Europe Robotics Strategic Agenda

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THE EUROPEAN EXCELLENCE NETWORK ON AI-POWERED ROBOTICS

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EDITORIAL

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The euROBIN Strategic Agenda addresses key challenges in robotics that require further research and technological advancements for full-scale deployment. There are also numerous commercial and legal challenges, most of which pertain to use of AI. These broader challenges are tackled in the ADRA Strategic Research Agenda, developed in collaboration with euROBIN.Together, the euROBIN and ADRA SRAs are complementary, providing a comprehensive framework to address both technical and socio-economic aspects of robotics and AI deployment.

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EXECUTIVE SUMMARY

Robotics has achieved remarkable progress over the last two decades, progressively expanding its reach beyond industrial automation that was its first major application. **Robots are significantly more autonomous, smarter, lighter, more robust, and less costly than the first generation of industrial robots.**

Advances in control algorithms, computing power, miniaturization of electronics and batteries, new sensors, and soft material components have contributed importantly to revolutionize robotics. Now, these developments intersect with rapidly evolving AI techniques, creating **embodied AI**—robots integrated with physical bodies that interact with environments, intelligent agents, and humans. As a result, **a new generation of complex, cognitive and adaptive multi-purpose machines is within reach.**

Despite the immense progresses and promises we may hold for AI, achieving such multipurpose robots requires resolving short- and medium-term scientific and technical challenges that pertain not only to AI but also to advances in control and reasoning methods to develop **robots capable of interacting with unfamiliar and unpredictable environments and to collaborate safely and effectively with humans.**

While the world runs after who will develop the fastest the largest database and assorted AI model, one seems to forget a brain is nothing without a body. Current materials used to build machines remain strikingly similar to their counterparts from a few decades ago. **It is crucial to designing better hardware** to offer robust, scalable and affordable, sensing, computing and actuation, while **prioritizing lifecycle extension, circularity, and resource conservation.**

For decades, Europe has been at the forefront of robotics research and technological development, driven by robust support from the European Commission. H2020, FET and ERC programs, among others, have played a pivotal role in fostering collaborative research and technology transfer globally across Europe and strengthening international partnerships.

Europe has a vantage position in robotics, and it will be crucial that it retains and strengthens the whole value chain, from design to manufacturing, without repeating past mistakes that have led to dependence for critical technologies (i.e. microchips). **A balanced approach to AI development requires investing not only in algorithms, but also in the ecosystems in which they will operate and in the underlying technologies.**

The path to the next generation of robots and machines can take two distinct approaches. One option is to rely entirely on AI black-box systems and proprietary robot controllers, hoping they gain consumer acceptance. Alternatively, we can adopt a **human-centric perspective** that considers not just technological advancement but also the **broader context of robotics deployment,** particularly in addressing climate change and sustainability. This approach requires critical evaluation of **where robots are truly needed and where they are not**, and a strategic plan to identify **which areas of robotics benefit from AI integration and which do not**.

Technological development must be accompanied by research on the **social, psychological and legal dimensions of the relationship between humans and robots**, to understand how humans can develop trust - while avoiding excessive trust - in robots, and how attitudes to robots change in time and across different cultures. This will ensure that **future advancements in AI-based robotics work in the interest of sustainable development, equality and social justice**.

EUROBIN'S PROPOSAL FOR EUROPE ROBOTICS STRATEGIC AGENDA

Foreword: This document provides a brief overview of the key challenges facing robotics from both research and technology perspectives. We include in the annexes four more elaborated documents that review state of research, technology, and gives our vision on the short-medium-long-term challenges, that are currently under review as perspective articles. The articles were written by members of the euROBIN's consortium and other internationally renowned scholars.

WILL AI ALONE BE SUFFICIENT TO SOLVE THE CHALLENGES OF ROBOTICS?

Deep learning, large-language models, and other AI technologies have gone from one breakthrough to the other. As a result, we are witnessing growing excitement in robotics at the prospect of leveraging the potential of AI to tackle some of the outstanding barriers to the full deployment of robots in our daily lives. However, action and sensing in the physical world pose greater and different challenges than analysing data in isolation. As the development and application of AI in robotic products advances, it is important to reflect on which technologies, among the vast array of network architectures and learning models now available in the AI field, are most likely to be successfully applied to robots; how they can be adapted to specific robot designs, tasks, environments; which challenges must be overcome. It is now time to ask: Will AI alone be sufficient to solve the challenges of robotics? The answer is likely no.

While the rapid advancements in AI offer hope for overcoming longstanding challenges in robotics, such as improving autonomy in complex environments and safe human interaction, the **success seen in perfect information games and software tasks like image recognition or text generation cannot be directly applied to robotics.** Physical sensing, planning, control, and navigation involve larger state spaces, limited training data, and stricter safety and reliability demands, presenting fundamentally different challenges.

Today, there is excitement to train robots by watching thousands of human examples and fine tune this in simulation. But, training robots to blindly mimic human movement or imagine what they could do is one thing; enabling them to perform those tasks in the real world, when faced with sorts of unexpected events, is another. This is not solely due to the so-called "sim-to-real gap"—the discrepancy between simulated results and hardware performance. While simulators do still offer a poor account of deformation of soft objects, fluid dynamics, and frictions— all so important in manipulation—the real obstacles lie elsewhere.

What has AI for robotics achieved to date?

A brief historical review. Allowing robots to operate autonomously in novel situations and to approximate the dexterity and agility of living organisms have been key challenges for robotics since at least the 1960s. For several decades, robotics researchers have been expe-

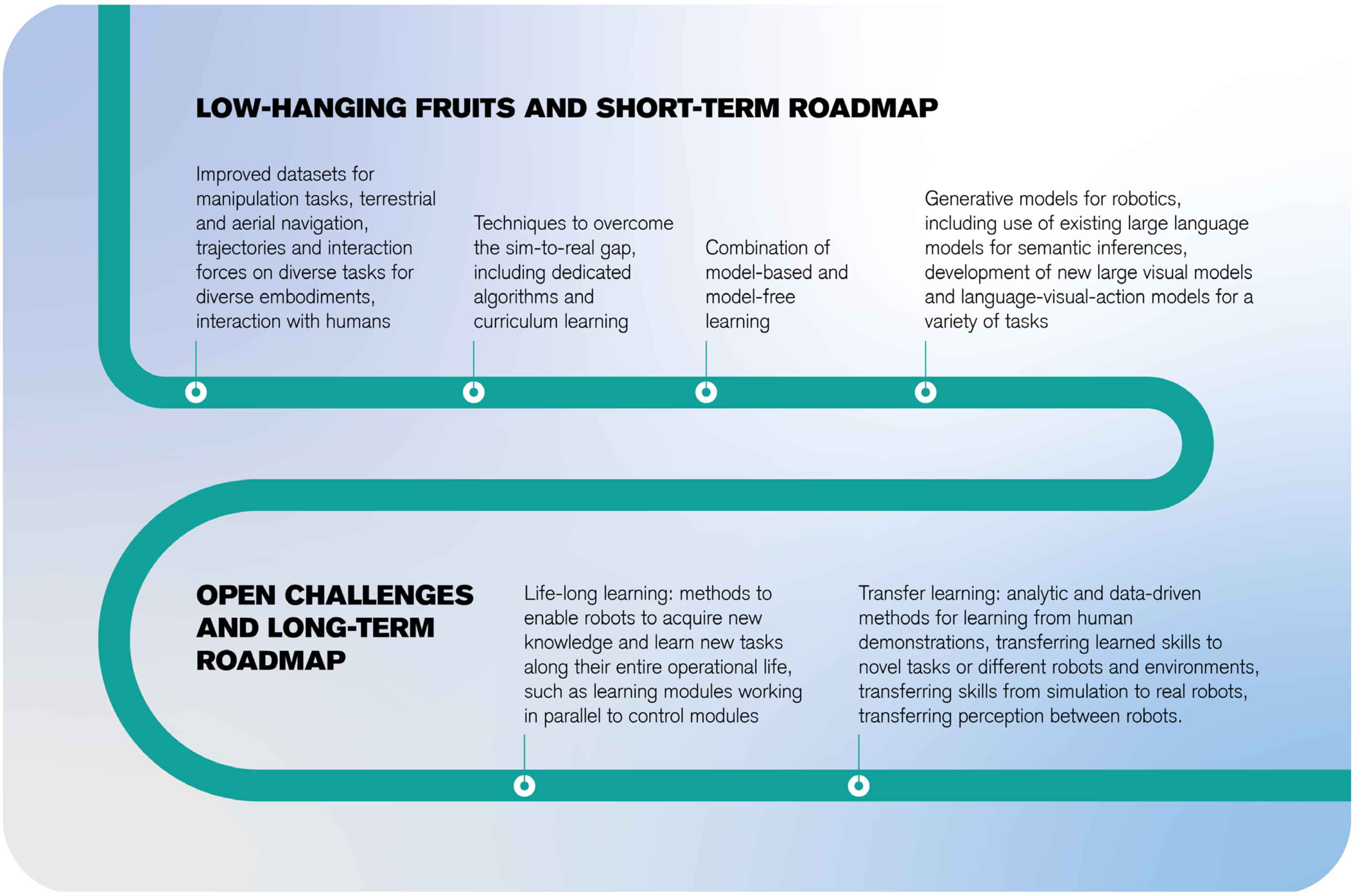

Figure 1: Short-term and long-term challenges for further endorsement of AI in robotics, order by increasing level of complexity. Note that these challenges may not be overcome sequentially and proceed in parallel.

rimenting with neural networks and machine learning as a potential solution to those challenges, and there is now a sizable literature on how to leverage these techniques to tackle robotics problems that had previously proven hard to solve.

Today, techniques to teach robots still rely on the two principal styles of machine learning that have been employed in robotics since the 1990s. On one side there is a family of algorithms that allow robots to learn from expert data, typically provided by a human demonstrator who performs the target action while their movement is captured by visual or motion sensors. Called alternatively Programming by Demonstration, Learning from Demonstration (LfD) or Imitation Learning, this approach has proved applicable in tasks ranging from grasping to manipulation of complex objects. The other type of learning algorithms enables robotic systems to learn through trial and error without a prior formalization of what constitutes the correct control policy. Best exemplified by reinforcement learning (RL) this method typically relies extensively on computer simulations of the robots and its environment to create enough learning cycles and learn a robust enough policy before testing it on the actual robot. Use of RL in robotics was hindered, for a long time, by the exploration phase, which, if not properly bounded, can become too computationally and time intensive and its inability to easily scale to high dimensions. Recent advances leverage the increasing effectiveness of deep-learning and visually-realistic physics-based simulation.

What are the next short-term and long-term challenges? Scientists have only begun to scratch the surface of the potential of RL, LfD, and other flavors of AI and machine learning for robots. The most exciting, but also most challenging, long-term promise of AI for robotics is to enable robots to continuously acquire new knowledge, also knowns as **life-long learning**, a dream dating back to the 90's.

This presents significant technical and regulatory challenges, and raises questions like:

- How do we ensure evolving systems maintain safety and reliability standards for market certification?
- How can we ensure system performance with unpredictable scenarios, and how do we test the system if such future situations are unknown?

To address these challenges require *creating and maintaining representative datasets*:

- Developing **AI algorithms specifically tailored to robotics** challenges while remaining versatile enough to be applied across applications and robotic platforms.
- Maintaining diverse, up-to-date **datasets that reflect the variety of tasks robots may undertake** and environments they may encounter.
- Combining **prior knowledge** of robot and environment dynamics with control methods offering **provable guarantees** is a more effective approach than a purely bottom-up, knowledge-agnostic learning method.
- Creating **benchmarks** for **safety-critical scenarios** like autonomous navigation and close human interaction to assess control systems that may fail in unpredictable ways, with outcomes that cannot be fully explained afterward.

The main challenge for lifelong robot learning is scaling up current methods. **Many robots will not stay the same for their whole operational life**. After five or eight years of operation, a robot may have to mount a different gripper, or a different motor. The objects it has to manipulate and the environment in which it operates may also have changed. Currently, **we lack algorithms that can seamlessly transfer knowledge across even small changes without retraining or human intervention.**

To address these challenges we need robots to be able to *transfer knowledge and transfer learning*:

- Developing methods to enable robots to apply knowledge from one domain to new domains to handle unexpected situations.
- Designing algorithms to transfer knowledge from one robot to another to ease reuse of knowledge and acquisition of novel and more advanced equipment.
- Defining metrics to determine, **when, what and how** to transfer knowledge.

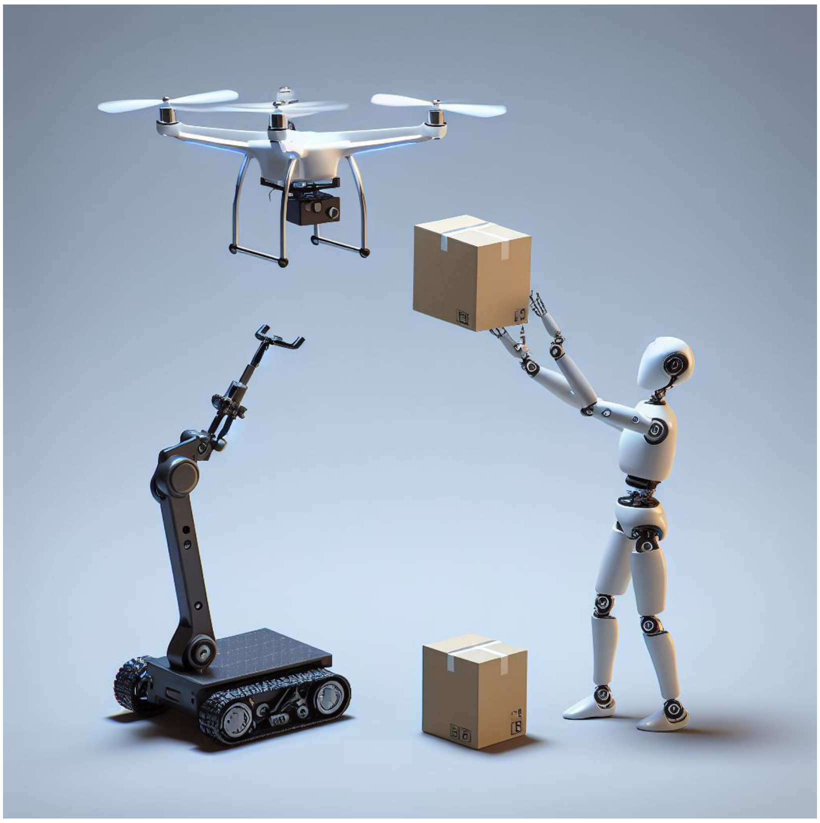

Figure 2: Handing a package from a drone to a humanoid robot or single-arm robot manipulator requires to reconcile drastically different perception, from different viewpoints and sensors, and distinct robot actions from unimanual to bimanual actions

CONTROL, PLANNING AND REASONING IN THE ERA OF GENERATIVE AI: SOLVED PROBLEMS AND REMAINING CHALLENGES

As it faces the overarching challenges of taking robots to complex and uncontrolled environments, **executing complex and partially unpredictable tasks** while operating autonomously, robotics will need to **expand the current scope of planning, control, and reasoning techniques and combine them with generative AI and learning.**

Planning and controlling the movements of robots made of mechanical parts is a cornerstone problem – if not *the* cornerstone problem - of robotics. Industrial robotics was born when computer programs were first applied to guide the movement of robotic arms, mounted over a fixed base, in a tri-dimensional space. Over the years, the scope of control and planning techniques has expanded to include the movements of mobile robots that have no fixed base and can navigate an environment while performing tasks within it.

The manifold and everyday applications we envision for the next generation of robots require **predictable control and explainable behavior** which can only be guaranteed if robots are endowed with **reasoning abilities that allow them to encode and use semantic knowledge to make inferences about the consequences of their actions**, interpret situations never encountered before, and make decisions.

The role of control, planning, and reasoning in shaping the future of intelligent robotics in the age of generative AI and foundation models, is hence closely tied to a broader philosophical question: **Do intelligent robots require explicit representations of their capabilities and bodies to operate effectively in human environments and perform human-scale tasks?**

We posit that the two approaches will need to be combined: **generative AI will offer real-time adaptive behaviors, while model-based techniques will ensure logical reasoning, safety, and long-term planning.**

We further believe that thanks to improvements in mathematical methods and computational technologies, there are still huge margins of advancement in model-based methods that do not rely primarily on learning.

Further advances in control and reasoning are required and encompass:

- **Novel AI-based control model that have an analytical interpretation** such as analytical models of manipulation of deformable objects and of robots that are themselves soft, using geometric mechanics and dynamics, differential geometry, and algebraic topology, that can mathematically describe highly nonlinear dynamics; models of complex interaction

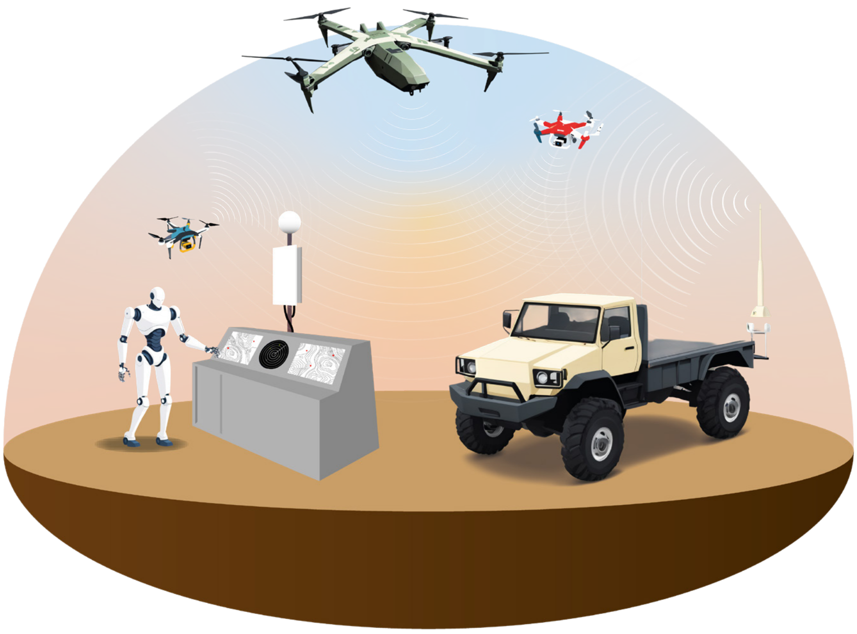

Figure 3. An open challenge is how to control multi-robot systems where several robots of different types co-operate on tasks and share representations of the environment. that they may observe from varying points of view and with different sensors.

with fluids such as air, water is crucial for many applications, from medicine to agriculture to the automation of the textile and food sectors;

- Methods that can reason about **action consequences over a long temporal period** when moving towards a symbolically specified goal, a mission rather than merely a target position; **incorporating abstract strategies** in task-planning routines;
- **Shared representations of the environment** that different robots may observe from varying points of view and with different sensors;
- Develop an understanding of how to integrate open-loop and closed-loop control, active and passive control, model-based and learning-based strategies in a **single theoretical framework**;
- **Integrate task planning with real-time feedback**, robots can effectively co-construct actions with humans, ensuring mutual understanding and efficiency;

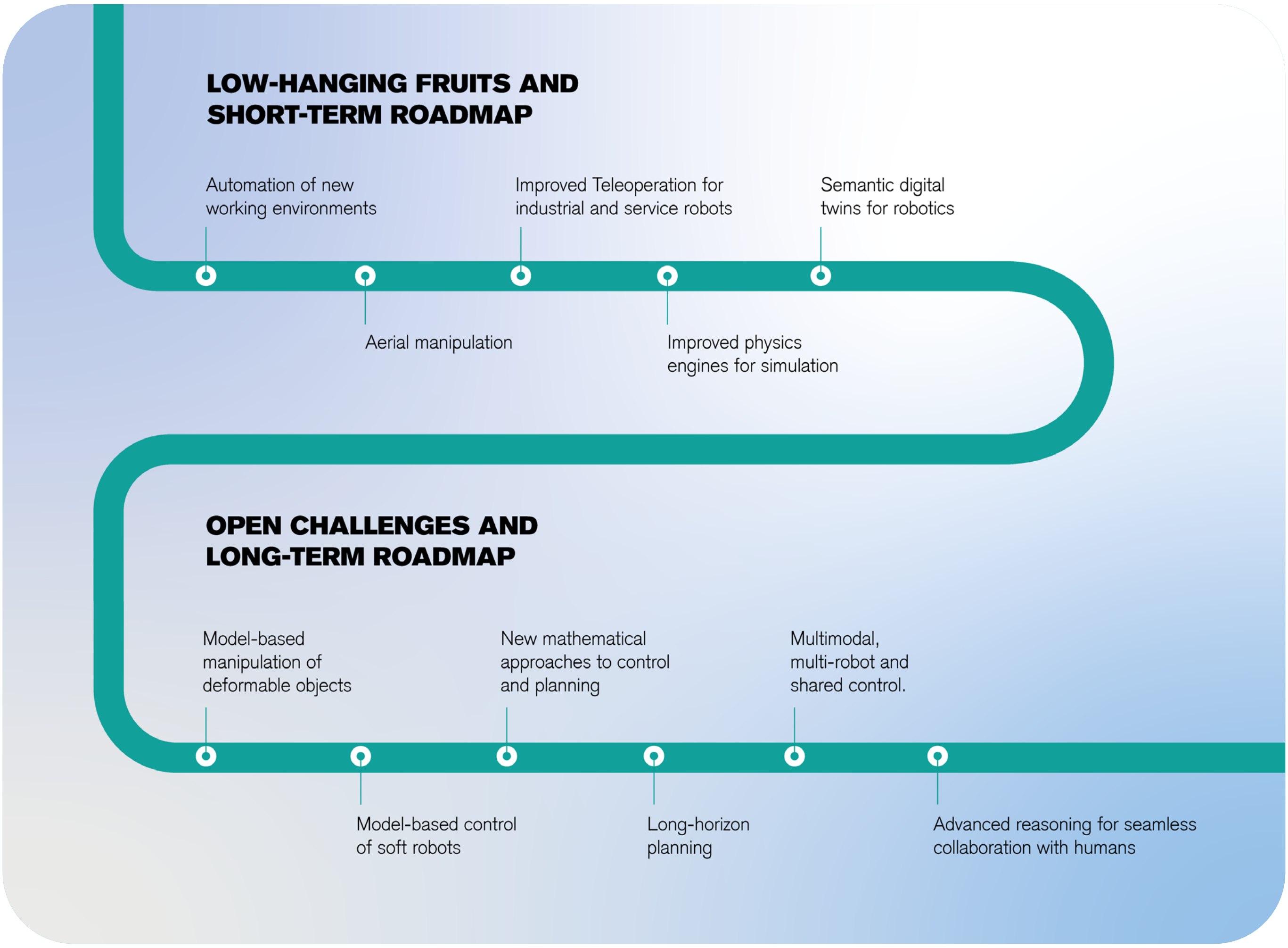

Figure 4. Summary of short-term and long-term research goals for control, planning and reasoning. The roadmap is not intended as a temporal sequence, but rather as a series of goals with increasing levels of complexity to be researched in parallel.

