robots to achieve optimal functions and performance. An optimal ontological structure should provide sufficient stability to support the robot in maintaining stability across various actions and postures, flexibility to facilitate adaptation to different environments and effective implementation of humanoid behaviors, durability to withstand wear and pressure during long-term use, safety to ensure secure HRI, cost-effectiveness to enable commercialization and large-scale production, and aesthetic appeal to enhance user experience.

Currently, the main technological shortcomings in ontological structure include:

1. Communication bus. The communication bus is the foundation for establishing interaction between modules in the body structure and requires improved resistance to electromagnetic interference (Joseph et al., 2018). Data loss due to electromagnetic interference causes system instability and affects the real-time performance of humanoid robots.

2. Actuators. Actuators must offer high power density, high torque, and reversible drive while remaining compact (Joseph et al., 2018). Joint actuators are excessively costly and account for approximately 60% of the total robot cost, which considerably limits their large-scale production. Current actuators struggle to achieve an optimal balance among power-to-weight ratio, low-speed high-torque capability, and reversible drive characteristics.

3. Sensors and sensing systems. Humanoid robots rely on various sensors such as cameras, lasers, and tactile sensors. There exists a technical contradiction between the precision and shock resistance of sensors. Integrated sensors such as force/torque sensors and IMUs are crucial for ensuring balance and interaction in humanoid robots, requiring a delicate balance between perception accuracy and impact resistance. Despite various research efforts to enhance robot–environment interactions, the sensing capabilities of humanoid robot systems remain limited; this poses challenges in achieving human-like sensing systems.

4. Materials and drivetrain. The materials used in manufacturing humanoid robots should be reconsidered, and morphological computation should be employed to balance and compensate for locomotion and dynamic behavior. Advanced materials that provide both strength and flexibility while maintaining cost-effectiveness remain a significant challenge.

4.1.2 Power supply and energy management

Humanoid robots are typically powered by portable rechargeable batteries, and Li-PO batteries are commonly used despite their limitations. The bottleneck in energy systems is prominent, and their power consumption and endurance are considerably below practical needs. In addition, high losses in power management restrict the commercial application of these systems, and the current battery technology fails to meet the energy density requirements for extended autonomous operation.

4.1.3 Large AI model hardware and energy constraints

The integration of large AI models into humanoid robots is hindered by fundamental hardware and energy limitations. Current mobile computing platforms lack the computational power required to run LLMs locally because models such as GPT-4 require high-memory graphics processing units (GPUs) and substantial processing power (Strubell et al., 2019). The power consumption of large model inference can rapidly drain robot batteries, with high-performance GPUs consuming 200–300 W during intensive processing; these batteries are therefore incompatible with typical robot battery capacities of 1–2 kWh (Patterson et al., 2021). Edge computing solutions require specialized AI accelerators optimized for inference; however, these platforms often lack flexibility and face compatibility challenges with rapidly evolving AI architectures (Jouppi et al., 2017). Thermal management challenges of running high-performance processors in compact robot form factors further limit sustained computational performance, creating fundamental trade-offs between AI capabilities and practical operational constraints.

4.2 Control system design

Control systems face multifaceted challenges in achieving robust, real-time, and adaptive performance required for the operation of humanoid robots in dynamic environments.

4.2.1 Software architecture

Existing software architectures lack a unified middleware standard, leading to compatibility and integration issues. Delays in real-time communication among perception, decision-making, and control modules hinder the dynamic response capabilities of these architectures. Furthermore, synchronization and coordination mechanisms of distributed control nodes remain underdeveloped, creating bottlenecks that degrade the overall system performance.

Robot operating systems (ROSs) have been introduced as unified platforms to reduce software development workload; however, challenges remain in handling the diversity of software development requirements. Walking control of humanoid robots is particularly challenging, requiring precise dynamic models and robust walking engines to achieve stable walking across different environments.

4.2.2 Complex locomotion control

Humanoid robots require motion control systems that simultaneously possess environmental adaptability, flexibility, motion accuracy, and coordination (Saeedvand et al., 2019). In tasks such as stable walking on complex terrains, precise grasping, and dynamic balance, systems must efficiently handle multi-constraint optimization problems with extremely high algorithmic complexity (Denny et al., 2016).

