PERSPECTIVE

# Artificial intelligence meets medical robotics

Artificial intelligence (AI) applications in medical robots are bringing a new era to medicine. Advanced medical robots can perform diagnostic and surgical procedures, aid rehabilitation, and provide symbiotic prosthetics to replace limbs. The technology used in these devices, including computer vision, medical image analysis, haptics, navigation, precise manipulation, and machine learning (ML), could allow autonomous robots to carry out diagnostic imaging, remote surgery, surgical subtasks, or even entire surgical procedures. Moreover, AI in rehabilitation devices and advanced prosthetics can provide individualized support, as well as improved functionality and mobility (see the figure). The combination of extraordinary advances in robotics, medicine, materials science, and computing could bring safer, more efficient, and more widely available patient care in the future. **–Gemma K. Alderton**



## Leveraging AI for medical image–guided robotics

*By* **Michael Yip**[1] *and* **Septimiu Salcudean**[2]

Medical image–guided robotics combines medical images, where locations of key anatomy, lesions, and objects can be identified, and robotics, where the precision placement of instruments or tools provides substantial advantages. Frequently leveraged imaging modalities include ultrasound, magnetic resonance imaging, computed tomography, and white-light or fluorescent endoscopy. The robot may be used to assist in imaging anatomy, or the imaging may assist the robot in guiding it to key targets.

Many early use cases for AI in medical image–guided robotics involved steering instruments, typically needles, to identify anatomy for biopsies. The AI focus was typically on the steering mechanics and planning algorithms because traversing soft tissue involved curvilinear paths that were constrained by the minimum radius of curvature through the tissue, as well as tissue displacements during instrument insertion. Although challenges persist with solving navigation for minimally invasive robotic tools with multiple and intermittent contacts with tissue, a large scope of solutions involving AI-driven planning for robotic steering of instruments are now available (*1*, *2*), and highly dexterous robotic systems have been proposed that can plan and reach targets with the aid of AI (*3*).

Most effort now concerns image understanding. Previous techniques used tedious, human-segmented (hand-annotated) anatomical features and/or weak, feature-based recognition of anatomy of interest. New AI strategies for image guidance leverages semantic information—i.e., higher-level reasoning about the type of anatomy and its characteristics, identified directly from pixel information, to provide improved, safer navigation. As with the considerable improvements in object localization and scene segmentation in computer vision, these techniques have begun their translation to surgical scenes and surgically relevant objects (*4*). These translated techniques can then be leveraged by robots to plan and reach targets with high accuracy.

An interesting use of image understanding is in image acquisition itself (*5*). For example, robot assistance makes medical ultrasound more consistent, enables autonomous scanning, and may improve access to examinations in remote and underserved communities. Moving the ultrasound transducer against the patient to identify the standard imaging planes used in medical diagnostics is a challenging AI problem involving deep learning networks to predict necessary probe motions (*6*), reinforcement learning (RL), and learning by demonstration (*7*). Robotic assistance is also used in endoscopy, where rigid or flexible endoscopes, and even capsules with magnetic actuation, are deployed in surgery, gastrointestinal tract imaging, and bronchoscopy (*8*). Maneuvering endoscopes is challenging and requires considerable experience to be mastered, making automatic motions attractive. Approaches based on learning by demonstration are promising, e.g., by using behavioral cloning (*6*). AI techniques are used in endoscope localization and mapping and in the analysis of the very large image datasets involved in diagnosis (*9*).

Intraoperative ultrasound and x-ray imaging enable the registration of preoperative medical images to the patients for biopsy and surgery. Localizing targets identified through intraoperative registration in the corresponding laparoscopic camera views remains a challenge. Maintaining such registration requires long-term tissue tracking using computer vision techniques, in the presence of tissue changes as the intervention progresses (*4*).