HUMAN-ROBOT INTERACTION: SUCCESSES, HURDLES AND REMAINING CHALLENGES

The past decades have seen an increasing number of robots deployed in the vicinity of humans, from vacuum cleaners roaming in our living rooms, drones flying over our heads, to prostheses attached to our bodies. **To increase trust and reduce risks**, it is urgent and necessary that **robots become cognizant of their environment and socially aware**. They must be able to interpret, predict and reason about both human behavior and their own behavior.

Today, all efforts globally are turned toward designing the next generation of robots, that of robots that will be employed and function in close or direct interactions with lay users. We are no longer in the realm of factory robots used by well-trained practitioners. It is not conceivable that these robots are programmed without a deep understanding of the social, ethical, cultural rules that underpin human environments. Developing robots that are cognizant of the world that surrounds them has led to a wide range of efforts worldwide, all of which fall under the general field of human-robot interaction (HRI).

HRI is comprised of two main types of interactions. HRI is either physical–when humans and robots get into actual contact with each other, as in the case of prostheses. It can be non-physical, relying on verbal or non-verbal interactions.

Advancements in sensors, both for forces and torques, as well as the availability of tactile signals collected by artificial skin played, jointly with three decades of research have led to the development of robots designed and programmed to be intrinsically safe for humans. **While robots can work safely nearby humans, they do so without being cognitively aware of their presence**.

More advances in HRI are required to:

- Scale up the use and deployment of collaborative robots, that is robots capable of operating outside the

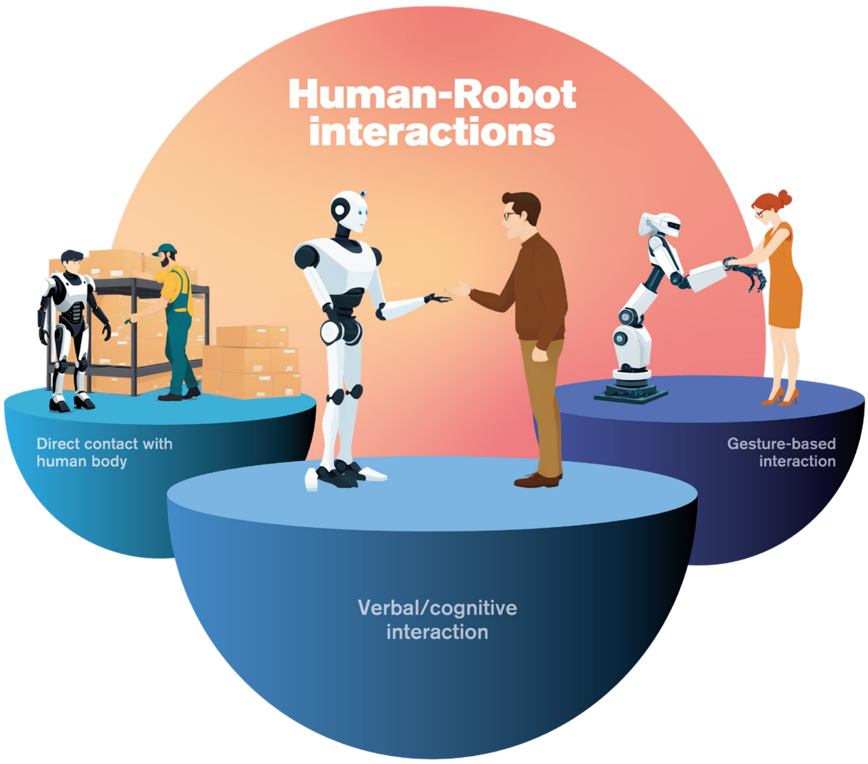

Fig. 5 Different types of human-robot interaction

confined environments of industrial settings—where they traditionally worked in cages or behind fences to prevent any interaction with humans.

- Expand usage of robots in the medical sector, wearable robots and exoskeletons, robots and drones for the inspection of remote locations and for search and rescue operations in collaboration with humans, mobile robots capable of navigating in crowded spaces, such as hospitals, airports, restaurants, and robots for social companionship.

- Enable the most challenging application, namely inside homes, the most unstructured and unpredictable environments.

Addressing these challenges requires:

- Striving to develop robots that do not overly constrain humans, by improving the intuitiveness, and ergonomy of human-robot interfaces, to facilitate their adoption by industrial operators

- Developing controllers capable of not only maintaining appropriate distance from humans, but also understanding how humans move when they are confused, to ensure safe navigation in crowds and other heavily populated areas

- Conducting broader assessments to evaluate robot interactions with multiple users, ensuring controllers do not exhibit bias against minorities, with a particular focus on protecting vulnerable populations.

In the long term, robots and their accompanying AI systems should explicitly account for human actions, preferences, mental states, and goals, enabling them

- To determine when to act or communicate effectively

- To recognize when to assist, such as when a human is unwell, and stepping back upon recovery

- To adapt and give priority to the human, allow them the freedom to make their own decisions, and assist rather than impose their working rhythm

When and when not to use AI in HRI. The integration of AI and machine learning into robotics promises to make robots more accessible to people without technical expertise. While this opens up new perspectives, it also entails risks that need to be addressed. For instance, use of Large Language Model can ease interaction and boost trust in robots, but it raises **concerns of over-reliance**, as seen in autonomous cars where users ignored malfunction alerts, assuming the system would self-correct.

Any usage of robots in direct interaction with humans require to find an intelligent way **to combine model-based AI systems with deep learning algorithms, to mitigate potential risks such as misinterpretation**. This requires defining in which situations misinterpretation can be accepted, because it poses no safety issues, and situations where we need instead that the machine really understands what happened, to assess it correctly, to avoid dangerous consequences.

A call for interdisplinarity at all levels from research to product design and deployment: Robotics cannot be designed by engineers and manufacturers alone anymore. The design and deployment of robots intended for direct human interaction must be guided at every stage by expertise in psychology, ethics, law, and economics.

European institutions should weigh in with meaningful regulations to enforce the principle of human-centered robotics, as they have already done concerning the use and exploitation of personal data and the deployment of AI systems.

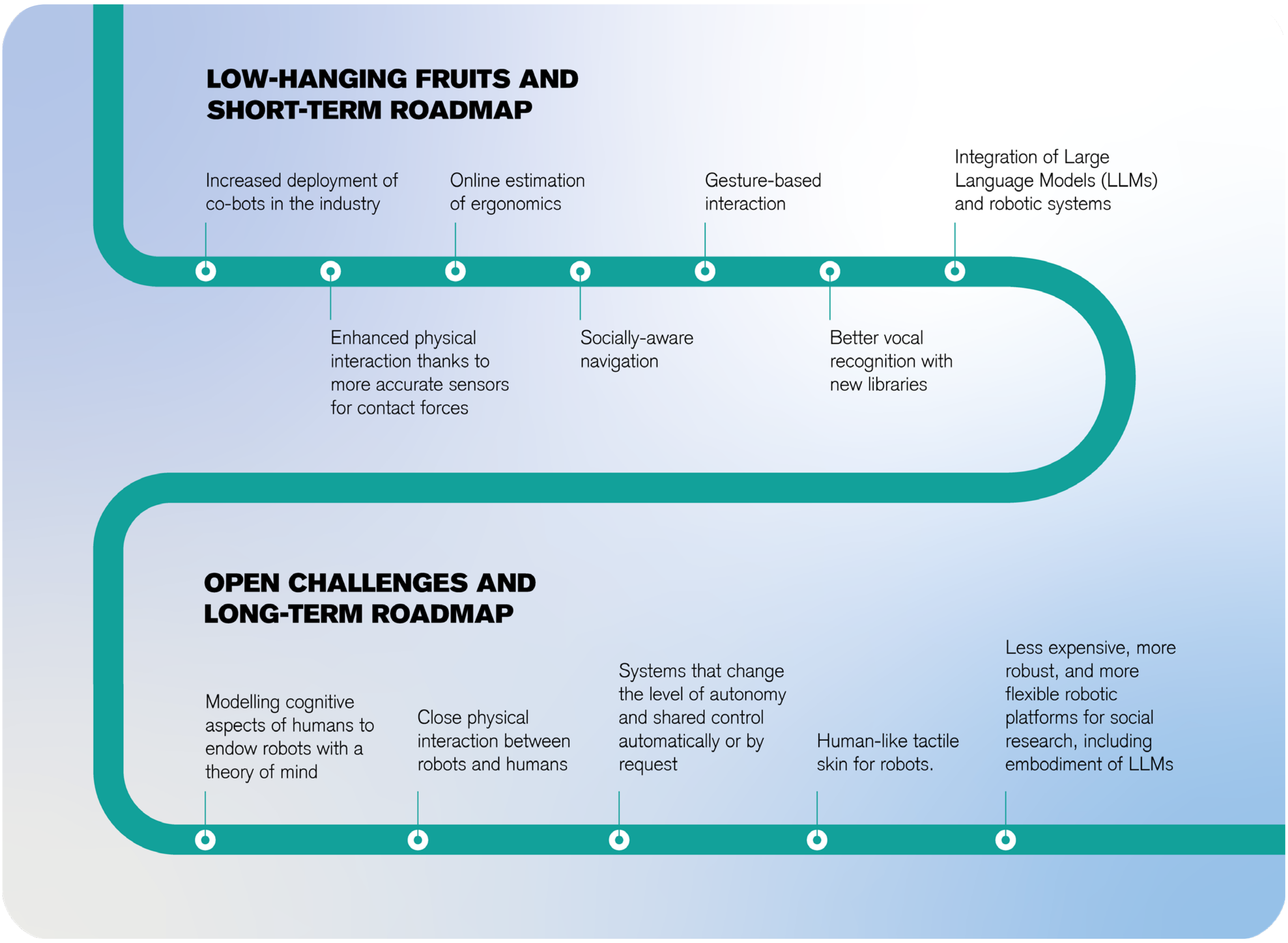

Figure 6: Short-term and long-term challenges in design and deployment of robots meant to interact with humans.

NEW TECHNOLOGIES FOR ENHANCING ROBOT DESIGN AND FUNCTIONALITY

Several advancements in core robotic technologies, i.e. materials, sensors, actuators, computing devices, are needed to obtain and turn into commercial products, robots capable of interacting with unfamiliar and unpredictable environments and to collaborate safely and effectively with humans. In advancing these technologies, **environmental sustainability should become a guiding principle**, i.e. by designing new materials that are self-healing, biodegradable and able to harvest energy from renewable sources.

Main challenges encompass the need to endow robots with a human-like sense of touch, artificial muscles and new batteries that can reduce the energy consumption of increasingly autonomous robots. This requires careful consideration of the interplay between hardware and software, that is to find new strategies to co-design robot's control and morphology.

A robot is an integration of several core robotic technologies, such as sensing, computing, actuation, and materials. In robots currently deployed in the industry, in service sectors, or as consumer products, **those capabilities and requirements are attuned at an affordable price**, Current commercial robots are typically categorized into three types: manipulators with articulated arms, wheeled or tracked mobile robots, and rotary-wing drones. Recently, four-legged robots are also being used for inspection and surveillance. **Most of current commercial robots are rigid, made of metal or plastic, and use electric motors.**

Robots powered by hydraulics are being gradually replaced by electrification for sustainability reasons. However, these advancements also highlight key limitations in traditional electrical actuation systems particularly in areas such as torque density, energy efficiency, transparency, and sustainability.

Despite the substantial progress in lithium-ion batteries over the past thirty years, **current battery technologies—both commercial and academic—still do not meet the stringent requirements for powering untethered robot.**

Many of the sensing, actuation, energy, and computational hardware used in robotics **relies on rare-earth materials or materials that are difficult to access.** For example, dysprosium can be found in electronics and sensors, cobalt in batteries, neodymium in motors. Also, they contain toxic elements, such as cadmium, lead, antimony, nickel, and mercury. This calls for an economically and ecologically sustainable EoL management of devices used in robotics to reduce electronic waste.

Main challenges to full deployment of robots for long-term, sustainable daily usage include:

- The robot's physical structure must be optimized to enable dexterous movements while ensuring stability and energy efficiency. **Developing lightweight yet durable materials in smart designs that can withstand repetitive movements and external forces** is crucial;
- Integrate **advanced sensors and perception systems that go beyond vision**, to allow the robot to navigate and physically interact with its environment autonomously, at natural yet safe speeds, and in close collaboration with humans;
- Power management is another critical challenge, as humanoid robots need efficient **energy sources to operate for extended periods without frequent recharging**.

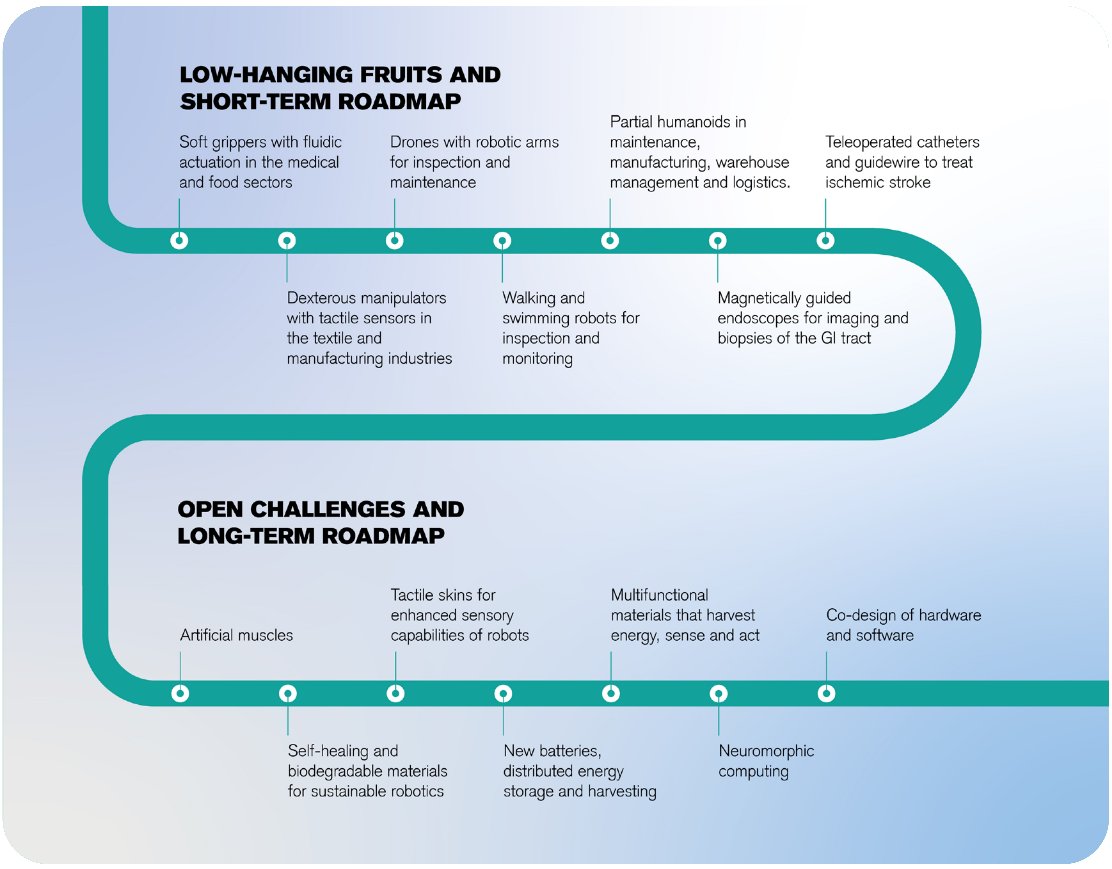

Figure 7 Summary of short-term and long-term research goals for new robotic technologies and applications.

Current trends bet on soft motors and sensors, made of deformable, at times biodegradable materials and flexible electronics. Design of soft structures for robots is not new and dates back the 1990s when several, soft materials capable of controlled deformation were developed, such as polymers, foams, gels, colloids, granular materials, as well as most soft biological materials. At the beginning of the twenty-first century, they became commercially available and easier to fabricate and started to be adopted in robotics. The most mature technologies in soft robotics currently concern actuation, with technologies that include fluidic and pneumatic actuation, actuation based on multi-functional materials, including but not limited to electroactive polymers and shape memory alloys.

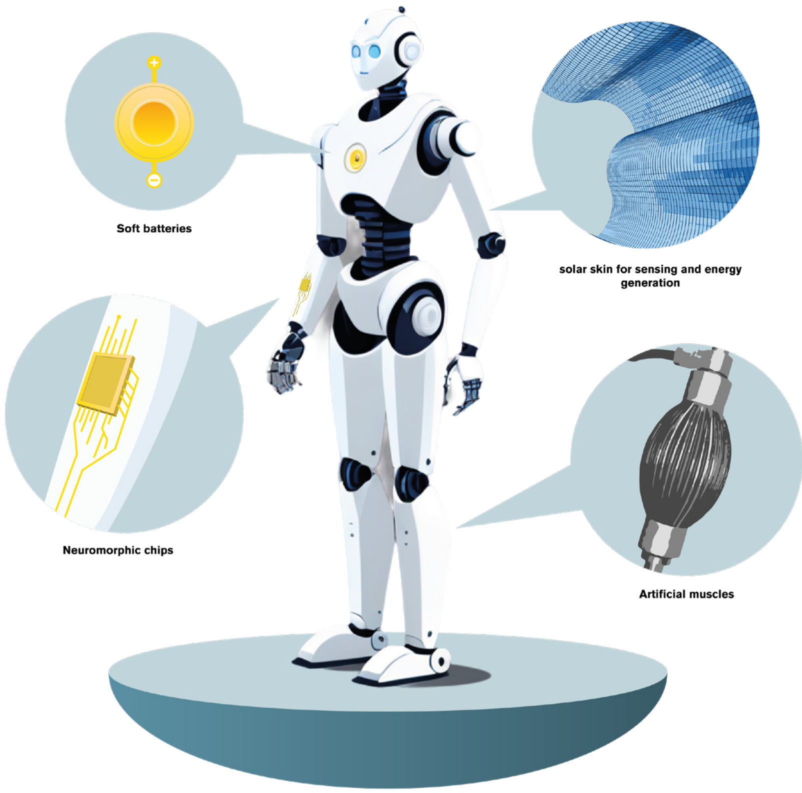

Figure 8: Humanoids and other platforms will benefit from the integration of new core robotic technologies to be developed over the next decades, including neuromorphic chips, tactile and solar skins, artificial muscles, soft batteries for energy storage.

Due to the popularity of fluidic actuation in soft robotics, there are many results and prototypes that can be used in simple grippers that can be applied in biomedical fields, for example for endoscopes. Some of these grippers are very close to market deployment in specific industries such as food and agriculture, where it is necessary to grasp and handle delicate objects.

Yet, soft mechanisms fall short of providing the strength and speed requirements to control full body robots capable of multi-purpose tasks. The future likely lies in either designs that combine a rigid skeleton with soft materials, or any combination thereof.

Advances are required in:

- New actuators with a **high-power output**, that are modular, redundant, and **self-healing** because soft materials could burn during physically intensive conditions;
- Decentralized control to **delegate portions of processing** to subpart of the robot to ease modularity and speed up real-time reflex-like computation;
- **Segmenting processors into smaller, specialized units**, chiplet technology allows for more efficient and cost-effective designs; integration of AI accelerators and memory, within a single package, enhancing performance and reducing latency;
- Integration of **batteries** into the mechanical structure, possibly in a decentralized and distributed manner; design of soft batteries, with self-healing properties, and **energy harvesting capabilities;**
- Multi-faceted **fault tolerance design** that offer redundancy in actuation and sensing to enable robots **to degrade gracefully in performance** despite problems like a missing limb, electronic malfunction, or software error.

CLOSING WORDS

Deployment of AI and robotics at large has become a more tangible target, possibly foreseeable in the next decade. Major hurdles on the road include ensuring understandability and controllability for safe deployment and usage and achieving scalable, cost-effective solutions to support autonomy and resilience.

The integration of AI and machine learning into robotics promises to make robots more accessible to people without technical expertise. While this opens new perspectives, it also entails risks that need to be addressed. Humans might over-trust robots, underestimating potential hazards, or fall victim to embodied biases—discriminatory behaviors stemming from imbalanced training data used in AI systems.