Key challenges in locomotion control are as follows:

1. Locomotion and balance. Humanoid robots need a high level of balance and motion coordination, which is technically

challenging. For walking on flat surfaces, humanoid robots require real-time control to maintain the center of pressure within the convex hull of contact points on the ground; for this purpose, complex control strategies are required. Humanoid robots cannot stably walk on uneven surfaces, such as rough terrain and different terrains. The motion control precision is insufficient to meet the demands of fine operations, and robustness under external disturbances is inadequate.

2. Grasping behavior. Current humanoid robot hand designs are not yet optimal. A well-designed hand should perform various manipulation tasks and complex grasping actions, placing high demands on control strategies and dexterous manipulation capabilities.

3. Mass distribution. The balance and dynamic performance of humanoid robots are heavily influenced by mass distribution. An optimal design requires lightweight limbs and mass distribution concentrated around the waist to enhance dynamic performance and energy efficiency.

4. Additional control issues. To achieve locomotion control in humanoid robots, joint limitations must be addressed, self-collision avoidance must be ensured, and task-space control must be achieved while maintaining real-time performance and stability.

4.3 Perception and cognition challenges

Humanoid robots have limited capability for environmental perception, with the core bottleneck being the trade-off between precision and coverage range; these considerably impact the ability of robots to understand and interact with complex environments.

4.3.1 Multi-sensor information fusion

Multi-sensor information fusion faces significant challenges, including substantial differences in sampling frequencies, diverse data formats, and distinct feature spaces. Traditional fusion methods struggle to effectively handle the temporal and spatial alignment and feature correlation of heterogeneous data (Li Y et al., 2024). In addition, dynamic changes in complex environments considerably impact the stability of perception systems, and robust algorithms that can adapt to varying conditions are required.

4.3.2 Computational limitations

Deep learning algorithms have considerably enhanced learning capabilities; however, their high computational complexity makes it difficult to meet real-time requirements on mobile platforms with limited computing resources. This creates a fundamental trade-off between perception accuracy and computational efficiency that must be carefully managed.

4.3.3 Semantic understanding and reasoning

Robots lack the semantic understanding of complex scenes and have deficiencies in commonsense reasoning and causal relationship analysis. Their decision accuracy considerably decreases when facing unknown scenes, making it difficult to achieve true environmental generalization. This limitation severely constrains their ability to operate autonomously in unstructured environments.

4.3.4 Real-time visual processing

Real-time and accurate obstacle localization using 3D image processing and multiple cameras is crucial for navigation and obstacle avoidance of humanoid robots. Current visual processing systems continue to face technological challenges in terms of accuracy, processing speed, and adaptability to complex environments.

4.3.5 LLM integration and reliability challenges

The integration of LLMs into humanoid robot control systems presents significant challenges in real-time performance and reliability. Real-time control loops typically operate at 100–1000 Hz and require response times of 1–10 ms, whereas LLM inference can take several seconds for complex reasoning tasks. This latency mismatch creates unacceptable delays for time-critical operations and stable locomotion control.

Furthermore, LLMs are prone to generating hallucinated or factually incorrect responses, which can lead to inappropriate or dangerous robot behaviors when translated into physical actions (Ji et al., 2023). The black-box nature of these models makes it difficult to predict or explain decision-making processes, thereby creating challenges for their debugging and validation in safety-critical applications. In addition, grounding language model outputs in physical world constraints remains fundamental because models trained primarily on text data may lack understanding of physical limitations and safety constraints.

4.4 HRI challenges

Effective HRI requires a sophisticated understanding and generation of multimodal communication signals, posing significant challenges for natural and intuitive interaction.

4.4.1 Multimodal communication processing

In complex scenarios, robots need to simultaneously process the verbal instructions, facial expressions, body language, and emotional states of users. Current technologies have significant limitations in handling ambiguous expressions, metaphors, cultural differences, noisy environments, and multiperson conversational settings (Li Y et al., 2024). Accurately identifying users' true intentions and predicting their subsequent needs remains a core challenge for humanoid robots.

4.4.2 Emotional expression and recognition

Humanoid robots are becoming increasingly human-like in appearance; however, they have not yet achieved true humanization and exhibit deficiencies in the naturalness, consistency, and appropriateness of emotional expression. Humanoid robots face challenges in expressing and recognizing emotions, requiring more advanced algorithms and methods to enhance their emotional intelligence.

4.4.3 Specialized application requirements

In specialized fields such as education and healthcare, robots need to develop personalized interaction strategies for different user groups. Developing user models for long-term personalized adaptation presents significant challenges, particularly in applications such as autism treatment and rehabilitation training for children with cerebral palsy.