Unlike building neural network models for everyday scenes, finding labeled data for training models for medical robotic applications is a substantial bottleneck. Accurate labeling must be done by trained professionals such as surgeons and radiologists. Thus, getting ground-truth data is very expensive and not scalable. Synthetically generated images help to address a part of this problem, but synthetic images are sufficiently different from real images and can lead to overfitting (*10*). Given the related challenge of human labeling of intraoperative video sequences to train neural networks, unsupervised or weakly supervised approaches are desirable (*11*).

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# Smart medical robots

Various applications of artificial intelligence (AI), including machine learning, machine vision, and haptic control, have resulted in the development of robotic devices that can be used in all aspects of patient care, including diagnostics, surgical procedures, rehabilitation, and limb replacement. The use of robotics in medicine aims to ensure consistent, safe, and efficient treatment, as well as allowing data gathering for improvement and potentially increasing access to treatment in underserved communities and remote regions, and to those affected by natural disasters.

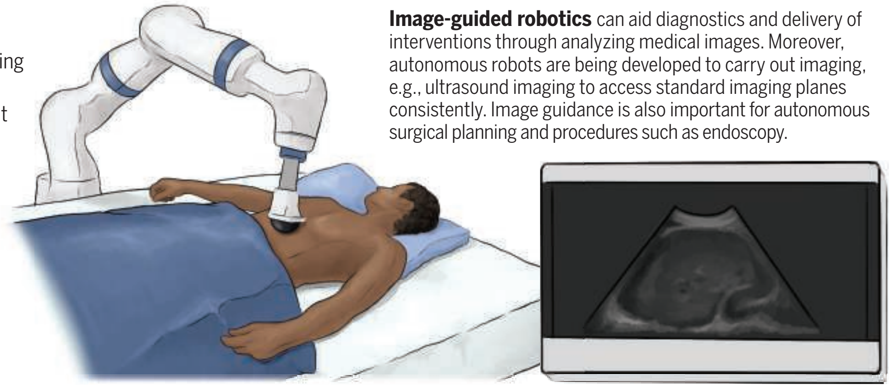
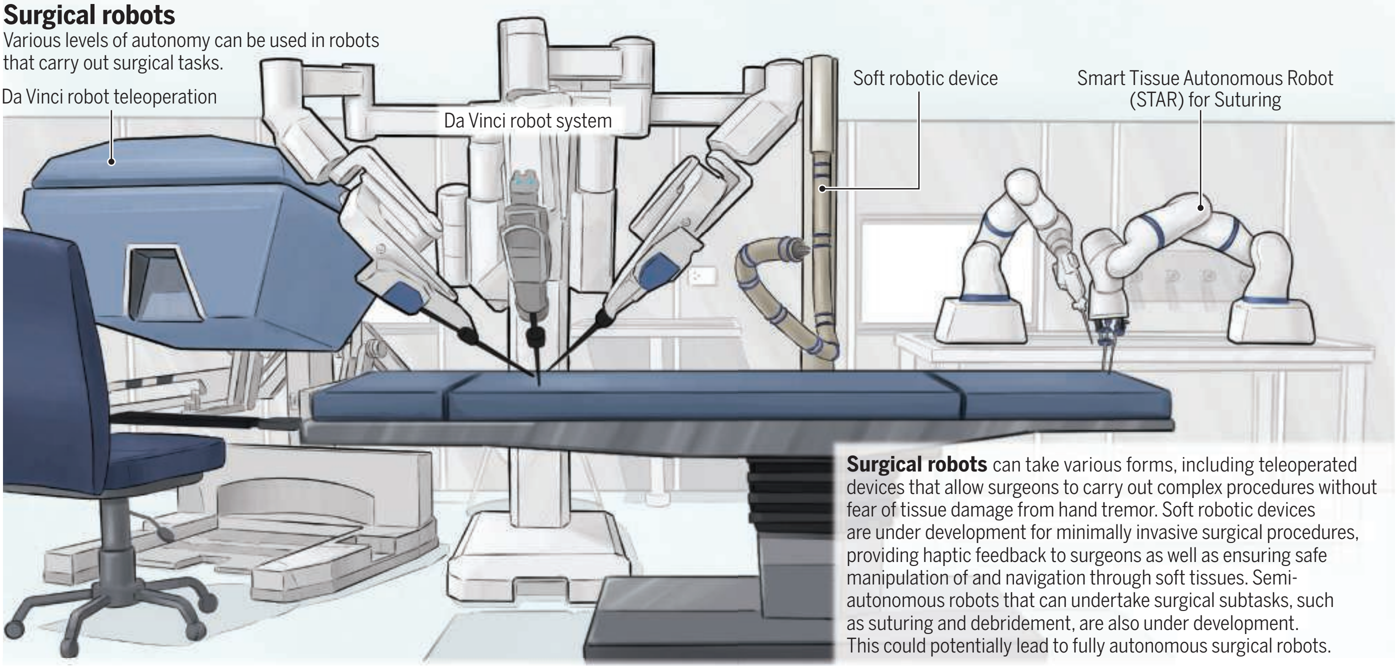