In several advanced applications, current technologies forming the core components of robots are not yet at a level that allows widespread deployment and commercialization. No advanced foundation or generative AI can work effectively without these technologies. Further research and technological development is needed to improve system performance and fully exploit their potential.

Most importantly, sustainability should be included in developing robot technologies, considering life cycle extension, circularity, resource conservation and usage, ethics, and environmental justice to have a positive impact on the UN Sustainable Development Goals (SDGs).

ROBOTS AND SUSTAINABLE DEVELOPMENT

The next generation of AI-powered robots can help tackle key challenges faced by our societies:

An aging population: the need for assistance to the elderly and disabled in homes, or the need for physical and cognitive rehabilitation after incidents and disease, will greatly increase in the next decades, with simply not enough human caregivers.

Humanitarian responses during natural and man-made disasters that are predicted to become more frequent because of global warming, pollution and international crises. Robots will be increasingly needed for search and rescue, or for environmental remediation and decommissioning of industrial sites, including nuclear plants, and inspection of infrastructures after the disaster.

The transition towards sustainable growth and a circular economy: robots can contribute to economic growth by increasing productivity in sectors that have not been automated so far, such as the textile or food industry, high-mix low-volume manufacturing, and maintenance of the European industrial and civil aging infrastructures. At the same time they can address the circular economy's increasing need to sort, recycle, and recover products and materials and keep them in the production cycle, including the handling of electronic components, batteries and toxic materials that should not be performed by humans.

Climate change mitigation: robots for environmental monitoring can contribute to a more precise assessment of the effects of climate change. Drones monitoring fields, mobile robots applying water and pesticides, robots picking and handling produce can help agriculture adapt to climate change, while relieving humans of some of the heaviest tasks and reducing food waste thanks to more efficient storing and transport.

AI AND ROBOTICS

From automatic translation to image recognition, from systems mastering complex board games to ChatGPT and the other language models, deep learning has achieved a lot in the last decade, and expectations on future developments of AI could not be higher.

Robotics has greatly benefitted from advancements in machine learning: for example, locomotion in legged robots has advanced greatly thanks to reinforcement learning, that allows to define a high-level target such as the speed of locomotion or a destination without a full mathematical description of the problem. Thanks to the advancements in deep learning, driverless cars are being tested as commercial service in major cities. Robot simulators have advanced thanks to deep reinforcement learning, which allows exploring policies with different environmental conditions in a reasonable amount of time before trying them on the actual robot.

But unlike language models and image recognition algorithms that only deal with bits, **embodied AI** poses specific challenges. Robots cannot rely on huge datasets that can be digested in relatively short times. Datasets themselves based on physical interactions (locomotion on different terrains or grasping of various objects) are simply not available and cannot be quickly assembled: having robots execute tasks in the real world takes time, and risks damaging the robot or its environment when attempts go wrong. A training dataset for flying robots, for example, would need to be impossibly huge, since drones can fly at vastly different altitudes and tilting positions with respect to the ground. The use of simulators is of great help, but for many tasks sim-to-real transfer is still a challenge.

Another crucial difference with non-embodied AI is that robots often perform safety-critical applications, and safety agencies would not approve a robot powered by an AI without enough transparency on when and why it may fail.

For this reason, AI-powered robotics will most likely include deep learning in combination with models that incorporate fundamental knowledge about the world and use it to guide and constrain the use of learned policies.

Ultimately, because no data set or simulation can live up to the complexity of real-world physical interaction, robots will require **lifelong learning** and **transferability of knowledge** across tasks, across robot bodies and across environments, as well as between humans and robots. Research will need to focus on understanding what to transfer (identifying relevant knowledge about environments, objects, and tasks constraints); how to transfer (formalizing prior knowledge on robot bodies and sensors, kinematics and dynamics, and for a given task/environment/body find feasible sets of motor commands); and when to transfer (learning to recognize similarities across environment, objects, and tasks constraints).

HUMAN-CENTERED ROBOTICS

Future robots - be they humanoids, drones, legged robots, manipulators, or entirely new soft robots - are expected to operate in much closer contact with humans, collaborating and interacting with them in homes and offices as well as in public spaces. Ultimately, the vision of AI-powered robotics is to enable humans and robots to share spaces and tasks, deciding and acting together, while preserving humans' privacy and autonomy. This creates several new challenges. On the technical side, we need to devise and build cognitive and interactive abilities that allow pertinent, transparent, and legible behaviours in robots, a necessary premise to ensure that they can be trusted to work in collaboration with humans. On the safety side, we need to evolve current safety standards so that they account for the use of robots not only in private, controlled spaces but also in public, crowded ones: robots must be able to account for the heterogeneity of pedestrians, the dynamics of crowds, for social norms, and for real people's disorderly and at times mischievous behavior.

Many future use cases – from autonomous vehicles to prostheses and exoskeletons in the medical field – imply shared-control systems where humans delegate part of the decision-making and control functions to artificial agents. This creates the additional challenge of how to ascribe responsibility for failures and potential damages. A clear regulatory and ethical framework is needed, one with human needs and values firmly at its centre.

It is only through tight coordination with human-centered disciplines such as ethics, psychology, social sciences, that robotics can deal with the social, societal and ethical issues related to the use of autonomous machines in professional, public and domestic environments.

ANNEXES

The following four perspective articles expand the key themes of the Strategic Agenda, and are currently under review at Nature Machine Intelligence (1) and IEEE Robotics and Automation Magazine (2-4).

1. Will AI alone solve robotics?

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Deep learning, large-language models, and other AI technologies have gone from one breakthrough to the other. As a result, we are witnessing growing excitement in robotics at the prospect of leveraging the potential of AI to tackle some of the outstanding barriers to the full deployment of robots in our daily lives. However, action and sensing in the physical world pose greater and different challenges than analysing data in isolation. As the development and application of AI in robotic products advances, it is important to reflect on which technologies, among the vast array of network architectures and learning models now available in the AI field, are most likely to be successfully applied to robots; how they can be adapted to specific robot designs, tasks, environments; which challenges must be overcome. This article offers an assessment of what AI for robotics has achieved since the 1990s and proposes a short- and medium-term research roadmap listing challenges and promises. These range from keeping up-to-date large datasets, representatives of a diversity of tasks robots may have to perform, and of environments they may encounter, to designing AI algorithms tailored specifically to robotics problems but generic enough to apply to a wide range of applications and transfer easily to a variety of robotic platforms. We close on what we view as the primary long term challenges, that is, to design robots capable of lifelong learning, while guaranteeing safe deployment and usage, and sustainable computational costs.

1. INTRODUCTION

The last decade has witnessed impressive advancements in the development and practical application of Artificial Intelligence (AI) technologies, in particular for systems based on Deep Learning (DL) over multi-layer artificial neural networks (ANNs). Though ANNs are not recent concepts, several factors have contributed to a fast-paced acceleration in their performance and scalability. On one side, computing platforms, such as Graphical Processing Units (GPUs), have become available, offering increased computational power and allowing to create "deeper" networks (i.e. with more hidden layers). On the other side, the exponential growth of multimodal, digital information available on the Internet has made vast amounts of data easily available for the creation of training and test datasets.

The first demonstration of the potential of these technologies came in the early 2010s, when deep networks started overcoming previous systems in visual recognition challenges[1]. Since then, there have been important applications of these systems on several different computational tasks.

Great expectations currently surround the applications of new AI systems (including ANNs, DL and LLMs) to robotics. Once again, this is not a novel concept, because learning algorithms have been used to control robots for decades. But there is hope that the current fast-paced scaling-up of AI's performances may translate into a similar scaling-up of robotic capabilities and help solve some long standing challenges that have so far limited robots' autonomy in challenging environments or their capability to interact effectively and safely with humans. For example, the classic control and state estimation methods for robots, that were developed for industrial applications in controlled environments, struggle to adapt to the high complexity and intrinsic unpredictability of outdoor natural environments, or even to the diversity of objects that can be encountered in a typical home. It is tempting to expect that advancements on these problems will mirror what happened for Go – a boardgame that was famously impossible for classic computer programs to master mathematically. Deep Learning came and vastly surpassed human abilities, albeit after playing billions of games with itself.

However, we cannot expect that what worked so well for perfect information games, which are purely data-based, software-level tasks, such as image recognition or text generation, can be applied with the same success to sensing, planning, control, and navigation for physical machines. Action and sensing in the physical world pose greater and different challenges than playing games: the state space is bigger, training data are not so easily available and cannot be easily generated, and safety and reliability requirements are higher. It is then paramount to identify which technologies, among the vast array of network architectures and learning models now available in the AI field, can be successfully applied to robots and which cannot; how they can be adapted to specific robot designs, tasks, environments; which challenges must be overcome.

2. A BRIEF HISTORICAL REVIEW

Allowing robots to operate autonomously in novel situations and to approximate the dexterity and agility of living organisms have been key challenges for robotics since at least the 1960s[2 3 4]. For several decades, robotics researchers have been experimenting with neural networks and machine learning as a potential solution to those challenges, and there is now a sizable literature on how to leverage these techniques to tackle robotics problems that had previously proven hard to solve. These studies have provided insight into which styles of machine learning are most suitable for robots, and which tasks are more amenable to be learned rather than formally programmed.

Overall, two principal styles of machine learning have been employed in robotics since the 1990s. On one side there is a family of algorithms that allow robots to learn from expert data, typically provided by a human demonstrator who performs the target action while their movement is captured by visual or motion sensors. Called alternatively Programming by Demonstration, Learning from Demonstration (LfD) or Imitation Learning, this approach has proved applicable in tasks ranging from grasping to manipulation of complex objects[5 6 7]. LfD algorithms could produce impressive results, such as catching objects in flight or control complex flying manoeuvres[8 9], while relying on very small datasets. The main limitation of LfD has historically been the intrinsic need to have a human operator with a good knowledge of the task available for training the robot, often across many training sessions. To address these challenges, current efforts are directed to learning from non-experts or suboptimal demonstrations, or from large collections of human and robot actions[10 11 12]. Other approaches, such as active learning[13], one-shot and behavioral imitation[14 15] or behavioral cloning[16], have also been proposed as a way to improve the efficiency of LfD: these techniques allow the robot to query the expert for demonstrations only when required, to learn a complete behavior from a single demonstration, or to start by acquiring experience in a self-supervised fashion and then use this experience to develop a model which is then used to facilitate learning of particular task by observing an expert. All of these have been shown to require fewer post-demonstration environment interactions than other techniques.

The other type of learning algorithms enables robotic systems to learn through trial and error without a prior formalization of what constitutes the correct control policy. Best exemplified by reinforcement learning (RL)[17], this method typically relies extensively on computer simulations of the robots and its environment to create enough learning cycles and learn a robust enough policy before testing it on the actual robot. Use of RL in robotics was hindered, for a long time, by the exploration phase, which, if not properly bounded, can become too computationally and time intensive and its inability to easily scale to high dimensions. Recent advances leverage the increasing effectiveness of deep-learning and visually-realistic physics-based simulation, achieving notable success in applications such as locomotion for legged robots – both quadrupeds and humanoids – as well as flying robots[18 19 20]. These methods are limited in that training must be conducted initially in simulation, far from the complexity of the real world, and the transfer from sim-to-real remains an issue[21]. In addition, RL success depends on a good prior knowledge of how to define an effective reward metric and assess the robot's performance against it.

Some of these challenges can be resolved when using LfD and RL in combination to leverage the strength of both techniques while mitigating their limitations. LfD can be used, for example, to reduce the search space in RL by bootstrapping it with good examples[22], reducing training time of large models[23], or to infer the reward and the optimal control policy simultaneously, a technique known as Inverse RL[24].

3. POTENTIAL FOR NOVEL APPLICATIONS AND COMMERCIAL DEPLOYMENTS

Many advances initiated in academic research have found their way to commercial applications. AI powered robots that can pick and sort packages of various sizes are regularly deployed in e-commerce warehouses. Learning enables online adaptation in tasks like pick-and-place on assembly lines, which were once rigidly pre-programmed. Robots can now adjust trajectories if an object is misplaced, or its shape or weight is unexpected. Autonomous cars, which started in the early 2000s, are now commercially deployed – ranging from partial autonomy in most models currently on the market to pilots of full autonomy underway, in limited situations, in several cities.

While AI is now pervasive in all areas of robotics, an area of application of particular interest is the field of soft robotics, where the deformable, continuum nature of robot bodies and their complex interaction with environments makes the processing of sensor data, state estimation, and control particularly challenging. Soft robotics is regarded as one of the many promising areas in robotics. Its natural compliance may ease the usage of robots in areas requiring direct interaction with humans and address global issues through biodegradable solutions. AI may offer an alternative to traditional control methods that cannot be used readily to control soft robotics and process their complex and heterogeneous sensor data stream[25], thereby easing usage and deployment of this new technology. A notable example is the recent application of convolutional neural networks to interpret the wealth of data streaming from a soft glove's artificial skin, enabling real-time recognition and control of grasps on objects[26].

4. SHORT- AND MEDIUM-TERM CHALLENGES

Scientists have only begun to scratch the surface of the potential of RL, LfD, and other flavors of AI and machine learning for robots. We next point out a list of short-term and long-term challenges, by increasing level of complexity, all of which form the corpus of current ongoing research directions (see Figure 1).

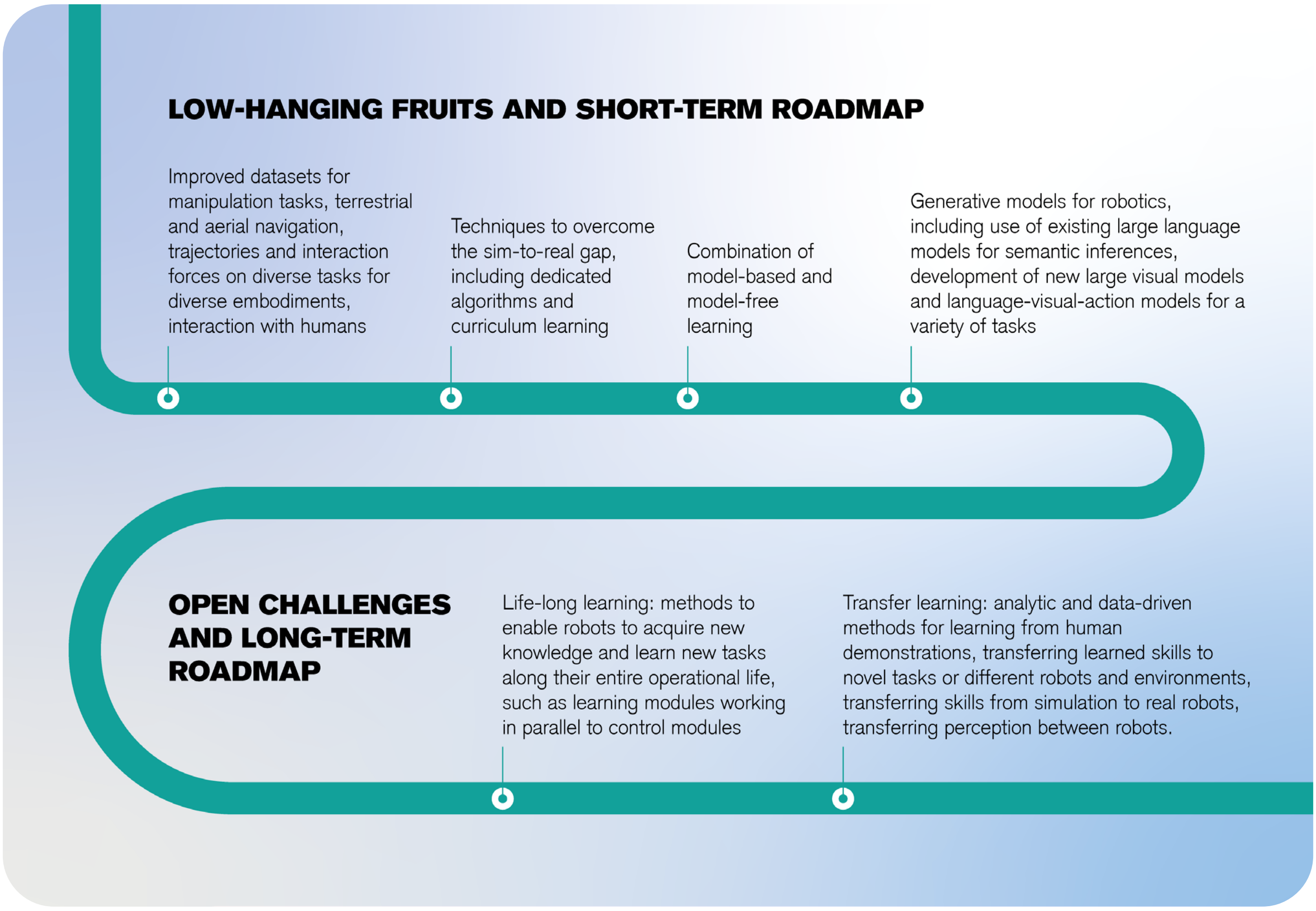

FIGURE 1: Short-term and long-term challenges for further endorsement of AI in robotics, order by increasing level of complexity. Note that these challenges may not be overcome sequentially. Rather, research proceeds in parallel along many of these directions.

Creating and maintaining representative datasets. An intrinsic limitation in robot learning as compared to other AI application domains is that there are no ready-to-use and easily available large datasets that can be used to train ANNs on sensing and control tasks, comparable to the vast repertoire of images and text that could be downloaded from the Internet and used to train image recognition or text generation algorithms. Generating *ex novo* enough iterations of a robotic task to train an ANN can be exceedingly costly and time consuming, or simply impossible. Too many robots would be destroyed during failed attempts at a task, and in some cases (such as autonomous flying robots) this would create risks for humans.

For some tasks, reference databases can indeed be created but require an organized and multi-centric effort. For example, in the case of visual imitation learning, attempts are being made at creating an analogue of ImageNet for grasping and manipulation, such as the Dexterity Network (Dex-Net) research project that develops code, datasets, and algorithms for generating parallel-jaw robot grasps and metrics of grasp robustness based on physics for thousands of 3D object models, with the aim of training machine learning-based methods to plan robot grasps. It supports researchers in finding robust grasps and training neural networks to generate a wealth of similar grasping strategies. The platform has allowed to learn deep policies to pick objects from a bin containing many unfamiliar objects at various orientations, the so-called "bin-picking" problem that has long been a benchmark challenge in the field[27].

Large datasets are also being created for terrestrial navigation tasks, thanks to cars now collecting large amounts of images routinely, from professional mapping services such as Google Maps to dashcams becoming increasingly common on private vehicles. These databases are typically available to companies on a proprietary basis, but if privacy and IP issues can be dealt with, it is foreseeable that some of them can become available to researchers. The challenge is bigger for aerial navigation, because of the many different perspectives from which a drone can observe the same scene, at vastly different altitudes and tilting orientations with respect to the ground.

Beyond visual data, robot learning needs datasets of robot actions in the form of trajectories and interaction force profiles associated with various tasks. Datasets on specific robot bodies and tasks do exist, but they are typically too narrow for large-scale machine learning. Combining datasets from diverse embodiments and on diverse robotic tasks can be a solution to reach the required scale. For example, an effort has recently been launched to combine several datasets on robotic manipulation, each one based on a specific robot body and skills and has provided a proof of concept that such a combined dataset could be used to train a policy for a given task more effectively than by using a dataset specific to that task[28].

Possibly the biggest challenges in terms of dataset creation are related to close interaction with humans, as the complexity and variability of both physical interactions and communication with humans and the need for enhanced safety guarantees currently prevents the rapid creation of datasets either through real experiments or in simulation. Ethical issues also put strict limits on what data can be collected and stored about human subjects and how they can be labelled, for example, by ensuring that subjects are not recognizable, that no sensitive information about them can be inferred from the data, or that images of a human subject cannot be reused in a different context, including being used for different training objectives than initially specified. An additional complication is that robots and humans perceive the world and interact with it in very different ways: while humans rely on multimodal information combining visual, acoustic, and haptic information, robots mostly rely on vision or on other bands of the electromagnetic spectrum, and while they can see more than humans do (including in low light or through obstacles) they remain incapable of analysing complex visual scenes.

From simulation to reality. Simulations offer a partial solution when it is not possible to create a large enough dataset. Several robotic simulators are available to the robotic community (examples include Algoryx, Bullet, Gazebo, Isaac Sim, MuJoCo, RoboDK,) and have been used for a long time to test and improve classic model-based control algorithms before applying them to real robots. The accuracy of their real-time physics-based simulation (the so-called physics engines) has greatly improved, also thanks to their commercial use in computer gaming. Reliable physics-based simulators can now, for example, simulate locomotion on complex terrains and manipulation on realistic objects in home environments, allowing the evaluation and selection of optimal controllers in simulation before being downloaded in the real robot. The use of simulators reduces the time needed for training, requiring only fine-tuning of parameters on the real robot. Randomized control policies generated by a neural network can be run in simulation over several thousands of iterations, generating a training set from which optimal policies can be learned and then transferred to the real world.

However, overcoming the sim-to-real gap, i.e. the discrepancy between the robot's performance in the real world and in the simulated environment, remains a challenge. This gap can be the result of multiple factors: the simulator's model can be exceedingly simplified with respect to the actual physical robot; the variability of the environmental conditions can be too large to be captured by a model; the physics simulator can fail to accurately capture the physics of the real world, especially when it comes to contact forces and deformable surfaces.

There are many techniques to overcome the sim-to-real gap. A small amount of data from the real world can be collected and used to increase the realism of the simulator[29]. Rapid-Motor Adaptation (RMA) has been successfully applied to achieve online real-time adaptation of quadruped locomotion to changing terrains, payloads, wear and tear[30]. "Curriculum learning", where the robot learns gradually more complex tasks in gradually more complex environments, has also been shown to improve the transfer of policies learned in simulation to the real world for legged robots' locomotion[31].