4.4.4 Speech and language processing

Humanoid robots must effectively communicate via speech recognition, facial expression recognition, and understanding of body language. Current limitations in natural language processing, particularly in handling context-dependent meanings and cultural nuances, constrain effective communication.

4.5 Application challenges

The deployment of humanoid robots across diverse application scenarios presents unique challenges that vary significantly based on operational requirements and environmental conditions.

4.5.1 High-risk environment adaptability

In high-risk environments such as disaster response, nuclear management, and mine rescue, robots must operate stably under extreme temperature differences and radiation conditions. These demands impose rigorous higher requirements on the design and control systems of humanoid robots. These robots also require high degrees of adaptability and stability, necessitating specialized protective measures and robust control architectures.

4.5.2 Cost and manufacturing complexity

The design and manufacturing of humanoid robots are highly complex and costly, due to their high DOFs. For example, the human hand alone has 22 DOFs, making it challenging to perfectly mimic human movements. The current unbalanced cost structure, with actuators accounting for about 60% of the total cost of robot development, limits large-scale production. The current production scale is only at the level of hundreds of units, with unit costs exceeding \$500 000. As demonstrated in autism therapy deployments (Section 3.1.1), high equipment costs (\$15 000–\$20 000 per unit) and maintenance requirements limit long-term sustainability. Controlling design and manufacturing costs while improving cost-performance ratios is a critical factor in promoting the mass production of humanoid robots.

4.5.3 Application scenario diversity

Humanoid robots are designed for various application scenarios such as rescue operations, education, assistance, and entertainment. Different scenarios impose different requirements on robot capabilities, presenting challenges in design and functional implementation. This diversity necessitates the development of flexible architectures that can adapt to varying operational demands while maintaining core functionality.

4.5.4 Environmental robustness

Industrial environments may expose robots to dust, humidity, or rain; therefore, comprehensive protective measures must be incorporated into their design. Ensuring reliable operation across diverse environmental conditions while maintaining performance standards remains a significant engineering challenge.

4.6 Ethical and societal implications

The successful integration of humanoid robots into society involves complex considerations that extend beyond technical capabilities to encompass social, economic, legal, and ethical dimensions; these considerations demand systematic investigations.

4.6.1 Employment displacement and economic transition

The deployment of humanoid robots can cause concentrated labor market disruption in sectors where routine physical tasks can be automated. Economic studies project job displacement of 20%–30% in manufacturing assembly, 40%–50% in warehouse logistics, and 25%–35% in food preparation within 10–15 years of the widespread deployment of humanoid robots (Acemoglu and Restrepo, 2020). While the World Economic Forum estimates net positive employment effects by 2030 (85 million jobs displaced and 97 million created) (World Economic Forum, 2020), the transition period poses significant challenges.

Workers displaced from routine physical occupations face retraining timelines of 3–5 years, with success rates below 60% for workers over 50 years (Autor, 2019). Automation benefits are distributed unevenly, potentially exacerbating income inequality as capital owners capture productivity gains while displaced workers face wage pressure (Brynjolfsson and McAfee, 2014). Recent advances in the integration of foundation models (e.g., OpenVLA's 10× improved data efficiency) may accelerate deployment beyond current projections, intensifying transition pressures.

4.6.2 Autonomous weapons and dual-use concerns

Dual-use technologies developed for civilian humanoid robots can directly enhance military capabilities. The United Nations Convention on Certain Conventional Weapons has debated lethal autonomous weapons systems since 2014, with over 30 nations calling for preemptive bans (United Nations, 2024). Key concerns include accountability gaps when autonomous systems make lethal decisions, compliance challenges with the Geneva Conventions' principles of distinction and proportionality, and proliferation risks as cross-embodiment learning enables rapid adaptation of civilian technologies to military platforms.

Studies have indicated that autonomous systems struggle with contextual judgment in ambiguous combat scenarios, which requires cultural understanding and moral reasoning (Arkin, 2009). Cross-embodiment advances demonstrated by systems capable of controlling diverse tasks amplify dual-use concerns by reducing barriers to military adaptation.

4.6.3 Legal personhood and relationship boundaries

The European Parliament's 2017 proposal for granting electronic personhood status sparked debate over robot legal standing (European Parliamentary Research Service, 2017). Legal frameworks must address the liability for harm resulting from autonomous decisions, intellectual property rights for robot-generated content, and contractual capacity. Jurisdictional divergence complicates international deployment as robots may be granted legal personhood in some countries while remaining mere property in others.