**Image-guided robotics** can aid diagnostics and delivery of interventions through analyzing medical images. Moreover, autonomous robots are being developed to carry out imaging, e.g., ultrasound imaging to access standard imaging planes consistently. Image guidance is also important for autonomous surgical planning and procedures such as endoscopy.

## Surgical robots

Various levels of autonomy can be used in robots that carry out surgical tasks.

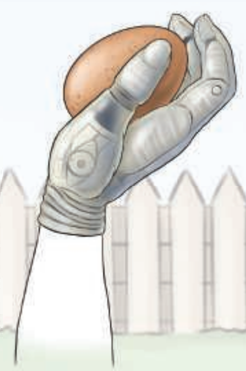



**Surgical robots** can take various forms, including teleoperated devices that allow surgeons to carry out complex procedures without fear of tissue damage from hand tremor. Soft robotic devices are under development for minimally invasive surgical procedures, providing haptic feedback to surgeons as well as ensuring safe manipulation of and navigation through soft tissues. Semi-autonomous robots that can undertake surgical subtasks, such as suturing and debridement, are also under development. This could potentially lead to fully autonomous surgical robots.

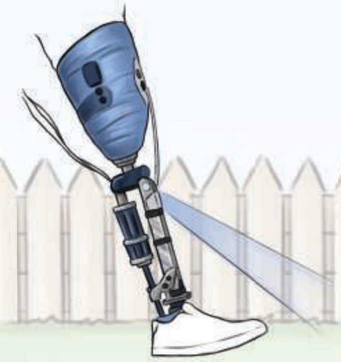
## Rehabilitation devices and advanced prosthetics

Wearable devices can improve recovery from injury and facilitate human-in-the-loop intervention.

**Soft exosuits**
Wearable robots in the form of soft exosuits can autonomously facilitate rehabilitation while capturing data to improve gait training and personalized performance monitoring.



**Upper limb prosthetics**
Recognizing user intent is important for upper limb prosthetics to, e.g., modulate hand grasping force and appropriate posture. This ensures human-prosthesis symbiosis to achieve robust control.



**Lower limb prosthetics**
Replacement of lower limbs requires prosthetics to adapt to the environment, e.g., through machine vision, to ensure stable and intentional limb motion.

GRAPHIC: A. FISHER/*SCIENCE*

Ultimately, the combination of new techniques in data-efficient learning, coordinated efforts in growing and retaining labeled medical image datasets, and advances in safe and dexterous robotic systems will push the relevance of medical image–guided robotics to the forefront of the next generation of interventional and diagnostic care.