Leveraging large generative models for robotics. Much of the current excitement around AI focuses on generative AI, and specifically on Large Language Models. They are mostly based on the "transformer" deep learning model, which around 2017 emerged as an alternative to both recurrent and convolutional neural networks, allowing the speedup of learning (in particular of textual information) by processing information sequences in parallel[32]. By learning statistical relationships in text documents, these systems have achieved remarkable efficiency in generating text. Based on the same principle, they have been applied to diverse problems such as computer coding or computational chemistry.

LLMs are attractive for robotics on multiple levels. Existing LLMs can be adapted to support human robot interaction based on natural language, essentially making it easier to control a robot through written or verbal instructions, in any human language, and allowing them to respond to humans accordingly. Attempts are also being made at using LLMs in robot navigation in new and unfamiliar environments, to support semantic guesswork, essentially using their inferences[33].

Another family of generative models are language-vision models, that are trained on text/image pairs or annotated videos found on the Internet, and that can be used to generate synthetic images and videos from text prompts[34]. These models can also be applied to robotics, for example, to improve object recognition in manipulation and navigation tasks, and allow tasks to be specified in terms of what can be seen by the robot. A new generation of large visual models can be purposely built for robotics, trained not (or not exclusively) on text/image pairs from the Internet, but on navigation datasets such as those described in the previous section, produced by cameras during actual navigation in real environments. A first step could be learning to generate expectations on domestic spaces, i.e. using datasets of images of homes and offices or information from sensorised objects to generate reliable predictions on what a robot moving around such an environment may encounter. The same approach could then be extended to terrestrial and aerial navigation, creating models that can understand and contextualize visual information and incorporate a model of the robot's own physics and behavior to predict what it will see next.

The most recent developments in the field are language-vision-action models that add action to the equation. Examples of such models are being proposed, trained by fine-tuning vision-language models with both Internet-scale visual-language tasks and robotic trajectory data. By expressing the robot actions as text tokens and incorporating them into the training set together with natural language tokens, these models can learn to output robot actions like LLMs output text[35]. Initial results are encouraging, but the challenge of feeding such models with suitable datasets (see section 2.1), effectively mapping vision to action, and providing the system with the reasoning capability to correctly anticipate the consequences of its actions, will have to be a core research focus for several years. Another challenge is to verify the logic and feasibility of the plan generated by LLMs, an issue that is well addressed in logic-based planning[36].

Prior knowledge and combining AI with control methods. For physical robotics, incorporating prior knowledge on both robot and environment dynamics in combination with control methods with provable guarantees, is a more sensible way forward than a totally bottom-up, knowledge-agnostic approach to learning. In aerial robotics, for example, neither learning nor aerodynamics-based control alone can help solve the challenge of approximating the agility of birds' flight: coupling sensing and perception with the full body dynamic, allowing a drone to have instant reactions in flight and cancel perturbations, or on the contrary profit from the wind, efficiently combining flapping of wings and gliding (in the case of a winged drone) to save energy. These challenges will require a combination of learning for building improved aerodynamics models with control methods for guaranteeing flight stability.

Another reason for combining models and formal knowledge with machine learning is that a system only based on the latter would be prone to failures that can neither be predicted beforehand nor fully explained afterward, as exemplified by "hallucinations" observed in Large Language Models. Many current deep learning models are intrinsically non-explainable, a problem that becomes even more critical when AI is applied to robots. And because most future robots are expected to operate in safety critical scenarios such as autonomous navigation or close interaction with humans, no regulatory agency would approve their use unless their behavior can be predicted, and performance guarantees met – failures must be explained and corrected which is currently not feasible with model-free deep learning. This is a serious limitation to almost all applications where harm to humans is possible, for example, in the medical field, aeronautics, logistics and transportation, and domestic use.

AI-powered robots will need models of the actions that they are about to do, and these models must be explicitly represented in order to reason about the consequences. For example, a robot designed to work in a chemical lab, whose task is to pour chemicals into different containers, needs to know what happens when an acid is mixed with a base. Whenever a human comes into play, the robot needs an actual theory of mind modelling what the human may do and how the human might interpret the robot's task. This model can quickly become more complicated than the model of the robot itself[37].

Numerous efforts are directed to merge control theory and machine learning, proving that this can ultimately speed up learning, increase the robustness of the learned model, and enhance its safety[38] [39]. For example, a standard machine learning algorithm optimization can be modified to encompass penalties for violations of Lyapunov stability, or bounded constraints to guarantee estimated plausible values for physical quantities such as stiffness and mass[40]. In a similar vein, training of deep RL can be guaranteed to generate stable trajectories[41], or be enhanced by incorporating reference motions generated through control model, covering a broad range of velocities and gaits[42], serving as targets for the RL policy to imitate. Control theory and deep learning have also been combined to optimize grasps, using DL to find an initial policy that is then refined with model-based algorithms, thus sizeably speeding up computing[43].

5. LONG-TERM CHALLENGES

The most exciting, but also most challenging, long-term promise of AI for robotics is to enable robots to continuously acquire new knowledge, a dream dating back the 90's[44]. It requires three ingredients, which we discuss next.

Life-long learning: If the goal of robot learning is to approximate the way living organisms – humans included – learn tasks, then future robots will need to be able to acquire new knowledge and learn new tasks along their entire operational life, instead of relying on an initial training dataset that could never prepare them for the complexity and variability of the real world.

Endowing robots with the ability to learn continuously poses huge technical and regulatory challenges. Lifelong learning requires new paradigms based on incremental learning and is able to convert input output learning to structured knowledge, combining the power of learning with the paradigms of expert systems. It requires a learning module working around the clock on the robot in parallel to the control module enacting the policies that were already validated.
It brings along difficult questions, such as: how do we get some assurance about the performance of the system? How can we test the system, provided we can't know in advance the situations it will encounter and how it will learn from them? How do we select the things the robot can forget to make room for learning new things? How do we make sure that whenever it learns something new, even minimal, it has not forgotten how to do something important that it could do yesterday? These problems will need to be investigated in close collaboration with neuroscientists and developmental psychologists, to understand how humans achieve continuous and diverse cognitive development transitioning from one task to another, how this mechanism can be reproduced in neural networks, and how they can be implemented in robots. These problems will also translate into major regulatory issues: how to check that an evolving system maintains the safety and reliability standards requested for market certification as its capabilities change with new learning?

Possibly the main challenge for life-long robot learning will be to be able to scale up the current learning methods. Many robots will not stay the same for their whole operational life. After five or eight years of operation, a robot may have to mount a different gripper, or a different motor. The objects it has to manipulate and the environment in which it operates may also have changed. When that happens, the acquired knowledge that allows the robots to pick up and manage different objects may not automatically transfer to a slightly modified platform. But we currently lack good algorithms to transfer automatically, without retraining or human intervention, across even small changes in the embodiment.

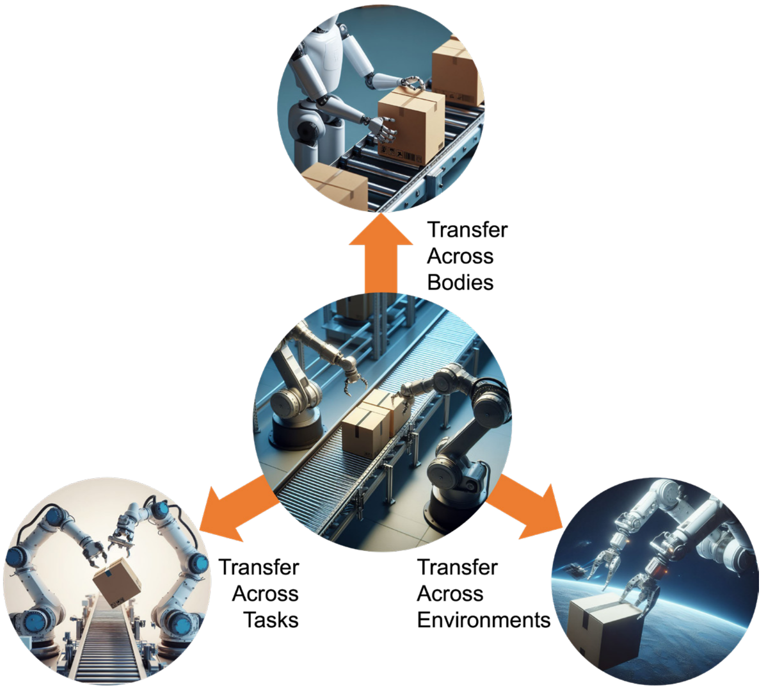

Figure 2: The ability to transfer learning across robot bodies, tasks and environment is fundamental for achieving collaborations of different robots on one task). Schematic makes use of images generated by Microsoft Bing Creator.

Figure 3: Handing a package from a drone to a humanoid robot or single-arm robot manipulator requires to reconcile drastically different perception, from different viewpoints and sensors, and distinct robot actions from unimanual to bimanual actions (inspired by 2023 EuROBIN Hackaton). Image generated by Microsoft Bing Creator.

Transfer learning: Future robots will need to be able to *transfer* what they learn: from one task to another, from one environment to another, and from one robot to another. Human intelligence relies on the ability to apply the knowledge acquired in one domain to new domains - thus solving new problems and facing unexpected situations – and to share knowledge among individuals. Similarly, robots need analytic and data-driven methods for learning skills from human demonstrations, transferring learned skills to novel tasks or different robots and environments, transferring skills learned in simulation to real robots, transferring learned perception routines between robots.

There are several open questions that need to be solved to reach transferrable robot learning. The first one is *what to transfer*: we need to develop criteria to select the learned knowledge about environments, objects, tasks constraints that can and should be transferred when dealing with new environments, objects, and tasks. A second question is *how to transfer*: for successful transfer to happen, prior knowledge of robot bodies may often be required, for example on sensors, kinematics, actuators, electronic hardware etc. Finally, we need to know *when to transfer*, developing algorithms to recognize similarities across environment, objects, tasks constraints, establishing if transfer of knowledge is at all possible in every specific case or if entirely new knowledge and novel learning cycles are needed.

6. CLOSING WORDS

Deployment of AI and robotics at large has become a more tangible target, possibly foreseeable in the next decade. AI has the potential to expand largely the capabilities and range of applications of robotics. At last, the multi-decade dream of intelligent, capable and useful robots is within sight. Major hurdles on the road include ensuring understandability and controllability for safe deployment and usage and achieving scalable, cost-effective solutions to support autonomy and resilience.

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2. Control, Planning and Reasoning in the era of generative AI

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As it faces the overarching challenges of taking robots to complex and uncontrolled environments, executing complex and partially unpredictable tasks while operating autonomously and interacting more closely with humans, robotics will need to expand the current scope of planning, control, and reasoning techniques and combine them with generative AI and learning. This article looks at the main challenges in adapting control, planning, and reasoning to the next generations of robots. It defines a roadmap to move from the current state of the art to goals that can be reached in the short and medium term, and to open scientific challenges that will keep researchers occupied at least for the next ten to fifteen years. Short-term goals include the automation of new working environments, aerial manipulation, improved teleoperation, improved physics engines for simulation and semantic digital twins. Long-term challenges include model-based manipulation of deformable objects, model-based control of soft robots, new mathematical approaches to control and planning, long-horizon planning, multi-robot control, advanced reasoning for seamless collaboration with humans.

1. INTRODUCTION

Planning and controlling the movements of robots made of mechanical parts is a cornerstone problem – if not the cornerstone problem - of robotics. Industrial robotics was born when computer programs were first applied to guide the movement of robotic arms, mounted over a fixed base, in a tridimensional space. Over the years, the scope of control and planning techniques has expanded to include the movements of mobile robots that have no fixed base and can navigate an environment while performing tasks within it.

For both manipulators and mobile robots, the fundamental steps to be taken include:

a) creating a mathematical model of the robot itself, including its kinematic and dynamic behavior, and a mathematical model of the environment where it is situated[1]

b) finding a trajectory to move the robot from an initial configuration to a final, desired configuration, without colliding with the environment and respecting all the kinematic and dynamic constraints of the robot (motion planning)[2]

c) using actuators and sensors to create the motion required by the planned trajectory (control)

While the first generations of industrial robots were bound to follow predetermined trajectories, decades of development in motion planning and control have now led to robots that can adapt their trajectories in real-time, either to compensate for changes in the position of the object that the robot must handle, or to guarantee the safety of human operators in the vicinity of the robot[3]. In mobile robots, research and industrial development have led to control policies for wheeled, tracked, flying or swimming robot coupled with navigation algorithms that allow those robots to move autonomously in environments for which a precise map is available, and even to a certain degree in environments that they have never encountered before[4]. In certain cases, finding optimal trajectories according to user-specified criteria (e.g. length) is possible. Ultimately, to approximate the capabilities of living organisms and to operate without humans' supervision, robots need to be endowed with reasoning abilities that allow them to encode and use semantic knowledge to make inferences about the consequences of their actions, interpret situations never encountered before, and make decisions.

As it faces the overarching challenges of taking robots to complex and uncontrolled environments, executing complex and partially unpredictable tasks while operating autonomously and interacting more closely with humans, robotics will need to expand the current scope of planning, control and reasoning techniques. While data-driven techniques and machine learning are currently attracting much attention[5], there are several robotic applications that require predictable control and explainable behavior which can only be guaranteed using underlying models (of the robot, the task, the environment and of humans). And thanks to improvements in mathematical methods and computational technologies, there are still huge margins of advancement in model-based methods that do not rely primarily on learning.

The role of control, planning, and reasoning in shaping the future of intelligent robotics in the age of generative AI and foundation models, is closely tied to a broader philosophical question: do intelligent robots need to maintain explicit representations of their capabilities and bodies to operate effectively in human environments and accomplish human-scale tasks? Kahneman's dual-process theory of decision-making and intelligence offers a compelling framework for integrating generative AI with model-based techniques in a synergistic manner[6]. The theory posits two complementary modes of reasoning: System 1, which is fast, intuitive, and associative, and System 2, which is slower, deliberate, and analytical. In robotics, generative AI can embody the rapid, adaptive qualities of System 1, leveraging large-scale data and multimodal learning to predict actions and generate flexible behaviors in real time. Meanwhile, model-based techniques align with System 2, providing structured, logical reasoning grounded in explicit representations to ensure correctness, safety, and long-term planning.

The main goals of the next decade of research in these fields will be to exploit the current modelling techniques at the best of their potential, making planning and control faster and more robust; to improve modelling itself, and expand it to systems that have so far being considered intractable, such as soft robotic systems; to leverage new hardware and software tools for better and faster motion planning; to scale up planning and control methods to have multiple robots work collaboratively; to advance reasoning abilities in robot and combine them with learning and generative AI.

This article looks at the main challenges in adapting control, planning, and reasoning to the next generations of robots. It defines a roadmap to move from the current state of the art to low-hanging fruits that can be reached in the short and medium term, to open scientific challenges that will keep researchers occupied at least for the next ten to fifteen years of research (*see Figure 1*).

2. STATE OF THE ART

Six decades of work on industrial robotics and automation, both in academia and in the robotics industry, have led to well-established techniques for the interconnected problems of modelling (the kinematic analysis of the mechanical structure of a robot), motion planning (the generation of trajectories to take the robot from a given initial configuration to a desired final configuration), control (the realization of the desired motion by actuators and sensors) and navigation (the ability of a mobile robot to know its position inside an environment and use it for planning and controlling new trajectories).

Model-based planning and control for manipulators operating in controlled environments and on rigid, a-priori known objects is solved and extensively deployed in the millions of robots operating in the automotive, chemical, electronic industry. Tridimensional, free-space motion planning with high degrees of freedom is fundamentally solved, allowing manipulators to work very efficiently

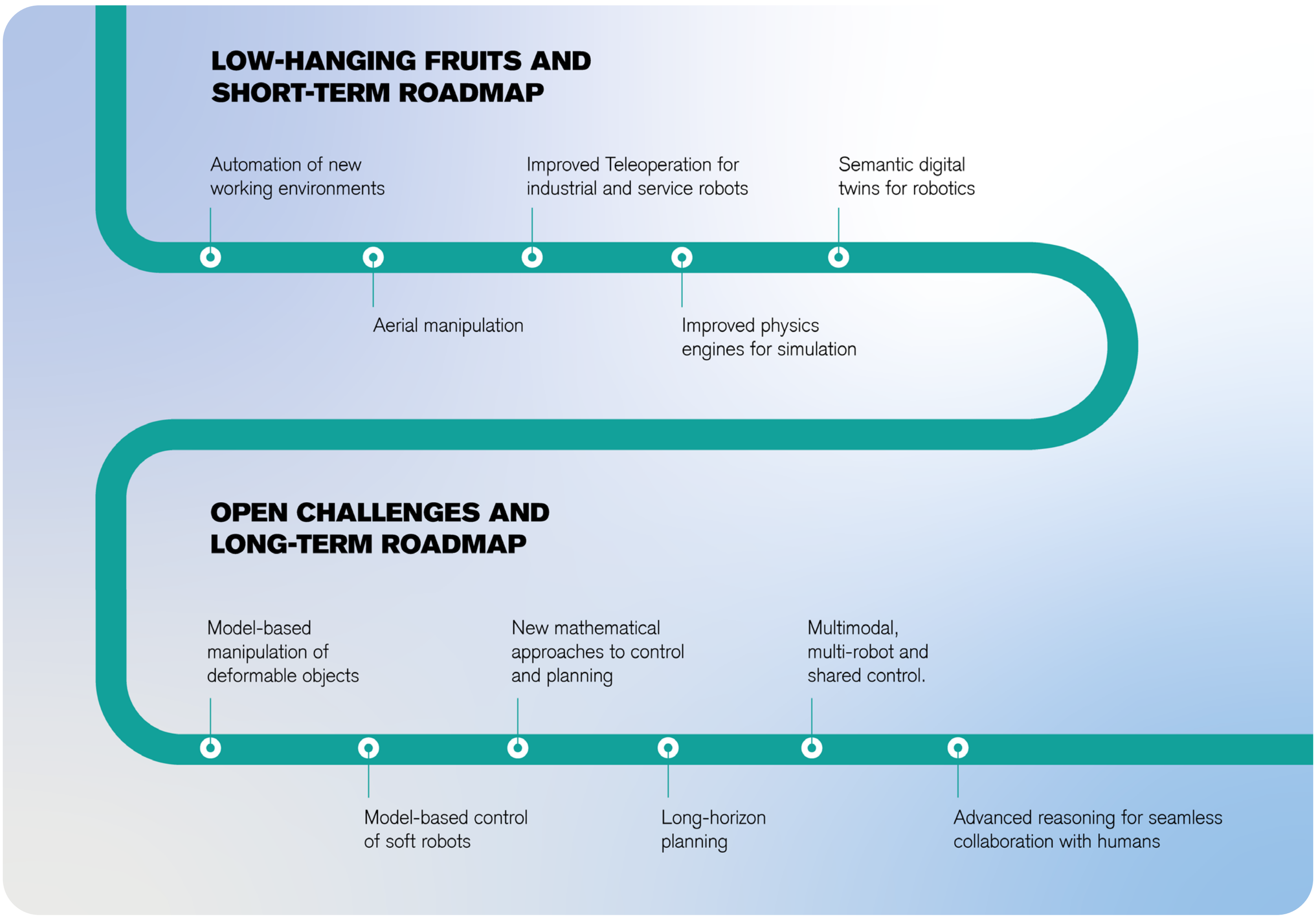

Figure 1. Summary of short-term and long-term research goals presented in the article. The roadmap is not intended as a temporal sequence, but rather as a series of goals with increasing levels of complexity to be researched in parallel.

in controlled environments such as assembly lines, warehouses, and automated laboratories[7]. A key advancement from the last two decades was the addition of on-line acquisition and elaboration of sensory feedback provided by visual, haptic, force/torque, laser sensors, that have allowed to develop more intelligent control algorithms for industrial robots based on principles such as proportional–integral–derivative (PID) control, adaptive control, tracking control[8 9].

Another essential contribution from research carried out in the recent decades has been compliant control, developed theoretically since the 1980s and deployed in the first two decades of the 21st century[10 11]. It allows controlling the energy injected in the systems and to allow interaction with humans rather than just following trajectories. Compliant control allows going from following trajectories to controlling the impedance and the interaction with humans and the environments. It has resulted in the development of co-bots (>link to HRI article) but has proven important also for classical industrial robots[12].

Hierarchical multitasking control has also greatly advanced at the research level. Control framework now exists that can create a priority scale of multiple tasks, making sure the tasks with lower priority are fulfilled only as long as they don't interfere with the highest priority task[13]. A humanoid robot could, for example, have a main task of manipulating an object, a secondary one of avoiding collisions with the environment and another of minimizing the effort. The methodical basis for these developments were laid down in the 1980s and 1990s and has been deployed during the last 20 years on humanoids or mobile robots equipped with arms.

Advancements have also been achieved in controlling complex dynamics that happen when the robots do not have a stable base attached to the ground, such as in the case of free-floating space robots equipped with manipulators, such as a satellite that can catch another satellite while floating in space and then stabilize the system. Algorithms have been introduced to control the center of mass, the momentum to or even free-floating robots with arms or in aerial manipulation, with an arm on-board a flying robot[14 15 16].

Teleoperation, e.g. the ability to control a robotic avatar over any distance in a closed loop, feeling the interaction forces and to achieve high-fidelity control, is state-of-the-art although not yet deployed on the large scale, and has been demonstrated in settings such as astronauts on the International Space Station controlling robots on the ground despite transmission delay and gravity effects[17] or deep sea operation of a humanoid underwater robot controlled by a human on the surface[18].