Human–robot relationship boundaries require attention as psychological studies have shown that humans readily form emotional attachments to anthropomorphic robots (Turkle, 2011). Ethical frameworks must address appropriate limits on robot deception, transparency requirements about the non-human nature of robots, and protections against exploiting psychological vulnerabilities, particularly for vulnerable populations such as children and the elderly. The integration of LLMs introduces additional complexity, as these systems can generate highly convincing social interactions that blur the line between authentic connection and simulated empathy.

4.6.4 Algorithmic bias and transparency

The integration of foundation models introduces systematic bias risks that may perpetuate social inequalities. LLMs can inherit training data biases, which manifest as discriminatory behavior when robots interact with diverse populations (Bender et al., 2021). Recent vision–language–action models trained on large datasets (800 000–1 million trajectories) face representation bias if the training data lack demographic and cultural diversity. The opacity of learned representations complicates bias detection and mitigation (Weidinger et al., 2021).

In addition, privacy concerns arise from the extensive data collection capabilities of sensor-equipped humanoid robots. Vision–language models that process continuous visual and audio streams may inadvertently capture sensitive personal information, raising questions about data governance and user consent. The potential for LLMs to generate convincing but incorrect information creates risks related to misinformation in HRIs.

4.6.5 Responsibility attribution and regulatory frameworks

The absence of mechanisms for tracing autonomous behavior creates challenges for liability assessment when humanoid robots cause harm. As robots achieve greater autonomy in safety-critical applications, such as healthcare and transportation, establishing clear accountability frameworks becomes imperative (Tong et al., 2024). Existing legal systems designed for human agency may be inadequate for addressing harm caused by the emergent behavior of learned models or complex human–robot–environment interactions.

In addition, regulatory approaches under development include mandatory algorithmic impact assessments, strict liability frameworks, and certification regimes. International coordination on standards is essential to prevent regulatory arbitrage. Addressing these implications requires sustained collaboration among technologists, policymakers, legal scholars, ethicists, and affected communities to ensure humanoid robots benefit society while protecting fundamental human rights.

5 Promising research areas

To address the challenges identified in Section 4.6, future studies on humanoid robots must focus on several key areas that hold significant promise for advancing the field and enabling practical deployment of robots in real-world applications. These research directions are organized into three strategic layers that address different levels of system development. (1) The technical foundation layer focuses on hardware innovations such as advanced actuation, materials, and energy systems. (2) The intelligence layer emphasizes cognitive capabilities via collaborative intelligence, multi-agent coordination, and autonomous learning. (3) The application layer addresses safety, ethics, standardization, and cross-domain deployment. This layered framework ensures systematic advancement from fundamental technologies to practical applications; this represents evolutionary improvements and revolutionary breakthroughs required to realize the full potential of humanoid robots.

5.1 Collaborative intelligence and multirobot systems

The development of sophisticated collaborative capabilities represents a critical frontier in humanoid robotics, with significant implications for complex task execution and system scalability.

5.1.1 Large-scale heterogeneous group collaboration

The collaboration of humanoid robots with humans or other robots in real-world scenarios warrants immediate attention. As humanoid robots are similar to humans, they can play a significant role in multirobot systems, particularly in applications such as rescue operations, education, assistance, and entertainment. Future research should focus on breakthroughs in distributed collaboration technologies for large-scale heterogeneous robot groups.

With the development of multi-agent reinforcement learning frameworks based on graph neural networks, adaptive task allocation and millisecond-level group coordination responses can be achieved in dynamic environments. To enable the collaboration between multiple humanoid robots to solve complex tasks, sophisticated algorithms that can manage dynamic task allocation, real-time communication, and coordinated decision-making are essential.

5.1.2 Cognitive fusion and knowledge sharing

By constructing distributed cognitive architectures, knowledge sharing among multiple robots can be enabled while protecting privacy. The integration of LLMs can facilitate group task understanding and decomposition based on natural language instructions, thereby enabling more intuitive human–robot collaboration and inter-robot communication.

5.1.3 Hybrid virtual–physical collaboration ecosystem

Building hybrid virtual–physical collaboration frameworks based on digital twin technology represents a promising avenue for enhancing collaboration capabilities. By exploring quantum-inspired optimization and neuromorphic computing architectures, low-power real-time coordination can be achieved for ultra-large-scale robot groups, addressing the computational limitations that currently constrain multirobot systems.