# Supervised autonomy in robot-assisted surgery and telesurgery

*By* **Ken Goldberg**[3]

Each year, more than a million surgeries are performed with robots (*12*). These robots are very sophisticated but not at all autonomous—they are fully controlled by human surgeons. This is because surgery is fault-intolerant, there are a vast number of rare but potentially dangerous edge conditions, and the consequences of even a single failure can be fatal. It may be a long time before fully autonomous robots are sufficiently safe and reliable for the clinic. In the meantime, substantial progress is being made in the use of "supervised autonomy," where specific subtasks are performed by a robot under close supervision of a human, who is ready to take over when necessary (*13*, *14*).

Consider a surgical subtask such as debridement: the removal of damaged tissues or foreign fragments from a wound. Debridement can be very tedious; it is easy for a surgeon to overlook fragments, which can lead to infections. Debridement is a surgical task that could benefit greatly from supervised autonomy, whereby a surgical robot and camera system could systematically identify and remove fragments under close supervision of the surgeon who is ready to take over if the system misidentifies a miscolored human tissue as a foreign fragment. Supervised autonomy for surgical debridement has been achieved in laboratory conditions (*15*, *16*), but research is still needed to extend these results and evaluate them in vivo.

Another example is surgical suturing. This surgical subtask is often left to medical residents because it is tedious and somewhat fault-tolerant. Surgical suturing requires even placement of sutures that balance tissue forces. Supervised autonomy could produce sutures that are more consistent, thus reducing healing time and scarring.

Researchers are studying how suturing could be performed using supervised autonomy, in which the surgeon can outline a wound by touching its boundaries with an instrument, and the system computes and displays an optimal placement of needle entry and exit points that evenly distributes tension across the wound. The surgeon can then adjust these points or allow the robot to autonomously perform the suturing under close supervision. Researchers have demonstrated initial results in the laboratory (*17*, *18*), but securely gripping surgical needles during insertion, handing needles back and forth between gripper tools, and managing the slack in surgical thread must be addressed before suturing can be considered for testing in the clinic.

Supervised autonomy also opens the door to "telesurgery," whereby an experienced surgical expert can guide a surgery at a distant location. Telesurgery has the potential to considerably increase access to skilled surgeons in remote regions or during a natural disaster (*19*). Direct control of all surgical instrument motions by the expert is not possible because of the inherent time delays of optical and electrical signals, which cause any direct control loop to be unstable. Supervised autonomy can solve this problem by allowing surgical subtasks to be locally controlled, with intermittent remote supervision. Telesurgery has been demonstrated with the use of dedicated high-speed fiber optic networks and is being actively explored by researchers, but it is not yet approved for clinical use.

Advances in sensors and ML have evolved robotics considerably in recent years, and there are many opportunities for AI in the operating room. AI can be used to enhance digital camera images and answer spoken queries from a surgeon during a procedure. But supervised autonomy offers the greatest potential for reducing tedium and improving patient outcomes. Researchers worldwide are exploring how supervised autonomy can be used to enhance robot-assisted surgery and telesurgery (*20*). As the original patents on surgical robotics expire (*21*), new commercial surgical robot systems are increasing the diversity of hardware and interfaces. This competition is motivating the commercial development of new functionality, and it is likely that supervised autonomy will be available in the clinic in the coming decade.

# Soft robotics for minimally invasive surgery

*By* **Kaspar Althoefer**[4] *and* **Arianna Menciassi**[5]

Over the past few decades, there have been considerable advancements in robot-assisted minimally invasive surgery (RAMIS). RAMIS systems use slender, straight-line instruments to operate through small incisions in the patient's skin. Robotics makes procedures simpler, filtering the manual tremor of surgeons, improving overall ergonomics, and restoring three-dimensional (3D) vision that is normally not possible in manual minimally invasive procedures. In addition, RAMIS allows the generation of a huge amount of data that can be used for improving safety and implementing some autonomous tasks (*22*). Despite the success of some RAMIS platforms, such as the da Vinci Surgical System for prostatectomy and abdominal or thoracic surgery, these systems are often limited by their rigid component design, which can make it difficult to access certain areas of the body and can lead to tissue injuries.