When it comes to mobile robots, 2-D path planning on flat terrains is largely a solved problem, including coverage path planning, that is the problem of computing the optimal path and project a collision-free trajectory to ensure the robot fully covers an area of interest within a certain time[19]. The problem of creating a map of a previously unknown environment, updating it continuously while keeping track of the robot's position in it has been solved by Simultaneous Localization and Mapping (SLAM) algorithm, that can operate efficiently in unknown cluttered environments using either lidars or cameras - or both[20 21]. Both coverage path planning and visual SLAM are successfully deployed in millions of robotic vacuum cleaners.

Kinodynamic trajectory optimization and control for wheeled in the absence of unexpected events is also state-of-the-art, as demonstrated by existing small-scale deployments of self-driving cars[22]. Multi Robot motion planning in known environments such as warehouses is achieved, at least when one is only concerned with the position of the robot and not with what is happening with its body[23]. Many aspects of the control of drones, especially quadcopters, have been solved and deployed. Autonomous navigation of flying robots using GNSS, or environment perception in partially denied environments where satellite signal is not available, is achieved. This allows controlling all the phases of the flight, including fully autonomous takeoff and landing even in constrained space, such as the perching of a flapping-wing robot on a branch[24]. Obstacle detection and avoidance is state of the art, both in indoor and benign outdoor environments, as long as there is no significant wind, which instead remains an unsolved problem for the control of drones.

Cognitive robot architectures exist that provide structured frameworks for integrating perception, reasoning, learning, and action capabilities within robotic systems, enabling them to exhibit intelligent, goal-oriented behavior. These architectures incorporate advanced cognitive reasoning mechanisms such as prospection, which allows robots to anticipate and simulate future scenarios; affordances, which enable the robot to perceive actionable possibilities within its environment; and attention, which helps prioritize relevant sensory information and tasks. They also include self-awareness for monitoring and adapting internal states, memory mechanisms like episodic and semantic memory for storing and leveraging past experiences, and situated reasoning for context-aware decision-making. Examples include the CRAM (Cognitive Robot Abstract Machine) architecture, designed to facilitate goal-directed tasks in everyday environments by using underdetermined plans that resolve into specific actions through runtime reasoning[25]; iSAC, that employs a multi-agent system combined with memory subsystems (e.g., sensory egosphere, semantic memory) and an internal rehearsal system for action simulation and selection[26]; and ARMAR which focuses on enabling humanoid robots to perform complex manipulation tasks in human environments by combining advanced perception, semantic reasoning, and action planning[27]. These architectures exemplify how cognitive frameworks enable robots to adapt to dynamic environments, interact with humans, and learn from experiences, bridging the gap between symbolic reasoning and sensorimotor interactions.

Knowledge representation and reasoning are fundamental to solve the robot body motion problem, enabling robots to infer and execute appropriate actions for complex tasks. This approach involves integrating symbolic representations, such as ontologies and axiomatic knowledge bases, to encapsulate information about objects, environments, and actions. For example, frameworks like KnowRob[28] and CRAM use such representations to infer the motion parameters required to achieve desired effects, such as grasping and lifting objects, while avoiding undesirable side effects like collisions or spillage. These systems combine abstract knowledge (e.g., social conventions or intuitive physics) with contextual information from sensors and episodic memories to adapt to dynamic and underdetermined scenarios, such as ”setting a table” in varying household environments. By leveraging structured reasoning mechanisms, robots can not only generate effective motion plans but also account for uncertainties and failures, thus enhancing reliability in open-ended domains.

3. RESEARCH PRIORITIES IN THE SHORT TERM AND LOW-HANGING FRUITS FOR INNOVATION

Applying research results to new industrial domains. Some important improvements in planning, control, and navigation would be relatively easy to achieve in the short term, as they are based on solutions that have been extensively studied in laboratories in the last decade and would mainly need additional effort (and adequate funding) to be scaled up, validated and commercially deployed.

A good example is the extension of automation to working environments that so far have remained only partially automated, such as large-scale research and testing laboratories. Laboratory automation with easy customization appears especially promising for chemistry labs, medical testing, and DNA sequencing. These contexts present varying degrees of complexity, ranging from tasks such as high throughput screening or quality control that are largely repetitive and can be addressed by traditional planning, control and programming, to more dynamic R&D setups in less structured environments that require novel robotics approaches with perception, knowledge representation, information sharing. Architecture models for the integration of existing solutions in life science laboratories in a plug-and-play fashion have been proposed and can be further developed[29]. The construction industry is another case where robots have a proven potential to improve productivity and enhance the safety of workers, and where new planning and control methods can be applied to tasks such as the on-site quality check and assembly of parts manufactured off-site.

For mobile robots, aerial manipulation has made great advancements and is a reality at the research level, with drones that can perform manipulation while flying or after perching to increase dexterity and force[30]; yet, deployment and commercial application require further technological development, in particular on expanding on-board real-time perception and planning capabilities to allow effective control of the forces exerted by – and felt by – the drone; and policy development, since the lack of a clear and consistent regulatory framework is currently constraining research and development.

Teleoperation for industrial and service robots is also ready for wider application thanks to the development of virtual reality and haptic feedback systems and can allow the automation of industrial processes (such as sanding, grinding, polishing) that are too complex for unmanned manipulators but where there is room to increase the safety and comfort of human workers, by physically removing them from the material being manipulated[31].

Physics engines and digital twins as enabling technologies. In terms of enabling technologies, hardware-accelerated motion planning for high-dimensional robots is close to the stage where it can be used for faster predictive control. Current motion planners can solve realistic and challenging problems in hundreds of milliseconds to dozens of seconds on consumer CPUs, which is too slow for reactive operation in evolving environments and prevents the achievement of higher-level autonomy. However, several strategies to accelerate motion planning have been demonstrated, typically combining some parallelisation of computation with hardware acceleration. While GPU-based acceleration implies a huge computational cost and introduces latency in communication, efficient acceleration can also be achieved on ordinary CPUs by exploiting some of their native features. Motion planning time for manipulators could thus be reduced to microseconds, significantly accelerating the movements of industrial arms with more than 7 DoFs[32]. Advancement in on-the-fly motion planning would also facilitate the development of socially adequate robots – not able to fully cooperate with humans but that can have limited interaction in structured environments like hospitals.

A key area of effort in the short and medium term must be the improvement of robotic simulators. These are key tools for modelling, motion planning, and control, as they allow testing planning and control algorithms safely and inexpensively before trying them out in the real world and on a real robot. The so-called sim-to-real gap is currently a limiting factor not only for data-driven and learning-based approaches, but also for model-based planning and control. Increasing the fidelity of physics simulators and physics engines is crucial to overcome this gap. Thanks in part to huge investments from the gaming industry, better physics engines and visual rendering of physical interaction are now becoming available and can be transferred to the robotic domain with relatively easy adaptation to obtain robotics-enabling simulations that are computationally lighter, modular, faster, and more resource-efficient than current ones[33]. However, for them to be used in robotics research it is important that different physics engines can work together by relying on unified modelling abstraction and hierarchies. Additionally, the needs and the objectives of physics simulation for robotics are very different from those of virtual reality and computer gaming, and more work is needed to define the ideal trade-offs between fidelity of the simulation, computational cost, and usefulness in helping define tractable control policies.

Digital twins go beyond pure simulation and modelling by creating a bidirectional interaction between the virtual and the physical. A digital twin can be defined as a “a set of virtual information constructs that mimics the structure, context, and behavior of a natural, engineered, or social system (or system-of-systems), is dynamically updated with data from its physical twin, has a predictive capability, and informs decisions that realize value”[34]. Digital twins of large natural and man-made environments, including factories, can be developed to enable robot programming at a more abstract level and facilitate the realization of robotics tasks of much larger complexity.

Semantic digital twins will substantially advance robotic capabilities by embedding rich, structured knowledge into digital representations of physical environments. These twins integrate detailed 3D models with semantic annotations, enabling robots to access context-specific information about objects, their properties, and relationships. For example, a robot can query a semantic digital twin to determine the precise 6D pose of a handle or understand the articulation model of a cupboard door, allowing it to create motion planning and control problems automatically. By serving as virtual knowledge bases, semantic digital twins not only provide data but also compute truth values of relationships dynamically, transforming how robots plan and execute tasks.

Ongoing research in generative AI is addressing the automated construction of semantic digital twins. This advancement has the potential to bridge the gap between data-driven and model-based approaches, enhancing robots' ability to create accurate digital representations of environments autonomously. As this technology matures, it will further enrich semantic digital twins, enabling robots to operate with greater precision, adaptability, and context-awareness across diverse applications.

4. OPEN CHALLENGES FOR A LONG-TERM ROADMAP

Model-based manipulation of deformable objects. An open challenge that robotics will need to address in the next decade, and most likely extending well beyond, is how to advance the model-based motion planning and control of soft systems. This problem covers two interrelated but distinct challenges.

The first one is the manipulation of deformable objects, that is currently a challenge for industrial robots and yet would be crucial for many applications, from medicine to agriculture to the automation of the textile and food sectors[35]. Progress will be needed on the hardware side, with the design of new soft grippers but also on the modelling, planning and control side. While machine learning has a significant potential in this regard, it is unlikely that industrial deployment of manipulation of deformable objects can be based on ML alone, especially in safety-critical applications that require predictability and explainability of robot performance.

Several methods exist in the literature for modelling the behavior of deformable objects[36]. Examples include mass-spring systems, position-based dynamics, and continuum mechanics. All have been applied with varying success at the experimental to cases including food, tissues, fabric, paper, and each has its own limitations. These methods have also been used to create physics-based simulators such as SOFA, PhysX, MuJoCo, that provide development environments for state estimation and motion planning in manipulation tasks involving deformable object, and that in turn allow planning and control approaches for deformable objects. Future research will need to evolve these methods and define the best mix of techniques to tackle specific manipulation problems – be it folding a shirt, in-hand manipulation of sponge-like objects, or tying a rope.

Model-based control of soft robots. The other challenge is the development of analytical models of robots that are themselves soft. The development of control algorithms in soft robotics has followed a reversed path compared to most domains in computation and robotics. For soft robots, learning-based approaches have been applied[37 38] before model-based ones, which were viewed as too challenging, or simply not applicable because of the virtually infinite degrees of freedom of a soft robotic system interacting with unpredictable environments. More recently though, researchers have found more and more effective ways to approximate soft robotics dynamics, paving the way for new modelling approaches[39]. In some cases, even simplified models have been shown to improve the performance with respect to model-free approaches[38 40]. For example, many soft robots have one dimension longer than the other two, and their whole configuration can be simulated by only considering deformations along that axis, vastly simplifying the problem. When that is not possible, new mathematical approaches – such as finite-dimensional modelling techniques that use partial differential equations to simulate infinite-dimensional systems – have been developed, that combine computational tractability with enough precision to describe the behavior of soft robots. By translating the volume of the robot into a mesh, that is a set of nodes and the information on their neighbors, it becomes possible to approximate the entire volume of the soft system using interpolation. The choice of the modelling technique determines the best control strategy to be used for the robot, which may focus on curvature, strain, or volume control, and that may or may not combine actuation and under-actuation. Research in the next decade needs to focus on further developing and testing modelling techniques and model-based planning/control for soft robots, including soft aerial robots, as well as understanding how they can be optimally combined with data-driven and learning-based techniques[41].

New mathematical approaches to control and planning. For both soft and rigid robots, a promising avenue of research is to look beyond the traditional approach to robot motion generation - that is to first plan trajectories on a kinematic level and then develop controllers for tracking the planned trajectories - taking the robot hardware as a priori. The study of intrinsic robot dynamics can translate into methodologies to generate highly efficient motions. New solutions are available to extend the methodical basis for modeling and controlling them, such as geometric mechanics and dynamics, differential geometry, and algebraic topology, that can mathematically describe the nonlinear oscillations that a robotic system may have. There are many examples of robotic motions, such as galloping or bouncing, that could be realized by exploiting intrinsic oscillation modes rather than being enforced on the system, in other words designing the robot so that it favours the desired set of movements[42].

For the next generation of mobile robots, fundamental research at the intersection with physics will be needed on how to effectively model the interaction of robots with their environment, and especially the complex case of interaction with fluids such as air, water, viscous substances). For example, in flying robotics, complex aerodynamic modelling will be needed to predict the unsteady lift and trust generated by a fixed-winged robotic bird because of the interaction with vortex formation around the wing, and particularly a flapping wing[43] [44]. Similar cases can be made for marine robotics, or for robots that have to move in viscous fluids such as oil or mud, or dig into sand and soil, to act autonomously in complex and extreme environments without human supervision.

Long-horizon planning. Long-horizon planning – the ability to consider action consequences over a long temporal period when moving towards a symbolically specified goal, a mission rather than merely a target position - is a necessary requisite for autonomous behavior in robots, but as of today it is still an open challenge because of computational cost and of the intrinsic difficulty in planning beyond a few short-term steps in realistic application settings[45]. Work is ongoing on new theoretical approaches to long-horizon planning – such as incorporating abstract strategies in task-planning routines and evaluating their affordance – that allow to practically accelerate long-horizon planning, with the goal of making it a tractable problem in realistic use cases.

Another significant open challenge will be fast motion planning under uncertainty, that requires computational approaches that incorporate from the beginning the uncertainty of the environment in motion planning algori-

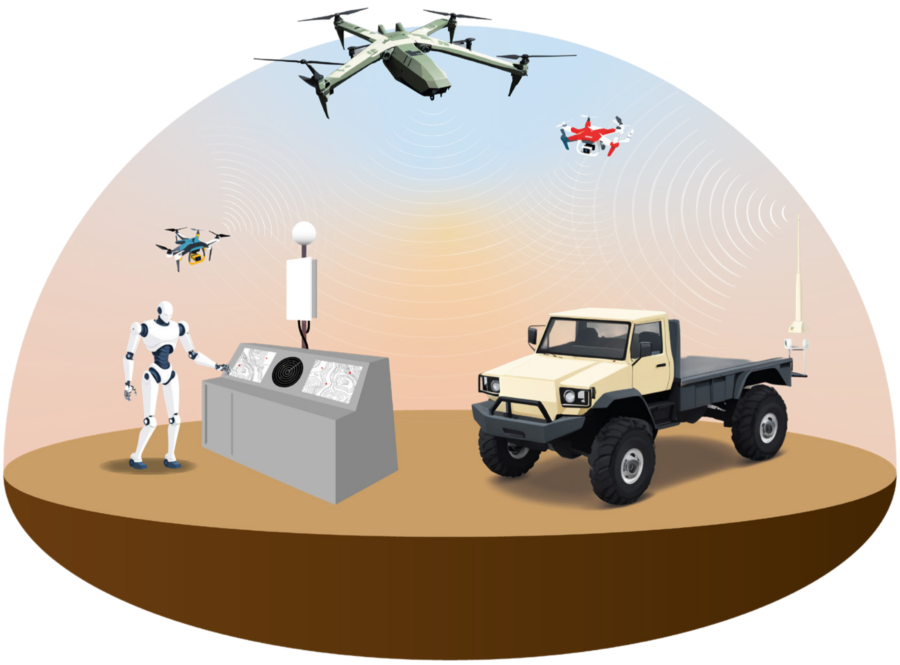

Figure 2. An open challenge is how to control multi-robot systems where several robots of different types co-operate on tasks and share representations of the environment. that they may observe from varying points of view and with different sensors.

thms[46]. Here the Finite Element Method (FEM) is proving useful in generating high-quality motion plans for use cases involving deformable objects, such as guiding steerable needles through deformable tissue for minimally invasive biopsies and drug-delivery, and manipulating planar tissues to align interior points at desired coordinates for precision treatment.

Multimodal, multi robot and shared control. For legged robots a key open challenge is planning and control of multimodal locomotion, that allows the robot to switch between walking, climbing, jumping, and squeezing through narrow passages. Fundamental interdisciplinary research will be needed to understand and model how living organisms achieve effective multimodal locomotion, and this bioinspiration will be key to understand how to integrate open-loop and closed-loop control, active and passive control, model-based and learning-based strategies to achieve multimodal mobile robots[47].

Significant improvements are needed on control of multi-robot systems where several robots of different types co-operate on tasks, including control of robotics swarms with several tens, or even hundreds, of individuals: here, progress will be required on creating shared representations of the environment that different robots may observe from varying points of view and with different sensors (see Figure 2) as well as on common operative systems and communication protocol that go beyond current standards[48].

Shared control between humans and autonomous agents will be another important area of research. Many future application scenarios will require robots combining an autonomous agent, which controls part of the robot and a human controlling the rest. For example, think of an assistive device made of a wheelchair equipped with a robotic arm. The wheelchair would have 3 degrees of freedom and the arm may have 8 additional ones, but the human should not be in charge of controlling all 11

Figure 3. A cognitive robot tasked with preparing a bowl of cereal for breakfast would face challenges with implicit knowledge that allows humans to do the same task without explicit planning. It would need to know that "a bowl of cereal" implies the use of milk, or what container can be used as the bowl or where to find the cereal. Without common-sense knowledge that provides answers to these challenges, the robot may search the whole kitchen for milk instead of starting with the most probable location (the fridge) or it would not understand that a found container could be used as the bowl (adapted from reference 49).

DoFs. She or he may be required to act on the main ones, indicating a direction or a desired action, and then the control system would need to take over and stabilize all other degrees of freedom.

Semantic reasoning for robots. Autonomous behaviour requires robots to have reasoning abilities to interpret their environment and cope with new and underdetermined tasks, new environments or new objects. Achieving this goal implies equipping robots with commonsense knowledge including physics, causality, objects with their locations, properties and relationships, the psychology of human beings - a so-called computational Theory of Mind[49].

The ultimate challenge is robots jointly accomplishing tasks for, and together with humans, as it is needed for robots that are co-workers of humans and robots that empower people to improve their quality of life. For this, robots require advanced reasoning capabilities that enable seamless collaboration in shared tasks. These capabilities include negotiating roles in joint activities, dynamically allocating subtasks, and adapting to human feedback to ensure alignment with shared goals. Robots must maintain a robust understanding of the context of the task, which involves reasoning about human intentions, the current state of the environment, and their own operational constraints. By integrating task planning with real-time feedback, robots can effectively co-construct actions with humans, ensuring mutual understanding and efficiency[50].

In addition to negotiation, robots must be capable of both giving and receiving help during task execution. This involves reasoning about when humans might require assistance, proactively offering help, and coordinating their actions without disrupting human efforts. Equally important is the ability to ask for help when needed, which requires self-awareness of their own limitations and the ability to articulate specific needs clearly. Robots must dynamically switch between autonomous operation and guided intervention, leveraging human input to overcome gaps in knowledge or capability. These interactions rely on the robot's ability to simulate potential actions, predict outcomes, and adjust its behavior to ensure that joint tasks proceed smoothly and efficiently.

Underlying these reasoning capabilities is the need for robust knowledge representation and decision-making frameworks (Figure 3). Robots must represent objects, events, and[51] relationships in structured formats that support real-time reasoning, enabling them to model their capabilities and limitations accurately. Incorporating probabilistic reasoning allows robots to operate under uncertainty, adapt to changes in the environment, and learn from both successes and failures. By combining intuitive physics and commonsense reasoning with task-specific knowledge, robots can anticipate human needs, avoid undesired outcomes, and continuously improve their performance in joint activities.

5. CLOSING WORDS

Control, planning, and reasoning have provided the foundations of robotics, and will remain central also in the age of deep learning and generative AI, shaping the future of intelligent robots. Intelligence ultimately involves maintaining representations and reasoning about them, and explicit models enable rigorous computational frameworks. The significance of such approaches lies in their ability to bypass data dependency and provide results that are correct, transferable, generalizable, and optimal. This ensures safety, trustworthiness, and reliability—qualities indispensable for robots operating in dynamic, human-centric environments.

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3. Human-Robot Interaction: Successes, Hurdles and Remaining Challenges

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The past decades have seen an increasing number of robots deployed in the vicinity of humans, from vacuum cleaners roaming in our living rooms, drones flying over our heads, to prostheses attached to our bodies. To increase trust and reduce risks, it is urgent and necessary that robots become cognizant of their environment and *socially aware*. They must be able to interpret, predict and reason about both human behavior and their own behavior.

This article aims to summarize existing solutions and open challenges over the next two decades towards the development of robotic applications capable of interacting with humans in a pertinent and helpful manner in any environment. Such applications can help tackle societal challenges, from assisting an aging population to monitoring the environment in order to mitigate and adapt to the effects of climate change and managing the impacts of natural hazards, such as earthquakes and floods. The article reviews successful examples of robots interacting and supporting humans, and delineates which breakthroughs, both in modeling and technology, have allowed such applications. It then highlights the low-hanging fruits, technologies that could improve the quality, effectiveness and versatility of the interaction and collaboration between humans and robots in the short- and medium- term that do not require scientific breakthroughs but rather clever strategies of technology transfer. It ends with a discussion of long-term scientific challenges that will require novel and interdisciplinary efforts to fulfill the vision of human-centered robotics.

1. INTRODUCTION

Today, all efforts globally are turned toward designing the next generation of robots, that of robots that will be employed and function in close or direct interactions with lay users. We are no longer in the realm of factory robots used by well-trained practitioners. We seek the design of autonomous wheelchairs, smarter and more dexterous prostheses and new drones and personal mobility devices that can navigate autonomously and safely to our doorsteps and on pedestrian lanes. It is not conceivable that these robots be programmed without a deep understanding of the social, ethical, cultural rules that underpin human environments.