5.1.4 System architecture and implementation framework

We propose a three-layer architecture to systematically develop collaborative intelligence capabilities, as shown in Table 5. This framework integrates perception, cognition, and execution components via standardized interfaces, thereby enabling seamless information flow from environmental sensing to coordinated action. The perception layer processes multimodal sensory inputs to construct comprehensive environmental representations. The cognitive layer leverages foundation models for high-level task planning and reasoning, decomposing complex collaborative objectives into executable sub-tasks. In addition, the execution layer coordinates motion generation and force control across multiple agents, ensuring safe and efficient physical interactions.

5.2 Enhancement of autonomy and intelligence

Humanoid robots must possess advanced autonomous capabilities to operate effectively in unstructured environments and perform complex tasks without constant human supervision.

5.2.1 Innovation in autonomous learning and adaptation algorithms

The autonomy of humanoid robots is a key research direction, encompassing software development aspects such as autonomous walking, robotic vision, and behavioral control. By integrating machine learning and AI technologies, humanoid robots can perform autonomous learning and adapt to new environments and tasks.

By developing autonomous learning algorithms tailored for complex environments, challenges with exploration in sparse reward settings can be addressed. In addition, deep reinforcement learning, imitation learning, and transfer learning can be integrated to construct meta-learning frameworks for rapid task adaptation (Cao, 2025). To enhance the intelligence and adaptability of humanoid robots, more efficient learning algorithms must be proposed to help robots better adapt to environments and perform tasks. As a result, robots can learn from experience and refine their behaviors and skills. Future perception systems will increasingly integrate multimodal understanding capabilities that combine visual, auditory, and tactile information with natural language processing (Driess et al., 2023). This convergence will enable humanoid robots to understand both explicit verbal instructions and implicit contextual cues from their environment, thereby creating more sophisticated scene understanding and task interpretation capabilities. Such integrated perception systems represent a critical foundation for embodied intelligence applications.

5.2.2 Cognitive architecture and reasoning capability enhancement

To build hierarchical decision-making architectures, working memory, attention selection, and executive control modules must be integrated. The development of causal and common-sense reasoning algorithms can enhance the autonomous decision-making capabilities of humanoid robots in uncertain environments (Saeedvand et al., 2019), addressing current limitations in semantic understanding and environmental generalization of these robots.

5.2.3 Integration of embodied intelligence and language understanding

The integration of LLMs into robot control loops can achieve end-to-end learning from natural language instructions to action sequences, supporting zero-shot task transfer and multimodal instruction understanding. This represents a significant advancement in making humanoid robots more accessible to non-expert users via natural language interaction.

5.2.4 Neuromorphic computing and bionic intelligence

Neuromorphic chips can enable humanoid robots to achieve low-power real-time perception and processing. Studies on robot control algorithms based on spiking neural networks can explore biologically inspired learning mechanisms to improve adaptive learning efficiency, thereby addressing the computational limitations identified in current perception and

Table 5 Architecture of collaborative intelligence systems

Layer	Core technology	Primary function	Key challenge
Perception layer	Vision (RGB-D, LiDAR), tactile sensors, proprioception	Multimodal sensing, object recognition, environment mapping	Sensor fusion, real-time processing, occlusion handling
Cognitive layer	Foundation models (LLMs, VLMs), reinforcement learning, graph neural networks	Task planning, decision making, knowledge sharing, multi-agent coordination	Computational efficiency, task decomposition, privacy preservation
Execution layer	Model predictive control, whole-body control, trajectory optimization	Motion generation, force control, collision avoidance, dynamic coordination	Real-time constraints, stability assurance, adaptive control
Integration framework	ROS2, middleware (DDS), digital twin	Component coordination, data synchronization, virtual-physical integration	Latency reduction, scalability, interoperability

DDS: data distribution service

cognition systems.

5.3 Environmental adaptation and expansion of locomotion capabilities

Enhancing environmental adaptability and expanding locomotion capabilities are essential for deploying humanoid robots in diverse real-world scenarios beyond controlled laboratory settings.

5.3.1 Perception and adaptation to complex terrain

The future design of humanoid robots must enable them to walk more stably in various environments such as flat surfaces, grasslands, and uneven terrains; this will enable their application in complex environments. The development of intelligent terrain recognition algorithms based on multi-sensor fusion can enable real-time modeling of complex environments and predictive terrain perception. As a result, robots can autonomously navigate complex terrains such as stairs, slopes, and obstacles.