Developing robots that are cognizant of the world that surrounds them has led to a wide range of efforts worldwide, all of which fall under the general field of human-robot interaction (HRI). The scope of HRI spans from developing algorithms and interfaces to facilitate seamless interaction between humans and robots, to conducting observations and experimental evaluations of how stakeholders utilize robots in various contexts. It encompasses both non-physical interaction—such as verbal and gesture-based communication—and physical interaction—where robots and humans are either in contact, as in prostheses, or in indirect contact, as when they jointly carry an object.

Originally an offspring of Human-Computer Interaction, HRI became a research field of its own in the mid-1990s, gaining increasingly more attention over the following three decades. It established itself with the launch of the IEEE-ACM International Conference on HRI in 2005 and subsequently of a few dedicated journals. HRI is fundamentally an interdisciplinary field of research, and requires close collaboration between roboticists and social scientists, cognitive scientists, psychologists, economists and philosophers. Their expertise is crucial to model human behavior and develop robots capable of interpreting and predicting the actions of the humans they interact with. It is also crucial to make sure that robots behave and speak in ways that are socially adequate and effective when communicating and collaborating with humans.

2. INTERACTION TYPES, SENSORS, AND INTERFACES FOR HRI

Human-robot interaction can be either haptic/physical–when humans and robots get into actual contact with each other–or non-physical. Physical human-robot interaction is being used extensively for teleoperation or for teaching robots to perform tasks through what is known as programming by demonstration or learning from demonstration. Moreover, modern collaborative robots (cobots) are designed to work together with humans, for example as a “third hand”[1] or for jointly manipulating large and heavy objects[2].

Non-physical interaction can be both verbal, when humans instruct robots what to do, and non-verbal, for instance by using robot’s eye gaze[3] to augment verbal communication, convey the robot’s internal state, or gather the attention of the human, possibly directing it toward an object involved in a joint task. This builds on the unique human ability, surpassing that of non-human primates, to infer others’ intentions from eye gaze. Physical and non-physical HRI can be combined in the most complex systems and tasks[4].

Over the last three decades, the type and complexity of both physical and non-physical HRI have evolved significantly due to several factors. First the introduction of new materials and new sensors, such as artificial skins and haptic interfaces, has enhanced robot’s ability to detect and interpret physical contacts with humans. Second, the design of more realistic human-like bodies, such as androids and human-like avatars, has enabled HRI to mimic certain aspects of human-human interaction. Finally, recent advancements in speech recognition and Large Language Models (LLMs) have greatly improved verbal interactions with robots, enabling more complex dialogues.

Physical HRI. In physical human-robot interaction, the key achievement that allowed the transition from the classical rigid, fixed-base robots to those capable of safely interacting with humans is compliant control[5], that is the possibility to regulate the energy injected in the systems thereby managing the interaction behavior rather than following predefined trajectories. This is especially relevant to guarantee safety of the human operator when interacting with a robot.

Compliance can be passive–or mechanical–when the mechanical properties of an actuator or another robotic part are tuned to determine what stiffness or damping it can adopt, thereby adapting to the force applied by a human. The introduction of soft and elastic materials on robot bodies, which prevents harm to humans in case of impact, can be seen as an example of better passive compliance. Active–or cognitive–compliance, on the other hand, implies the use of algorithms to actively model how the stiffness or the damping must change as an effect of task requirements[6].

Advancements in sensors, both for forces and torques, as well as the availability of tactile signals collected by artificial skin[7] played a crucial role in achieving cognitive compliance of robotic systems and making physical human-robot interaction safer. As a result, compliant control has allowed humans to control the robot movements with touch, for instance through haptic interfaces. It has increased precision and performance in tasks execution, as well as safety. Among the compliance control strategies, of particular importance was the development of variable impedance actuators[8], which was based on the intuition of bringing intelligence into the robot hardware.

Recent research in robotics has also addressed social compliance, that relates to the capacity of a system to conform to social norms and expectations. In particular, many works have studied how monitoring physiological signals related to social compliance could allow robots to change their actions, for instance stopping a task and waiting until those signals indicate that the human has regained some of the required trust before resuming the joint work[9].

Non-Physical HRI. In non-physical human-robot interaction, better computer vision algorithms have contributed significantly to improved navigation in various environments, to detect humans, to predict their intentions and behave appropriately. Simultaneous localization and mapping (SLAM) is now a mature technology deployed in a wide variety of mobile robots, such as drones

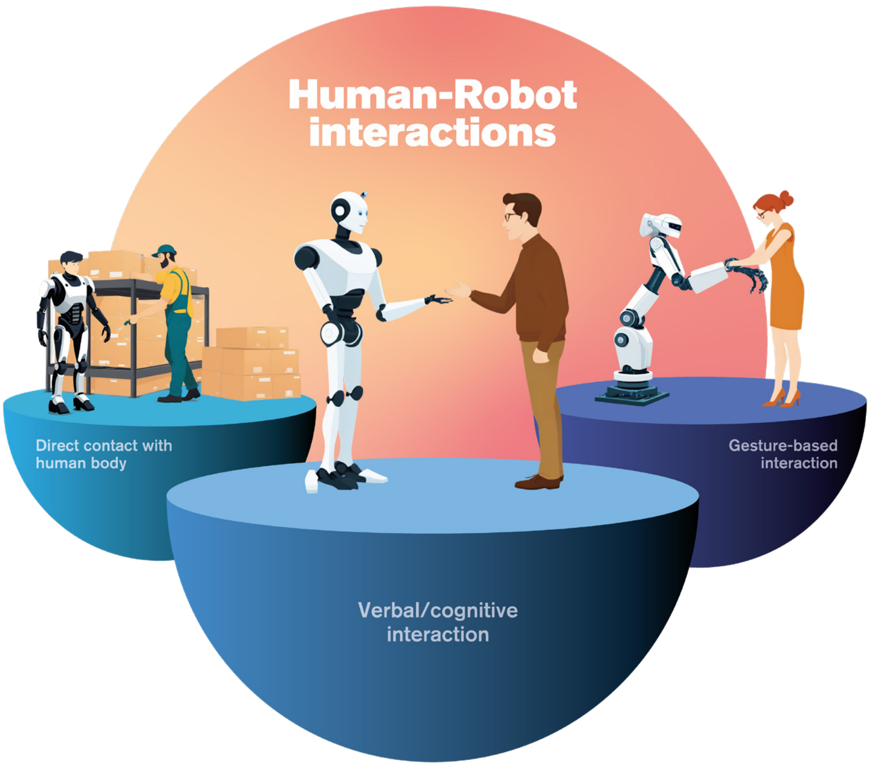

Fig. 1. Different types of human-robot interaction

and vacuum cleaners. It can detect human as well as non-human obstacles. Computer vision has also helped robots to improve their capabilities in manipulation tasks that involve interactions with humans[10].

Breakthroughs in speech recognition, thanks to recurrent neural networks and transformers, fueled the diffusion of voice assistants, such as Amazon's Alexa, Google Assistant and Apple's Siri. The latest developments in LLMs have boosted verbal human-robot interaction, allowing robots to conduct complex dialogues with humans. However, there is still a stark contrast between the advanced conversational abilities of LLMs and the still limited capacity of robots to interact with the physical world. A language model may allow a robot to engage with humans in a complex conversation on how to set up a dinner table for friends versus hosting a boss, but if the human were to ask the robot to fetch a glass from the table, the robot may not be able to identify the correct glass, or may prove much more clumsier and may knock over other objects along the way.

3. COMMERCIAL APPLICATIONS OF HRI

All together, these three decades of research have led to the development of robots designed and programmed to be intrinsically safe for humans—that is, capable of working safely near them without being cognitively aware of their presence. Several applications have emerged from this achievement.

Cobots started operating in the manufacturing industry outside of confined spaces[11]. The first industrial cobot to reach the market was the LBR iiwa single arm system, developed by the German Aerospace Center (DLR) and commercialized by KUKA in 2008[12]. It enabled force and torque sensing in all joints. Other single- or dual- arms systems became available in the following years, such as the UR5 by Universal Robots, Robonaut by NASA, that started operating on the International Space Station, and Baxter by Rethink Robotics, later evolved in a single-arm version called Sawyer. Even if both Baxter and Sawyer had an affordable pricing, they had mixed success. This was maybe due to the adoption of spring actuators coupled with force sensors, which make them safer than cobots that relied on more traditional positioning systems, like those designed by Universal Robots, but less precise[13]. The cobot industry in the end got dominated by Universal Robots single-arm systems. Competitors are emerging in Europe, such as Europe Technologies and Agile Robots.

Robots that navigate and share space safely with humans have been deployed satisfactorily in many environments. Autonomous vehicles have been deployed in factories and warehouses, as in the case of Carter developed by Robust.AI[14], but their interaction with human workers is still carefully structured. Domestic robots performing household tasks, such as vacuum cleaners, are produced by the million each year. Mobile robots work quite well in public spaces such as hospitals and airports. Robots have also been deployed in restaurants to serve people, where they can navigate without ground signaling, finding their way among customers and servers.

A significant leap forward in terms of robots that physically interact with humans has been the development of wearable robotics, especially exoskeletons. Thanks to the development of lighter and more robust materials, such as titan, exoskeletons are now commercially deployed, not only to help physically impaired people but also to assist humans in heavy duties, reducing the social cost of work[15].

One step beyond there are those robots that, thanks to the very anthropomorphic or biomorphic design of their body and of the controller, can interact with humans and be human-aware cognitively. For example, they can talk and respond to humans, simulate facial expressions and recognize human's expression, predict human motion and adapt to it. Robots for rehabilitation and companionship have been deployed and their effectiveness has been demonstrated to a certain extent. One of the most successful examples is PARO, the baby seal robot, whose deployment has been proved useful in hospitals and elderly homes, especially with people affected by dementia[16]. Other examples in this category are CLEO and AIBO, a robot cat and dog respectively which are used mainly with children with well-documented benefits. ROBOTA, an imitating doll robot and Keepon, a small friendly ball-like robot, were both successfully used to engage with children in autism research. Social robots have been developed also with highly realistic human faces, such as Geminoid by Hiroshi Ishiguro Laboratories and Sophia by Hanson robotics. Robots capable of interacting with humans have also been developed for educational purposes. An example is the Sphero robot, employed in programming classes for children.

As for the more theoretical work on human-robot interaction, that is the study of how humans interact with robots and of certain aspects of human behavior which employ robotic platforms, the most robust findings concern how people interact with robots in controlled laboratory settings, one-to-one interaction with humans trained to interact with the robot. One of the pioneering works in this field of research is Kismet[17], the robotic platform developed at MIT in the late 90s. Kismet is a social robot designed to engage in natural and expressive face-to-face interaction with a human. It was inspired by infant social development, behavior and psychology. The human and the robot are led to interact like in a parent-infant relationship. Around 2010, several new robotic platforms for social human-robot interaction emerged, such as NAO, iCub, Kaspar and Pepper. NAO has been among the most widely used social robots in human-robot interaction research due to its affordability and broad functionality. It has been used in various applications, such as education, autism therapy and elderly care[18].

In the last three decades, research on human-robot interaction has achieved important results, bringing robots to interact with humans in different contexts. However, the goal of developing fully autonomous robots capable of interacting usefully and pertinently with humans is still quite far away. Next, we offer our view on the most pressing challenges which HRI must resolve, and the most rapid new deployments of HRI we can expect.

4. SHORT-TERM CHALLENGES AND LOW-HANGING FRUITS

HRI is crucial to scaling up the use and deployment of collaborative robots, that is robots capable of operating outside the confined environments of industrial settings—where they traditionally worked in cages or behind fences to prevent any interaction with humans. It is also needed to expand usage of robots in the medical sector, wearable robots and exoskeletons, robots and drones

Fig 2. Robots interacting and collaborating with humans. A: Collaborative human-robot sawing experiment performed at Italian Institute of Technology in 2016 (Credit: Luka Peternel, CC BY-SA 4.0). B: A journalist speaking to humanoid robot Sophia at the Deutsche Welle Global Media Forum in 2019 (Credit: Deutsche Welle, CC BY-NC 2.0). C: Pepper robot interacting with a waiter in a Tokyo cafe, 2019 (Credit: International Labour Organization/K. Hongladarom, CC BY-NC-ND 2.0). D: PARO therapeutic seal robot interacting with an elderly woman in a nursing home in 2012 (Credit Amber Case, CC BY-NC 2.0). E: AIBO ERS-7 following pink ball held by child (Credit: Stuart Caie, CC BY 2.0). F: Child interacting with Robota during a behavioral study conducted in 2007 (reproduced with permission from[19]).

for the inspection of remote locations and for search and rescue operations in collaboration with humans, mobile robots capable of navigating in crowded spaces, such as hospitals, airports, restaurants, and robots for social companionship. Ultimately, the most challenging application is inside homes, which are among the most unstructured and unpredictable environments.

Even if the market for collaborative robots in the industry has been growing dramatically in the last ten years, they still represent only 5 to 8% of the robots sold to industries. Their presence in manufacturing and logistics could increase soon as they become safer to interact with, more robust and capable of performing highly dynamic motions similar to what humans do[20].

The physical interaction with robots could be enhanced by providing the robot with tactile sensors that can measure more accurately the contact forces[21]. The idea of an artificial skin has been proposed a long time ago, but so far it has been implemented mainly in robotic platforms for research. One of the first examples was the iCub robot developed at the Italian Institute of Technology that already ten years ago was covered with 200 tactile sensors, one the largest implementations of tactile skin at the time. More recently, researchers at TU-Munich implemented[22] tactile skin based on off-the-shelf components integrated on hexagon shaped printed circuit boards, with which they covered a full-size humanoid robot (H1). One of the key elements was to reduce the computation in a way that allowed the humanoid robot to operate autonomously without needing additional computation or external energy source. Deploying robots with tactile sensing small covering surfaces is achievable

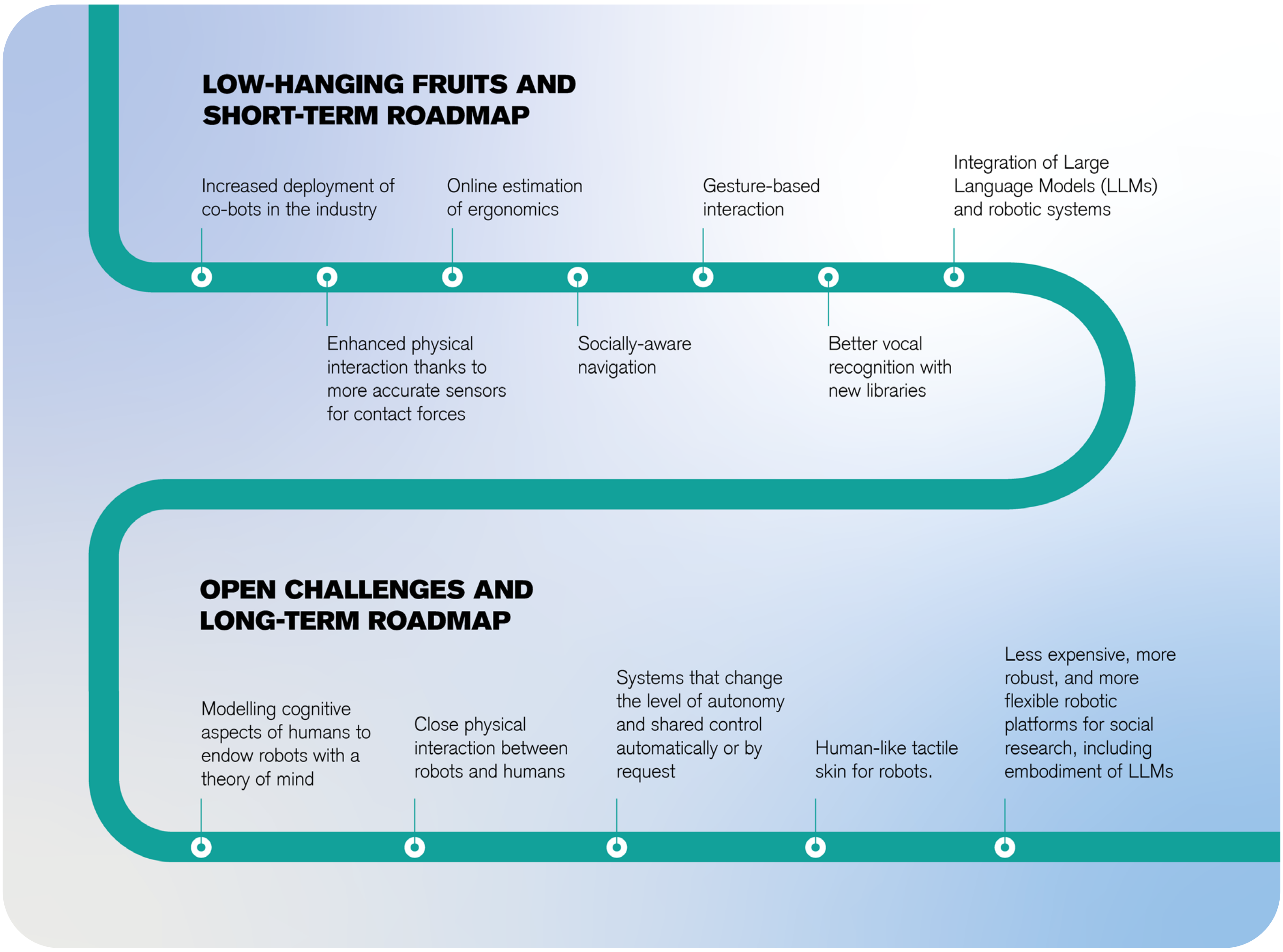

Figure 1: Short-term and long-term research goals on human-robot interaction

in the short term and could be driven also by the need to improve the manipulation performance of robots employed in the agrifood and textile industries.

Research on online estimation of ergonomics has been extremely active and industrial applications could be achieved soon, facilitated by the fact that the technology works independently of the context. Recently there have been several attempts to offer solutions based on wearable inertial sensors and pressure or force sensors rather than systems based on optical motion capture, which can be easily occluded in cluttered environments such as factories[23 24]. Also, researchers have been working on improving the intuitiveness of ergonomic evaluation and visualization tools based on digital human models to facilitate their adoption by industrial operators[25]. These technologies could be employed in devices that alert workers performing heavy tasks about damaging postures to prevent musculoskeletal disorders and enhance safety in the workplace.

Significant progress on socially-aware navigation is now within reach for the research community, especially in Europe[26]. In the next few years, there could be robots capable of navigating among humans, not only maintaining appropriate distance from humans, but also understanding how humans move when they are confused. Deploying this kind of robots will require refinement of the algorithms that allow the robots to detect and perceive humans, and also predict what will happen in the next second. This would help find a trade-off between safety and usefulness of robots navigating among humans. Socially-aware navigation would also greatly benefit from a better understanding of the interaction between naive users and robots in unstructured settings. As an example, last-mile delivery robots need to share the sidewalk with humans, and more work is needed to model humans' expectations regarding the behavior of these robots[27].

Gesture-based interaction is quite mature now, as there are many algorithms that work well in laboratory conditions. More research is needed to make them work in the real-world environment, where humans do not act perfectly and there could be occlusions and disturbances, but the science is now solid.

Vocal and audio recognition is mature too, with several well-performing libraries. Deploying it could be slightly more challenging than gesture recognition because of the great variance with which people speak, and of course each application can have a different vocabulary. To address real-world acoustic conditions, the signal processing community offers numerous libraries capable of denoising audio signals. For instance, these libraries can effectively extract speech from a drone's onboard microphone despite high levels of ambient noise.

The integration of LLMs and robotic systems holds promise to transform the human-robot interaction paradigm, allowing robots to act upon high-level instructions expressed in natural language and generate plans in the form of step-by-step procedures or code. This field of research is just starting but it is rapidly evolving, with several examples of this integration already available[28]. These include the models developed by Google DeepMind[29] or LaMi by the Honda Research Institute Europe[30]. LaMi converts various forms of human input, such as behavior, position, gaze, dialogue, and scene information, into a language that the LLM can process. The LLM then analyzes the situation and determines how and when the robot should assist humans, following predefined guidelines. Additionally, it synchronizes the robot's movements (lid, neck, ears) with speech output to create dynamic, multi-modal expressions.

As for the more theoretical work on human-robot interaction, researchers will need to understand much more about the interaction of robots with multiple users. This last setting can be used to study how discrimination and social exclusion[31] arise and how biases in various robot components can affect the group members depending on their features[32]. Examples of these so-called "embodied biases" are natural language understanding models and voice recognition models that are known to be better at recognizing male voices than female ones, or image recognition models which are better with white people than with people of color. This is largely due to the underrepresentation of females and people of color in the datasets used to train these models. All these elements will be embedded in robotic platforms and biases can arise in multiple ways[33].

There is also research about the possibility to mitigate some of these risks, making robots aware of discrimination but also that other humans can discriminate. Besides making robots aware of this risk, one could program them to apologize when they are discriminating or if they are at risk of discriminating, explaining why they are doing so to start some process to reintegrate a person in the group.

5. OPEN SCIENTIFIC CHALLENGES

The long-term goal of human-robot interaction research is to design robot systems and AI systems which explicitly consider the human in terms of their actions, their preferences, their mental state and their goals and therefore understand when they need to act or communicate. All these questions are far from being solved today.

One open challenge is modeling basic cognitive aspects of humans, to endow robots with a theory of mind that allows them to understand the human's expectations during a joint task and to engage in a negotiation which leads to results that align with the human's preferences, objectives and values[34].

Robots should also be able to update these models with time. As an example, they should understand when a human is not feeling well and performing with less dexterity and pitch in to help, but they should take themselves back as soon as the human recovers. They should be able to do this in open environments where new people may come into play and take roles in the joint actions.

To achieve human-centered robotics, researchers should strive to develop robots that are easy to interact and work with and do not overly constrain humans. In logistics, where robots are already deployed, this kind of problem has already arisen, leading to a high degree of turnover among human workers. These workers often feel replaceable as they work to complement robots. The development of future cobots should be centered around human workers to ensure they do not refrain from intervening with robots out of fear of the consequences this could have on their jobs. The robots of the future should be able to adapt and give priority to the human, allow them the freedom to make their own decisions, and assist rather than impose their rhythm. It is thus crucial to involve experts from fields such as psychology, economics, philosophy, and cognitive science to understand thoroughly what it means to collaborate with humans[35]. European institutions should weigh in with meaningful regulations to enforce the principle of human-centered robotics, as they have already done concerning the use and exploitation of personal data and the deployment of AI systems. Moreover, robots should be well integrated with existing infrastructures, also digital ones.

To fulfill this long-term vision several more specific challenges should be addressed.

In physical human-robot interaction, a challenge will be that of designing systems that allow to change the level of autonomy and shared control. This could happen automatically or by request, so that it fits exactly what the human wants and needs in terms of ergonomics, but especially what the human feels comfortable with. This would allow the human to preserve its own sense of agency and not feel completely dominated by the robot. Solving this challenge will be crucial for exoskeletons, especially active ones, which will be more and more deployed in assisting humans in various tasks, such as lifting heavy payloads, and for manipulators on a mobile base in a factory.

Tactile human-robot interaction would be enhanced by developing human-like tactile skin for robots. One of the necessary steps in this direction is to build electronics and algorithms capable of locally processing the vast amount of sensing data collected over large surfaces. This would reduce the quantity of data processed by the central processing unit, which should only handle high-level decisions about perception.

Currently, AI and machine learning algorithms in robotic sensing are implemented using digital electronics. A new computing paradigm inspired by the human brain, which is based on analog signals, is required. This could be achieved by developing neuromorphic devices—hardware that implements neuromorphic arrangements and is capable of learning, similar to how synapses between neurons create plasticity in the brain. An example is printed synaptic transistors placed close to the sensor that can learn[36].

Other problems that need to be solved to have humanoid robots performing a wide variety of tasks in collaboration with humans concern the ability to learn in a continuous way, and the ability to personalize behavior to different people. Also, such robots need to be soft enough. A major development step is required also on all levels of hardware and control to enable close physical interaction, for tasks like feeding or undressing, washing and dressing again a person, currently performed by caregivers. Humanoid robots can play multiple roles because they fit in the environments we have built for us humans, both in terms of shape and size. Moreover, getting assistance from a humanoid robot is more effective because humans know how to behave in such situations, e.g. they know they can put a hand on the shoulder or how to walk together.

As the interaction between robots and humans becomes more unconstrained, more interdisciplinary research is needed, especially on managing humans' expectations of the robots' capabilities.

To investigate the social aspects of human-robot interaction, cheaper, more robust, and more flexible robotic platforms are needed. Currently, the choice is between robot toys, which are very robust and very cheap but with a very specific application area which cannot be changed easily, and research platforms, such as Pepper and NAO, which are instead quite expensive. In between there are platforms developed by computer scientists and engineers that are often too complex to customize. As a result, the choice of the platform is rather restricted. Today, a long-term study on social robots requires major investments. Real-world data on long term interaction between robots and humans is not yet available, since companies like Jibo or Blue Frog Robotics that aimed to develop robot companions did not take off[37]. Their products didn't make the step into people's homes as expected.

AI and machine learning techniques, especially deep learning and LLMs will play an important role in developing the robots of the future. The integration of LLMs into robotic systems could enable individuals, irrespective of their technical knowledge, to interact with robots and direct their actions. An essential step forward compared to LLMs today will be the capability to generate safe and reliable actions in the physical world, based on a physical architecture which is fully aware of the robot's internal state and capabilities. This would require at the same time to build versatile robots, which are capable of doing many different things, navigate, pick objects, interact safely with the environment, avoid obstacles, etc. It is a huge endeavor, but it will change the way in which humans interact with robots.

The use of LLMs could prove highly effective in social science research. For example, studies on the impact of language tone in communication, both between humans and between robots and humans, are challenging to perform by asking humans to change their tone, whereas LLMs can do this very efficiently. However, attention must be paid to reproducibility, especially in long-term studies. Given that LLMs evolve rapidly due to the availability of new training data, their consistency over the course of experiments or across experiments performed at different times should not be taken for granted.

However, as for other fields of robotics, the challenge in human-robot interaction lies in finding an intelligent way to combine model-based AI systems with deep learning algorithms, to mitigate potential risks such as misinterpretation. This requires defining in which situations misinterpretation can be accepted, because it poses no safety issues, and situations where we need instead that the machine really understands what happened, to assess it correctly. As of today, we cannot rely on LLMs for this, and we need to complement them with conservative measures to avoid dangerous consequences.

Embodiment of LLMs will also require dealing with safety and trust, since people are going to be able to use and interact with the robots even without knowing how they work and what their limits are. The integration of ChatGPT into a robotic arm that collaborates with human workers on an assembly task has demonstrated that it significantly increased trust in human-robot collaboration[38]. This is an opportunity, but it also poses the risk of over-trusting, as it has been observed in autonomous cars where, even with the vehicle alerting them that its sensors are malfunctioning and asking them to take over, people did not intervene, trusting that the car will recover. Strategies to recognize excessive trust and refusing to execute dangerous plans in such situations should be developed and deployed.

6. CLOSING WORDS

To fulfill the vision of robots interacting with humans in unstructured environments and collaborating with them to perform a wide variety of tasks, human-robot interaction research is becoming increasingly central to robotics. The first steps toward that vision were made over the last three decades, thanks to compliant control, both mechanical and cognitive, new sensors for vision and touch, and progress in voice recognition and natural language processing, thay has enhanced the complexity of dialogues between humans and robots. As a result, cobots entered factories and started navigating public spaces, and several platforms are now employed in the treatment of neurodevelopmental disorders and neurodegenerative diseases, as well as for companionship. However, as of today interaction is still quite constrained and where it is more widespread, such as in logistics, humans often perceive robots as imposing their rhythm rather than adapting to human needs. To progress further towards human-centred robotics, it is crucial to conduct research on managing autonomy levels and understanding humans' expectations and preferences. Additionally, advancing tactile sensing will be critical if robots are to help humanity to tackle the societal challenges it is facing, such as supporting an aging population and mitigating the impacts of climate change. Finally, the integration of AI and machine learning into robotics promises to make robots more accessible to people without technical expertise. While this opens up new perspectives, it also entails risks that need to be addressed. Humans might over-trust robots, underestimating potential hazards, or fall victim to embodied biases—discriminatory behaviors stemming from imbalanced training data used in AI systems.

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4. Emerging core robotic technologies for the future of robotics

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Several advancements in core robotic technologies, i.e. materials, sensors, actuators, computing devices, are needed to obtain and turn into commercial products, robots capable of interacting with unfamiliar and unpredictable environments and to collaborate safely and effectively with humans. In advancing these technologies, environmental sustainability should become a guiding principle, i.e. by designing new materials that are self-healing, biodegradable and able to harvest energy from renewable sources. This work summarises existing solutions and open challenges that need to be tackled over the next two decades to take new core robotic technologies from labs to industrial deployment. Achieving this will require the careful consideration of the interplay between hardware and software, that is to find new strategies to co-design robot's control and morphology. The article starts by presenting the most important recent breakthroughs that have allowed robotics research to go beyond the established hardware paradigms. It then highlights the low-hanging fruits, technologies that are ready to be deployed. It ends with a discussion of long-term scientific challenges that are needed to endow robots with a human-like sense of touch, artificial muscles and new batteries that can reduce the energy consumption of increasingly autonomous robots.

1. INTRODUCTION

A robot is an integration of several core robotic technologies, such as sensing, computing, actuation, and materials. Robot applications set the requirements, while technologies provide capabilities. For different applications as currently deployed in the industry, in service sectors, or as consumer products, those capabilities and requirements are attuned at an affordable price, leading to commercial products that belong to three main categories. The first one includes manipulators with articulated arms attached to a fixed base, equipped with rigid end-effectors with limited degrees of freedom. The second one comprises wheeled or tracked mobile robots, while the third one consists of rotary-wing drones. More recently, four-legged walking robots have also started being applied for inspection and surveillance tasks. Most of these robots are rigid, made from metal or hard plastics, and use electric motors as actuators.

In several other applications, such as humanoids, wearable robots, flapping wings, or drone manipulation, one or more of the core robotic technologies are not on a level that allows widespread deployment and commercialization, requiring further research to improve system performance and fully exploit their potential. Typically, robotics integrates technologies developed in other fields or use cases, such as gaming (e.g., depth cameras), GPS, 5G from smartphones, and LiDAR from autonomous vehicles. This means that from the robotics side, there is little to no influence on how the technology is developed for the specific robotics needs. That is why it is important, and should be prioritized in the future, that core robotic technologies are developed with the specific requirements of robotics itself.

In advancing technical performances of core robotics technologies, sustainability should be carefully considered, making life cycle extension, circularity, resource efficiency and conservation, ethics, and environmental justice guiding values in robotics research. In doing so, not only the application of robots will enable the different pillars (economy, planet, and environment) of the United Nations' Sustainable Development Goals (SDGs), but robots themselves will also have a positive sustainability impact.

Industrial and service robots have so far been based on a rather limited repertoire of core robotic technologies. New paradigms are emerging in robotics hardware that will significantly expand that repertoire, ranging from soft components, new sensors and actuators, new computing and memory technologies, new batteries and new systems for energy harvesting and production[1]. These new core technologies open up possibilities for improving platforms such as walking robots, humanoids, exoskeletons, drones and robotic hands, and for new applications ranging from manipulation of soft materials to medical applications and collaboration with humans.

This work summarises existing solutions and open challenges that need to be tackled over the next two decades to take new core robotic technologies from labs to industrial deployment. Achieving this will require the careful consideration of the interplay between hardware and software and to co-design them.

The article starts by presenting the most important recent breakthroughs that have allowed robotics research to go beyond the established hardware paradigms. It then highlights the low-hanging fruits, i.e. technologies that could allow robots to enter new industrial fields, such as agriculture and the textile industry, and that do not require scientific breakthroughs but rather clever strategies of technology transfer. It ends with a discussion of long-term scientific challenges. This will require a strong interdisciplinary effort and a rethinking of the balance between data driven and model-based approaches.

2. STATE OF THE ART

Core robotic technologies. Starting from the 1990s several new soft materials capable of controlled deformation were developed, such as polymers, foams, gels, colloids, granular materials, as well as most soft biological materials. At the beginning of the twenty-first century, they became commercially available and easier to fabricate and started to be adopted in robotics[2]. The use of soft materials and deformable structures in building robotic systems has been recognised as a promising way to advance robots' capabilities and make them more efficient[3], especially in unstructured and unpredictable environments and when acting in close contact with humans or collaborating with them. Among soft materials, the most widely used in robotics are polymers — such as elastomers, thermoplastics (mainly polyethylene and ethylene-vinyl acetate), and electroactive polymers gels — but also granular materials and smart fluids have been employed especially in robotic grippers.

The most mature technologies in soft robotics currently concern actuation, with technologies that include fluidic and pneumatic actuation, actuation based on multi-functional materials, including but not limited to electroactive polymers and shape memory alloys.

Robots powered by hydraulics are being gradually replaced by electrification for sustainability reasons. However, these advancements also highlight key limitations in traditional electrical actuation systems particularly in areas such as torque density, energy efficiency, transparency, and sustainability. Innovations in the important components of drivetrains, both active or passive compliant, include motor drives, new electric motors with also high torque density electric motor[4], transmissions[5], dual motor systems[6], locking mechanisms[7], energy buffers[8], with serial and parallel elasticity, remote actuation[9], torque sensing[10]. They will enable robots to be more effective and allow safer interactions, forming the foundation for cutting-edge robotic solutions like exoskeletons, powered prostheses, collaborative robots, and humanoid robots.

Advances related to flexible and stretchable form factors in electronics allowed the development of soft sensors. Initial results were obtained by making electrically conductive materials into soft forms but also by making soft materials to be electrically conductive[11]. One of the first applications has been a contactless deflection sensor with a light-emitting diode (LED) element and a photodiode placed onto two connected substrates, that could monitor the body shape of a soft robot[12]. 3D printing sensors favoured integration with the soft substrates that compose the robot[13].

Soft sensors have also been beneficial in advancing tactile sensing, with the aim of transforming robot skin from a passive protective layer into an essential means of interacting with and adapting to ever-changing, unfamiliar environments. Different technologies are produced from camera-based tactile sensing at the fingertip[14] to also magnetic[15] and capacitive[16] touch sensors, where it is to measure not only normal forces, but also shear forces. Giving robots a sense of touch is a prerequisite for manipulation of objects by robotic grippers with human levels of dexterity. Force sensing is also necessary in wearable human-machine sensorized interfaces for intent detection of the human user of a prosthesis or exoskeleton.

Covering the robot body with a touch-sensitive skin is also needed for safe interactive human-robot collaboration. The HEX-o-SKIN[17] is a multimodal tactile sensing module integrating sensors for pre-touch, light touch, vibration, and temperature to achieve comprehensive whole-body touch sensation. Beside touch sensors, safety systems also need proximity sensors that have been developed exploiting various technologies, such as capacitive, inductive, ToF, SoDAR, Radar[18]. However, to bridge the gap between vision-based perception and tactile/force perception, more accurate proximity sensors with extended sensing ranges need to be developed.

Event cameras have been shown to offer significant advancements with respect to standard ones, namely a very high dynamic range, latency in the order of microseconds and no motion blur. VoxelSensors' Switching Pixels® Active Event Sensor technology offers ultra-low latency and low power consumption, making it ideal for real-time 3D perception in robotics[19]. Computer vision solutions based on these cameras, as alternative to or in combination with classic ones, have proven promising for various robotic platforms, such as aerial robotic manipulators[20], autonomous driving[21] and for simultaneous localization and mapping[22].

For agents to collaborate in the physical world, they are often required to know the relative pose between them. When the pose of all agents is known in a shared reference frame, this relative pose is directly observable, e.g. with GPS. In GPS-denied environments, the general assumption is that SLAM (Simultaneous Localization and Mapping) will provide a shared reference frame. However, SLAM is unobservable and only works well in feature-rich environments. Therefore, active relative pose estimation involves placing communication devices, such as Wi-Fi, UWB, or Bluetooth, on the agents to facilitate precise positioning and orientation tracking.

Sensorized interfaces are needed for wearable robots to measure the intention to move for performant, safe and comfortable operation, since only kinematic data from sensors placed on the body (encoder-based systems, IMUs,) is often not sufficient. Touch sensors are needed for the internal forces and pressure distribution, as measuring information from the muscles, without the need for intrusive devices. Surface electromyography (sEMG) to measure muscle activation is used[23], but it can pose challenges since it depends on correct placement, adhesion to skin and sweat, and it's affected by motion artifacts and bad signal-to-noise ratio. Electrical Impedance Tomography (EIT) is an imaging modality that is used to image conductivity distribution inside the subject under test, used for pressure distribution and to create cross-sectional images of limbs to unravel bone features like shape, size and position[24]. Also, wearable ultrasound (US) transducer are developed for muscle activity sensing[25].

Applications. In robotic manipulation, the availability of soft materials and soft sensors has led to a new range of designs for flexible grasping of objects with diverse shapes, sizes, and textures. Soft robotic grippers based on pneumatic actuators and the jamming of granular materials[26] were developed starting at the beginning of the 2010s. Other actuation technologies, based on cables, shape-memory alloys and electroactive polymers, have also been exploited in soft robotic grippers[27].

The idea of exploiting the physical constraints imposed by the objects in the environment instead of considering them obstacles led to the development of several soft hands that exhibit robust and adaptable grasping as well as dexterous manipulation. Among the anthropomorphic designs, the RBO Hand 3[28] developed at TU Munich and the PISA/IIT SoftHand 2[29] developed by the Italian Institute of Technology and the University of Pisa are both based on the study of human grasping. The RBO Hand has a five-finger configuration and uses silicone pneumatic-based actuators. It employs several actuation degrees and very few sensors. A different approach was followed in the design of the PISA/IIT SoftHand, where the actuation degrees are limited, and insights about synergistic actuation in the human hand are encoded in the compliant hardware.

Cobots, in contrast to high-speed but heavy industrial caged-robots, achieve enhanced safety by transitioning in actuation technology from position-controlled to torque-controlled actuation, allowing them to detect and respond to external forces more effectively, thereby minimizing the risk of injury during human-robot interactions. However, no commercially available cobots with a payload-to-mass ratio greater than 1:2 exist, far underperforming the capabilities of biological systems. Further hardware innovations on the drivetrains and structure design are needed, especially if cobots are to be placed on mobile platforms such as drones, UGVs and quadrupeds.

Safety represents an additional and relevant problem. Current safety systems are inadequate for mitigating risks when robots work near human operators. This is due to the systems' lack of adequate situational perception and collaborative intelligence. To maintain safety, cobots must operate at reduced speeds, which limits their productivity. As a result, traditional caged industrial robots remain more productive than cobots.

Drones also benefited from the development in core robotic technologies. Thanks to the miniaturisation of sensors and processors, combined with increased power to weight ratios of actuators and more performant batteries, drones are now lightweight enough to take off and complete missions of suitable lengths. Wings have also become lighter. Materials science advancements made blades less noisy and motors more efficient. Propellers have also become less noisy[30]. New materials have also allowed the building of protective cages for drones. An example is the drones by Flyability[31], where cages are based on carbon fibre and origami materials. They are more resilient to collisions, and they can harvest energy from them. 3D printed resin-based materials were at the basis of Morphy, a flying robot with flexible joints that can resiliently withstand collisions at high speeds and squeeze through openings narrower than its nominal dimension[32].

Advancements in quadrupedal robots were possible thanks to lighter and more robust materials, more efficient and reliable actuators, compact sensing technologies, such as LiDARs and IMUs, the possibility of 3D printing parts with variable stiffness and complex geometries, together with improved control algorithms. State-of-the-art platforms are Spot developed by Boston Dynamics, Mini Cheetah by MIT and ANYmal by ETH Zurich. They exhibit robust locomotion on fairly regular terrain and perform well also on more complicated terrain.

Exoskeletons, wearable robots, robots for rehabilitation, prosthetic limbs and autonomous vehicles have all benefited from advancements in sensing and actuation technologies. In particular, a new generation of lightweight, partially soft exoskeletons have appeared and are now being deployed for rehabilitation and assistance, significantly improving the usability and accessibility of these technologies compared to the bulkier and more expensive exoskeletons of the previous generation[33 34]. Bioinspired robotic platforms were also used to gain insights into human and animal locomotion. They have contributed to the design of prosthetic devices that take human locomotion principles more closely into account[35].

Humanoid robots have significantly advanced their agility, stability and dexterity, thanks also to the DARPA Robotics Challenge programme[36] that has directly contributed to the development of advanced platforms such as Boston Dynamics' ATLAS platform. In Europe there have been various successful projects that led to the development of humanoid robots, such as the iCub robot at the Italian Institute of Technology, the ARMAR series at the Karlsruhe Institute of Technology, and the various designs conceived at the Institute of Robotics and Mechatronics of the German Aerospace Center. Moving forward, one of the primary issues is achieving a balance between size, weight, and mobility. The robot's physical structure must be optimized to enable dexterous movements while ensuring stability and energy efficiency. Developing lightweight yet durable materials in smart designs that can withstand repetitive movements and external forces is crucial. Additionally, there is the need

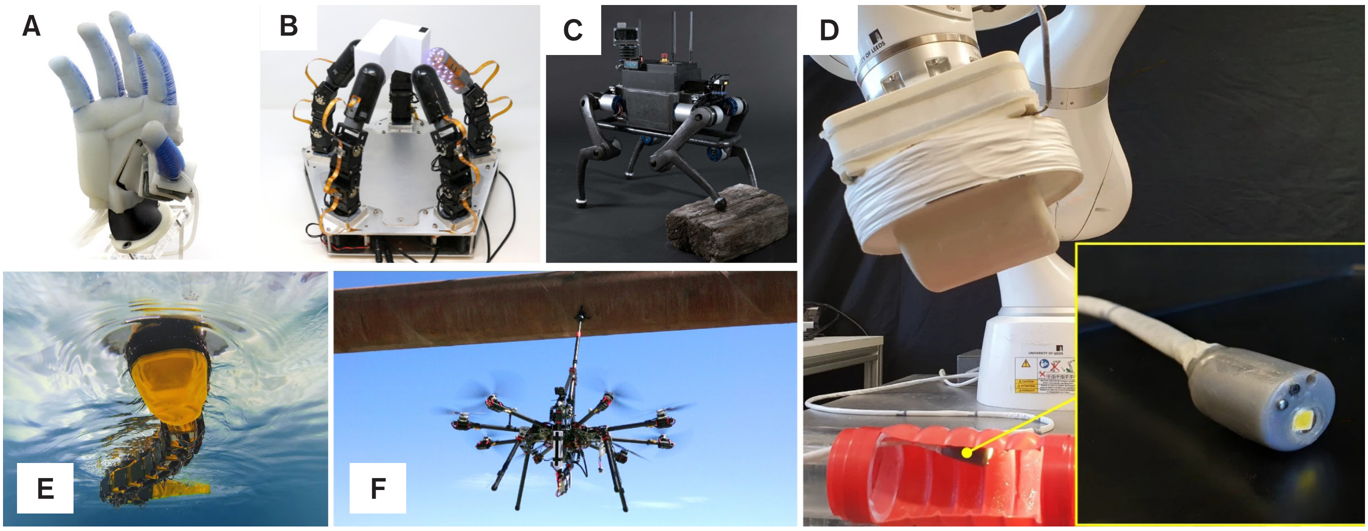

Fig.1. Robotic platforms that have been developed over the last three decades thanks to advancements in core robotic technologies. A: RBO Hand 3, Credit: IEEE Transactions in Robotics CC-BY 4.0. B: image reproduced with permission. Credit: Columbia University ROAM Lab. C: ANYmal quadrupedal robot, image reproduced with permission. Credit: ETH Zurich Robotic Systems Lab. D: Mangetically guided flexible endoscope for colonoscopy, image reproduced with permission. Credit: University of Leeds STORM lab. E: AgnathaX swimming robot, image reproduced with permission. Credit: Kamilo Melo, EPFL. F: Drone with manipulators attached, image reproduced with permission. Credit: AEROARMS project

to integrate advanced sensors and perception systems that go beyond vision, to allow the robot to navigate and physically interact with its environment autonomously, at natural yet safe speeds, and in close collaboration with humans. Power management is another critical challenge, as humanoid robots need efficient energy sources to operate for extended periods without frequent recharging. Finally, ensuring the safety of both the robot and its surroundings involves implementing robust collision avoidance mechanisms and reliable sensing and control systems.