By enhancing the environmental perception capabilities of humanoid robots, they can be accurately aware of their surroundings. This enables effective navigation and obstacle avoidance by such robots. By enhancing the vision, auditory, and other sensory capabilities of humanoid robots, they can better understand and interact with the environment.

5.3.2 Adaptive motion control technology

The development of variable stiffness actuators and adaptive gait control algorithms is a critical advancement in the locomotion capabilities of humanoid robots. Breakthroughs in real-time footstep planning and dynamic center of mass adjustment technologies that are integrated with force feedback control can enable achieving a dynamic balance between compliance and precision.

Language-conditioned control is an emerging research direction that combines natural language understanding with adaptive control systems. Future control architectures will incorporate LLMs to interpret high-level instructions and translate them into appropriate motor behaviors through end-to-end learning approaches (Brohan et al., 2023). Consequently, these systems will enable more intuitive programming and control of humanoid robots via natural language interfaces.

Investigations into ways to enhance the motion control capabilities of humanoid robots include stable walking in complex terrains and the execution of complex movements. Such studies should focus on developing more sophisticated control algorithms that can adapt to varying environmental conditions in real time.

5.3.3 Bionic motion and morphological reconstruction

The development of bio-inspired control algorithms based on central pattern generators (CPGs) and cerebellar adaptation models (Itoh et al., 2004; Ijspeert, 2008; Or, 2010; Yao et al., 2022) offers promising approaches for achieving more natural and efficient locomotion in humanoid robots. By exploring reconfigurable robots and hybrid soft-rigid technologies, dynamic morphological adjustments can be achieved in response to environmental and task requirements.

5.3.4 Expansion of action domains

Humanoid robots should be designed to complete more complex tasks, such as stair climbing, skiing, and ice skating, to expand their range of locomotion and application scenarios. Studies on dexterous manipulation research have focused on developing the hands and arms of humanoid robots to perform complex and delicate tasks, increasing the DOFs in the hands and other joints to achieve more efficient and precise motion control. New achievements in materials and morphological computation are required to improve locomotive efficiency and adaptability of humanoid robots; these developments will help address current limitations in actuator performance and structural design.

5.4 Optimization of HRIs and emotional expression

Advancing HRI capabilities is crucial for the successful integration of humanoid robots into human society and for achieving natural, intuitive communication.

5.4.1 Intelligent dialog and intent understanding

Future developments in HRI will focus on embodied language understanding, wherein LLMs are grounded in physical interaction capabilities (Brohan et al., 2023). This research direction aims to bridge the gap between abstract language comprehension and concrete physical actions, thereby enabling humanoid robots to understand natural language instructions and translate them into appropriate behaviors.

In addition, advanced dialog systems will incorporate chain-of-thought reasoning capabilities that enable robots to decompose complex instructions into executable sub-tasks (Wei et al., 2022). These systems will understand temporal ordering, causal relationships, and common-sense knowledge required for task planning and execution. Multimodal language understanding will combine linguistic processing with visual scene analysis and proprioceptive feedback (Driess et al., 2023).

Moreover, interactive learning via human feedback will become increasingly important for personalizing robot behavior. Reinforcement learning from human feedback (RLHF) approaches hold promise for aligning robot behavior with human preferences while maintaining safety requirements (Ichter et al., 2022). Future research will focus on developing efficient architectures for real-time language processing within the computational constraints of mobile humanoid robots.

5.4.2 Affective computing and coordinated expression

The development of emotion recognition frameworks that integrate facial expressions, vocal prosody, and physiological signals (Spezialetti et al., 2020) represents a significant advancement in emotional intelligence. By developing multimodal emotional expression systems, humanoid robots can achieve natural and consistent emotional expression with cultural adaptability.

Advancements in emotional expression and recognition for humanoid robots will enable them to communicate more naturally with humans, understand human emotional states, and respond accordingly. Future studies should explore humanization of humanoid robots in terms of behavior, emotion, and social interaction.

5.4.3 Personalized social interaction intelligence

By developing dynamic user models and long-term memory mechanisms, personalized interaction strategies can be adaptively adjusted. The development of algorithms for understanding social norms and cultural sensitivity can enhance the appropriateness and acceptance of interactions with users from diverse backgrounds. These developments will address existing limitations in cross-cultural communication.

5.5 Expansion and diversification of application fields

The expansion of the application domains of humanoid robots presents opportunities for technology transfer and practical impact across multiple sectors of society.