3. SHORT-TERM CHALLENGES AND LOW-HANGING FRUITS

Due to the popularity of fluidic actuation in soft robotics, there are many results and prototypes that can be used in simple grippers that can be applied in biomedical fields, for example for endoscopes. Some of these grippers are very close to market deployment in specific industries such as food and agriculture, where it is necessary to grasp and handle delicate objects[37 38]. One of the designs where soft grippers are being massively deployed in the industry is the one that uses suction cups and vacuum-based fingertips capable of handling delicate objects, such as fruit and vegetables, are being explored[39]. Innovations to improve energy efficiency are possible with self-closing suction cups[40].

The next step after grasping is achieving dexterous manipulation, similar to what humans do. In the last couple of years, there have been tremendous advances in this field, with several multi finger designs capable of performing complex manipulation tasks. Examples include the extension of light-based tactile sensors to the entire finger surface[41] and their integration in a multi-fingered robotic hand[42]. Having a wider area of the robotic manipulator covered with tactile sensors would also improve the capabilities of grasping in cluttered environments, which are essential for robots to be able to act in unstructured environments such as homes. The first deployment of such configurations outside from the lab could be manufacturing, where robotic manipulators could perform manipulation tasks that are complex but that rarely change or never change and thus do not require versatility. An example is a long production run that requires an assembly step, which requires dexterity. The agri-food and textile industries could also benefit from the improved dexterity of these manipulators.

Manipulators have been combined with unmanned aerial vehicles with convincing results. Drones that can perform manipulation task after perching and while flying have been demonstrated[43 44] and could be useful for inspection and maintenance of infrastructures at great heights, such as high-power electrical lines. Manipulation while flying poses more challenges though. Keeping the drone steady especially with strong winds is still problematic. Taking inspiration from birds could suggest reliable strategies to achieve this goal. Some birds with very light bodies, like the kestrel, can maintain their body steady, in particular the head, even within a few millimetres under wind perturbations by using morphing wings that are able to adjust their surface area and the tail to maintain the stability. Reducing the drones' body weight could thus improve their performance.

Walking robots are ready to be used for inspection tasks in many environments since they can perform good and robust locomotion and also good navigation and self-localization. An example is the ANYmal robot, which has been used for the inspection of offshore platforms to check the status of pipes and sensors[45]. Swimming robots could be used in the medium term to monitor fish farms and to assess the environmental status of sensitive areas where it's essential to move gently and avoid getting entangled in water plants. It will also be interesting to aim at robots that can switch between different modes of locomotion, for instance, walking, swimming, and flying. The research community has demonstrated the feasibility of building full humanoids or partial humanoids, such as systems on a mobile base without legs, which can perform collaborative tasks in specific application domains. With sufficient commitment and funding from industrial research and development, it is feasible to advance these systems to a higher technology readiness level (TRL), reaching a TRL between 4 and 6 within the next 5 years. This would allow to gradually introduce this technology in areas like maintenance, repair, manufacturing, warehouse management and logistics.

Multi robot systems have been proposed so far in different configurations, ranging from different types of robots that collaborate to perform a wide variety of tasks faster using parallelism and redundancy, to swarms comprising several tens, or even hundreds, of identical robots. Part of the challenge to advance multi-robot systems lies in the control field, but also improvement in hardware could contribute, such as in communication protocols and localization technologies.

In the medical field, several groups are exploiting magnetic fields to control endoscopes and capsules for imaging and biopsies[46]. Endoscopes guided by a surgeon through a joystick that regulate a magnetic field have been demonstrated to increase patients' comfort during colonoscopy in a phase 1 human trial[47] and, together with similar systems, are now mature to be brought to the market. They will also allow to study the small intestine, which is still unchartered territory to a large extent. Magnetic fields have also been used to perform heart ablation with catheters to treat arrhythmias.

Another possibility that has been explored is to use catheters and guidewires into the brain to treat ischemic stroke, which is caused by blood clots in the brain and is the second leading cause of death in the world. This approach to the treatment of ischemic strokes could allow teleoperated surgery, which would improve the outco-

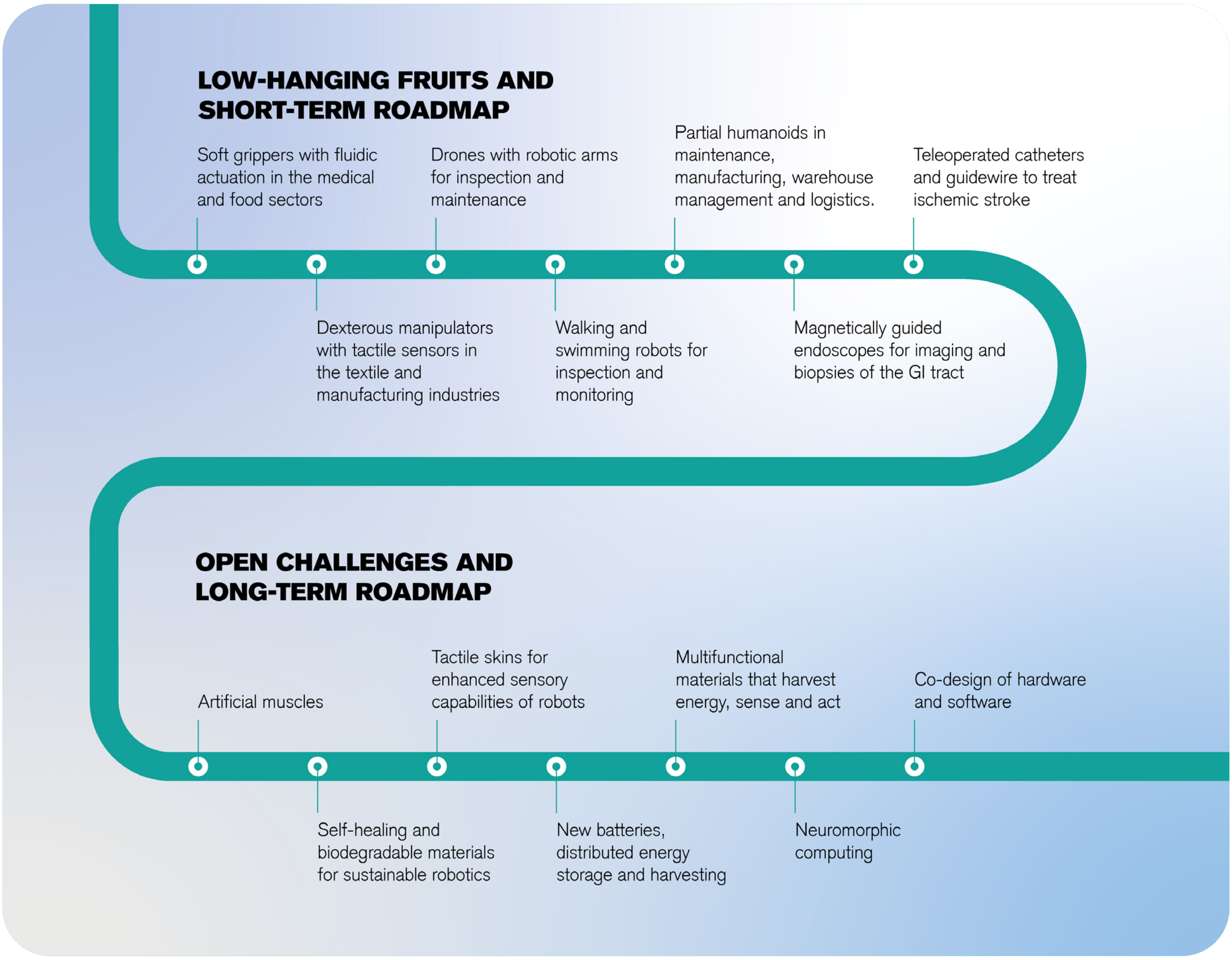

Figure 2. Summary of short-term and long-term research goals presented in the article. The roadmap is not intended as a temporal sequence, but rather as a series of goals with increasing levels of complexity to be researched in parallel.

mes of patients leaving far apart centers where those procedures are performed.

4. LONG-TERM OPEN CHALLENGES

Core robotic technologies. In the field of actuation, the long-term challenge will be that of developing artificial muscles with large power-to-weight ratios, inherent compliance, and large range of motions. There are interesting solutions such as electroactive polymers, shape memory alloys, but they do not replicate important features of artificial muscles[48]. They should be safe to use with a high-power output, they should be modular, redundant, and self-healing because soft materials could burn during physically intensive conditions. In robotics, each joint typically has a motor, with its size varying depending on the type of joint. In our body instead all the skeletal muscles are built of the same basic actuation unit, the muscle fibre. A varying number of fibres is combined to reach the needed muscle size. Such a basic element exists in computation and is a transistor, needed for the processing power in a chip, while for actuation this is completely lacking. Some early trials were developed of highly redundant actuators[49].

To endow robots with a human-like sense of touch, researchers are aiming at covering large areas of the robot bodies with tactile sensors. However, this requires finding new ways to handle the large amount of sensory data collected. Currently they are processed by the central processing unit of the robot, but as the sensing area expands and sensor density increases, this approach becomes increasingly impractical.

New approaches are being developed to delegate portions of processing to the robotic skin itself. Several promising solutions have been proposed at both the hardware and software levels to address this challenge. Most of these systems are inspired by the mechanisms of human tactile sensing, where the peripheral nervous system provides preliminary perception capabilities, reducing the cognitive load on the central nervous system. The development and deployment of neuromorphic devices will be crucial to achieve this goal.

Neuromorphic devices include neuromorphic chips that can elaborate and transmit analog signals, unlike conventional electronics that are fundamentally switches to process digital signals. Versatile and autonomous robots, in particular those based on soft materials and complex embodiments, will require neuromorphic devices that are capable of learning, similarly to how the building of synapses between neurons creates plasticity in the brain. An example of transistors with these characteristics are memristors. Such devices can remember previous history and based on that decide whether a certain stimulus requires action or not. However, this technology has not yet been scaled to the level required for applications.

Chiplet technology is also highly relevant for meeting the computational demands of AI especially in multi-purpose robots as humanoids due to their modular and scalable nature. Segmenting processors into smaller, specialized units, chiplet technology allows for more efficient and cost-effective designs. This modularity enables the integration of various components, such as AI accelerators and memory, within a single package, enhancing performance and reducing latency. Additionally, chiplets can be customized to optimize specific AI workloads, leading to faster development cycles and better energy efficiency.

Despite the substantial progress in lithium-ion batteries over the past thirty years, current battery technologies—both commercial and academic—still do not meet the stringent requirements for powering untethered robots[50]. The limited operating times of untethered robots (for example, TESLA's Optimus Gen 2 runs for hours, while drones operate for 20-30 minutes) underscore the need for batteries designed specifically for robotics. Several additional technologies can be added to overcome the inherent limitations of batteries, albeit often at the expense of extra weight, complexity and cost. These include Battery Management Systems, Thermal Management Systems, Recharging and Battery Swapping and Hybrid Architectures.

Future research directions encompass the integration of batteries into the mechanical structure and soft batteries, the development of batteries with self-healing properties, and of soft batteries. Soft batteries together with soft energy harvesting devices would enable distributed energy solutions. These solutions would be particularly relevant for humanoids, where batteries have been so far concentrated in a single backpack affecting the whole design and stability.

Multifunctional materials could offer solutions that couple sensing and energy harvesting, as in the example of the solar skin[51] based on solar cells whose energy output can be processed for multimodal sensing. Multifunctional materials can also combine sensing and actuation, as in the case a 3D printed mixture of a shape-memory polymer and piezoelectric nanoparticles[52].

Research on new core robotic technologies should also consider sustainability. Many of the sensing, actuation, energy, and computational hardware used in robotics relies on rare-earth materials or materials that are difficult to access. For example, dysprosium can be found in electronics and sensors, cobalt in batteries, neodymium in motors. Also, they contain toxic elements, such as cadmium, lead, antimony, nickel, and mercury. This calls for an economically and ecologically sustainable EoL management of devices used in robotics to reduce electronic waste. In soft and bioinspired robotics sustainable materials are being increasingly used, in all components from actuators to energy storage and electronics[53]. How the robot navigates in the environment, also has an impact on the environment itself. For example, in forestry, legged robots are preferred over wheeled or tracked robots to minimize environmental damage. Swimming robots with fins instead of screws, drones with flapping wings instead of propellers. Solutions that minimize environmental impacts often also promote energy efficient locomotion and are better suited for negotiating challenging environments.

Robots that get damaged are a threat for the environment, therefore scientists are working on intelligence so robots can perform self-diagnosis and come with a mitigation plan or also bio-based self-healing and biodegradable materials for robots are under developmenti[54]. Achieving fault tolerance across multiple levels should be another central objective for robotics research in the long-term. This includes mechanical components (such as actuators, structure, and materials), electronics (distributed systems could help to achieve the high fault tolerance the animal nervous system has), and algorithmic architecture (where robustness to internal bugs, sensor failures, noisy data, and even missing limbs is essential). Such multi-faceted fault tolerance would enable a robot to degrade gracefully in performance despite problems like a missing limb, electronic malfunction, or software error. Fault tolerance is especially crucial for robots intended for deployment in hard-to-reach environments, such as other planets, where retrieval may be challenging.

Solving the challenges in hardware listed so far will not be enough to achieve robotic agents with desired behaviours. Achieving this goal requires to consider the interplay between hardware and software, that is between the robot's body-or morphology- and its control program. Robot's behaviour in the real-world is indeed determined by control, body and the interaction with the environment. Co-designing control and morphology is a massive scientific challenge, though. There have been attempts to automate this procedure, but they required introducing constraints to reduce the computational burden[55]. An approach to the co-design of hardware and software is morphological computation, i.e. designing the robot's body and generally the intrinsic body dynamics in a way that facilitates control, and also perception[56].

Applications. Building a versatile and general hand is still an open problem. The level of actuation and sensing that the human hand possesses in an extremely compact package is something researchers should take inspiration from. Trying to reproduce what evolution did on the human hand, researchers are looking for ways to optimise the mechanical design of robotic hands at the same time as the computational policy. This approach goes in the direction of co-design, i.e. recognising that there are problems easy to solve in hardware than in software and vice versa.

Soft hands represent a competing paradigm for robotic manipulation. They will come to a test ground in the next few years, also by exploiting the robotic platforms developed in this field in the last two decades. The challenge

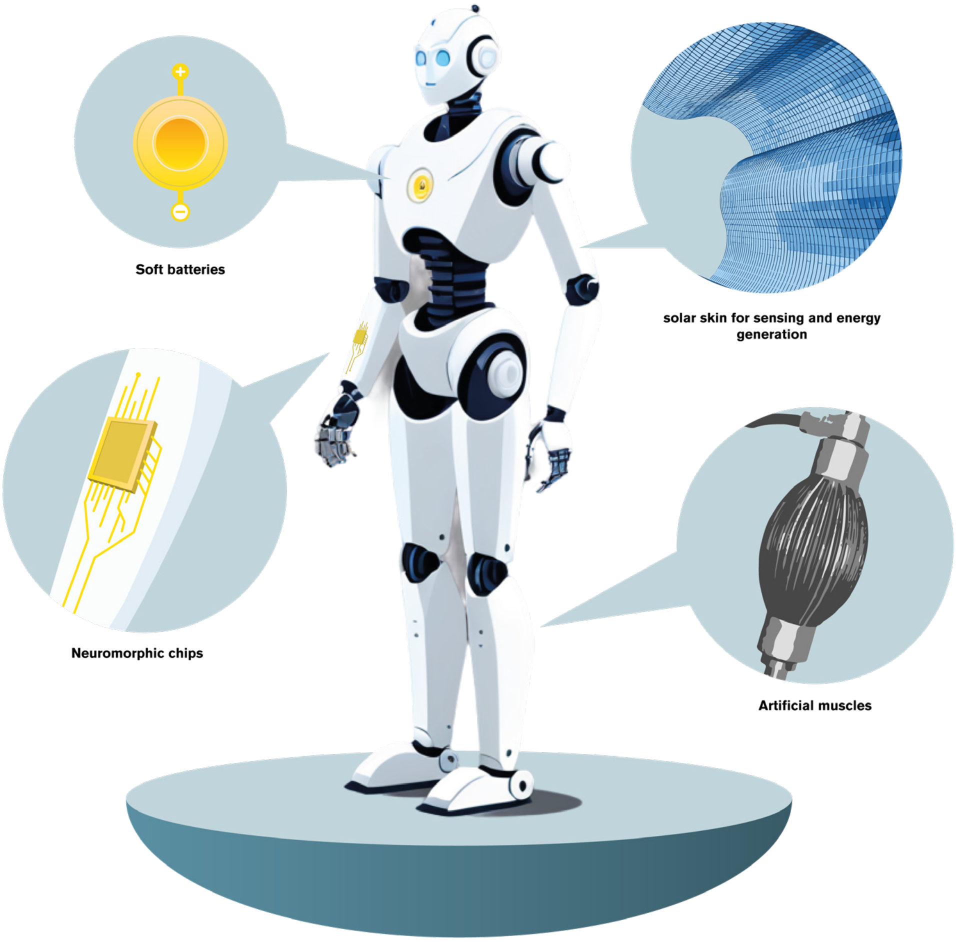

Figure 3: Humanoids and other platforms will benefit from the integration of new core robotic technologies to be developed over the next decades, including neuromorphic chips, tactile and solar skins, artificial muscles, soft batteries for energy storage.

will be that of demonstrating that soft hands can achieve the same performance as their rigid counterparts but with a simpler and more efficient approach, that is using less energy, less perception, and making less error.

Ultimately, research will need to look beyond single manipulation tasks that robots need to perform for a long period of time, toward tasks that change relatively often. This kind of versatility will be crucial to deploy robots in the service industry. The goal is deployment in homes, where anything could possibly happen, and the highest level of versatility will be required.

To fully exploit the potential of robotics in the medical field, advancements in materials science and soft robotics will be of paramount importance to minimize the damage caused to the human body by capsules, endoscopes, catheters, and guide wires. Materials science and soft robotics can also contribute to the deployment of microrobots in the medical field, leading to new diagnostic and therapeutic approaches. These microrobots could be used to treat conditions like strokes, glioblastomas, and gliomas in the brain, which are types of cancer that are difficult to reach. They could also be used to deliver drugs directly to disease sites, limiting their toxicity.

Legged, and other types of animal-like, robots can benefit from the research on artificial muscles, tactile skins and power efficiency described above to advance towards the long-term challenge of achieving human and animal-like agility, acquiring the ability to jump and squeeze through narrow passages, perform multimodal locomotion, and adjust their gait when necessary.

An interesting field of applications would be underwater exploration, both in the deep sea, where soft robots would be able to stand the high pressures, but also the sea floor to monitor biodiversity and pollution or the impact of offshore industries. Having robots made of biodegradable materials could be desirable for one-off tasks, where the robot does not need to collect data over long periods of time. Swimming robots will benefit from the availability of new waterproof materials, improvements in high-band communication underwater as well as from advancements in 3D navigation. In the longer term, amphibious robots could also prove useful in inspecting pipes or sewers.

As for drones, flying in windy conditions calls for a paradigm shift also in aerial robotics. Soft aerial robots could better imitate solutions found in nature. Using flapping wings to fly rather than propellers could allow them to exploit flow currents, akin to the dynamic soaring observed in birds like the albatross. Furthermore, flapping-wing configurations would also lower the risk of people getting hurt because their weight is reduced and better distributed. Also perching could be improved by using soft materials. Current systems, such as spring-based claws, consume considerable energy. Soft claws could also be used to perch the body of a person to perform collaborative tasks.

5. CLOSING WORDS

A robot is an integration of core robotic technologies, such as sensing, computing, actuation, and materials. These technologies provide the capabilities required by different robot applications. Reaching them means that from a hardware perspective the robot becomes feasible. To be commercialized, they must also be robust, scalable and affordable. In several advanced applications, core robotic technologies are not yet at a level that allows widespread deployment and commercialization. Further research is needed to improve system performance and fully exploit their potential. No advanced foundation or generative AI can work effectively without these technologies. Additionally, sustainability should be included in developing these technologies, considering life cycle extension, circularity, resource conservation, ethics, and environmental justice to have a positive impact on the UN Sustainable Development Goals (SDGs). To realise this, interdisciplinary collaboration is crucial in advancing robotic technologies. This collaborative effort will drive innovation, ensuring that robots are designed with a comprehensive understanding of their potential impacts and benefits.

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