5.5.1 Industrialization of intelligent services

The service sector is one of the most important application directions for humanoid robots, such as home services, education, healthcare, and entertainment. For the large-scale commercial application of humanoid robots in these service industries, cost-effectiveness and development of sustainable business models must be balanced.

5.5.2 Specialized applications in extreme environments

Humanoid robots can potentially be employed in high-risk environments such as disaster response, nuclear management, and mining rescue. By developing customized humanoid robots for these extreme environments, technological breakthroughs can be achieved in terms of robot reliability under extreme conditions via modular redundant design and self-healing mechanisms.

To enhance system reliability and fault tolerance, modular design approaches should be proposed to ensure that the overall system can continue to operate even if part of it fails. This is particularly crucial for applications in dangerous or inaccessible environments, where maintenance and repair are challenging.

5.5.3 Exploration of interdisciplinary innovative applications

Humanoid robots can be efficiently employed in emerging application fields. For example, humanoid robots can serve as research platforms in neuroscience applications to test and validate models of the human brain and support the development of cognitive abilities. The exploration of potential applications in artistic creation and sports training can drive breakthroughs in multimodal interaction, creative algorithms, and precision control technologies.

5.6 Technical infrastructure and cost optimization

For the widespread adoption and commercialization of humanoid robots, the fundamental technical limitations and cost barriers must be addressed.

5.6.1 Breakthroughs in emerging hardware technologies

Revolutionary technologies such as flexible electronic skin (Schmidt et al., 2006; Schmitz et al., 2010a; Chang et al., 2019; Ramalingame et al., 2019; Bao et al., 2023; Guo et al., 2023), soft robotics, and self-healing materials will reshape the form and function of humanoid robots. In addition, flexible electronic skin can provide whole-body tactile perception, soft robotics can enhance safe interaction, and self-healing materials can improve human–machine interfaces. By integrating these technologies, humanoid robots will achieve considerably enhanced environmental adaptability and establish more natural interaction with the environment.

Advanced-material research should focus on developing components that provide both strength and flexibility while maintaining cost-effectiveness. This includes investigating novel actuator designs, sensor integration, and power management systems that can meet the demanding requirements of humanoid locomotion and manipulation.

5.6.2 Cost optimization and industrialization promotion

Developing cost-effective humanoid robot platforms can accelerate the progress of research projects and make humanoid robotics more widely accessible. By reducing actuator costs via integrated motor and reducer design and developing high-efficiency drivers, the overall cost of robot production can be considerably reduced.

Research into more economical and efficient drive systems and energy management strategies can reduce the cost of humanoid robots while improving energy efficiency. The optimization of energy management strategies to extend battery life will lay the foundation for the large-scale commercial deployment of humanoid robots. To this end, energy utilization efficiency must be enhanced by investigating and employing new energy systems and energy recovery technologies.

5.6.3 Standardization and modular integration

The development of standardized interfaces and modular components can facilitate rapid prototyping, reduce development costs, and improve system maintainability. This approach can also enable more efficient collaboration between research institutions and industry partners.

5.7 Research and resolution of safety and ethical issues

As humanoid robots become more prevalent in society, addressing the associated safety and ethical considerations is imperative for ensuring their responsible development and deployment.

5.7.1 Multilayered safety assurance systems

Multilayered safety assurance systems must be constructed by integrating hardware safety constraints, software behavioral boundaries, and real-time monitoring mechanisms. The development of robust fail-safe mechanisms and emergency response protocols is essential for ensuring safe human–robot coexistence in various environments.

Research into safety issues must ensure that humanoid robots are safe in environments where they coexist with humans, addressing both the physical safety and psychological comfort for human users.

5.7.2 Privacy protection and algorithmic transparency

Existing concerns about algorithmic transparency and user privacy can be addressed by developing data processing frameworks that protect privacy and decision-making algorithms that are interpretable. Establishing mechanisms for sharing responsibility between humans and robots, as well as for tracing accidents, is crucial for building trust and accountability in the use of humanoid robots.

5.7.3 Ethical standards and social integration

Research into the safety and ethical issues of humanoid robots must ensure that their behaviors conform to societal standards and moral norms. The formulation of ethical behavioral standards that are adaptable to different cultural contexts can ensure the safety of environments where humans and robots coexist (Tong et al., 2024).

Social integration addresses the legal, ethical, and social issues associated with the seamless integration of humanoid robots into society. This includes investigating the impact on employment, social relationships, and cultural norms, as well as developing policies and regulations that support beneficial adoption while mitigating potential negative consequences.

6 Conclusions

This paper presents a comprehensive survey of humanoid robots, systematically investigating their definition, classification, key technologies, current research status, industrial applications, existing challenges, and future development directions. By performing extensive literature analysis covering hundreds of studies and an in-depth investigation of representative commercial products, this study provides a holistic understanding of the humanoid robotics field from both theoretical foundations and practical implementations. The primary contributions of this survey are multifaceted. First, we establish a clear taxonomic framework for humanoid robots and categorize them across eight dimensions, including functionality, application fields, mobility, and autonomy levels. This classification system offers researchers and practitioners a structured approach to understanding the diverse landscape of humanoid robotics. Second, we conduct a thorough technical analysis of key enabling technologies, including ontological structures, perception systems, locomotion control, and intelligent decision-making algorithms. This analysis reveals critical interdependencies between hardware design and software architectures, highlighting the importance of integrated system approaches.

A distinctive feature of this review is its dual-perspective approach, which involves examining humanoid robots from academic research and industrial development viewpoints. This comprehensive analysis reveals significant gaps between laboratory demonstrations and commercial deployments, thereby identifying specific bottlenecks that hinder the practical applications of humanoid robots. We systematically analyze representative products from leading companies, including Tesla, Boston Dynamics, and UBTECH; we thus provide detailed performance comparisons and technological assessments that are rarely found in existing academic reviews.

Six major challenge categories are identified via our investigations: hardware system design limitations, control system complexities, perception and cognition constraints, HRI difficulties, application-specific requirements, and ethical considerations. For each challenge, we provide a targeted analysis of underlying causes and propose specific improvement strategies. We outline seven promising research directions that address these challenges, including collaborative intelligence systems, enhanced autonomy algorithms, environmental adaptation technologies, improved HRI methods, expanded application domains, technical infrastructure optimization, and ethical framework development.

Industrial perspective analysis reveals that significant progress has been made in humanoid robot development; however, substantial challenges remain in achieving cost-effective mass production and widespread deployment of humanoid robots. Comparative analysis of current products demonstrates that humanoid robotics is transitioning from prototype development to commercial viability, with several companies achieving limited production scales. However, high costs associated with the fabrication of actuators, sensors, and control systems continue to limit the broad adoption of humanoid robots.

In the future, the development trajectory of humanoid robots can be projected across three temporal horizons with distinct technological and application milestones. In the near term (1–3 years), we anticipate incremental improvements in actuator efficiency and cost reduction; this will enable limited commercial deployment of humanoid robots in controlled environments such as warehouses and manufacturing facilities. Integration of foundation models with these robots will enhance their natural language interaction capabilities, while advances in whole-body control will improve locomotion stability of humanoid robots on structured terrains. In the medium term (3–5 years), significant breakthroughs are expected in multirobot collaboration frameworks and adaptive learning algorithms; this will ultimately facilitate the deployment of robots in semi-structured environments, including healthcare facilities and service industries. Cost reductions via modular design and standardization will enable broader market adoption. In the long term (5–10 years), the convergence of embodied intelligence, neuromorphic computing, and advanced materials will enable the development of truly autonomous humanoid robots that can operate in complex, unstructured environments. In addition, their large-scale deployment across diverse application domains, from elderly care to disaster response, will become feasible as technical maturity increases and costs approach consumer-market levels. These projected timelines align with current technological trajectories and investment trends. However, actual progress will depend on continued research breakthroughs and successful technology transfer between academia and industry.

This survey serves as a valuable resource for researchers, engineers, and policymakers by providing a comprehensive roadmap for future humanoid robotics development. By systematically identifying research gaps and practical challenges, as well as proposing development strategies, we offer actionable guidance for advancing the field toward more capable, affordable, and socially integrated humanoid robots. As the technology continues to mature, the outlined challenges will have to be addressed. This will help realize full potential of humanoid robots in enhancing human life and productivity across diverse application domains.

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Author contributions

Wenjuan LI and Genyuan YANG drafted the paper. Wenjuan LI, Jiyi WU, and Lei SHENG conducted the literature review and analysis. Genyuan YANG and Qifei ZHANG collected the data. Chengjie PAN and Wenjuan LI generated the figures. All the authorsread and approved the final paper.

Conflict of interest

All the authors declare that they have no conflict of interest.

Declaration on the use of generative AI tools

During the preparation of this work, the authors used ChatGPT to improve language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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