Soft robotics is a promising avenue for developing more flexible and adaptable surgical robots, with the necessary dexterity and stiffness modulation to perform surgical procedures safely. The key feature of soft robotics is the use of materials that can deform, bend, shrink, and change stiffness (*23*), pushing the paradigm of robotic surgery in a safer and softer direction. These robots address different body regions, such as the ear, abdomen, and thorax, and they can be dedicated both for diagnosis and intervention. For example, a fluid-driven soft robotic system was developed for increasing patient comfort during ear therapy and safely steering a needle to the desired injection site (*24*). Diagnosis of gastrointestinal tract pathology is also a key application for soft robots, because these tissues are flexible, stretchable, and often collapsed, requiring a spectrum of soft and stiff working modalities (*25*). A capsule robot for endoscopy that uses eversion navigation and a soft shape-shifting mechanism has been recently demonstrated (*26*).

A large-scale project to explore soft robotics for RAMIS was the European Union project STIFF-FLOP (stiffness controllable flexible and learnable manipulator for surgical operations) from 2012 to 2015 (*27*). The soft robotic systems that were developed were made from biocompatible silicone rubber and pneumatically actuated, by using new fabrication methods that allow for the creation


The Smart Tissue Autonomous Robot (STAR), which is holding a needle driver, needle, and suture in preparation for suturing intestinal tissues, is inspected.

of reliable structures that are also safe and effective. In addition, advanced ML techniques were employed to intuitively teleoperate the soft robots in the abdominal cavity of the patient, and haptic systems allowed surgeons to discern interactions of the robot with the soft tissue environment.

There remain substantial technical challenges (*28*). A major issue is the lack of precision and accuracy in soft robotic systems. In traditional surgical robots, electrical motors are used directly or by means of tendons to move the robot's arms, and effectors are made from rigid components that do not deform during operation. However, soft robotic systems rely on deformation of the material that the robot is constructed from to achieve movement. The resultant motion is more difficult to model and can result in lower positional accuracy, which could be a critical concern in surgery (*29*). To overcome this challenge, advanced strategies based on AI, ML, and data-driven control that can cope with the highly nonlinear motion behavior of soft robots are being developed. Recent advances in computer power, computer vision, ML, real-time modeling, and simulation can make operation of soft robots for surgery possible without cumbersome teleoperation modalities and extensive training sessions for surgeons (*30*).

Will soft robots for RAMIS replace well-established surgical robots, or will soft robotic design rules, relying on morphological computation (*31*), permeate traditional technologies for RAMIS? What benefits the patient most needs to drive research in soft robotics surgery.

# Bringing highly autonomous surgical robotics to the clinic

*By* **Justin D. Opfermann**[6,7] *and* **Axel Krieger**[6,7,8]

Autonomous surgical robots are the surgeons of the future. They have the power to standardize patient outcomes independent of a surgeon's experience and skill (*32*), they integrate AI and dexterous tools to perform tasks with more consistency and accuracy than expert surgeons (*33*), and they can provide essential care in environments where no surgeon is available such as human space flights (*34*). Such robots will democratize health care by making quality surgery ubiquitous and by minimizing the incidence of corrective surgery, thereby reducing health care costs. Although most systems are not clinically approved today, they will certainly play a role in the future.

Generally, autonomous surgical robots are classified by their respective level of autonomy (LoA) and incorporate algorithms that are responsible for increased surgical decision-making (*35*). As the level of autonomy increases, so too does the complexity of the robot's role in surgery and the amount of AI integrated with the system. For instance, the LoA 0 (no autonomy) da Vinci Surgical System uses human teleoperation without AI to perform surgery, whereas the LoA 1 (robot assistance) EndoAssist camera holder uses algorithms to restrict tool motions (*36*). For higher levels of autonomy, the surgeon defers control to the robot, which uses AI to execute surgical tasks. During LoA 2 (task autonomy), a robot may use learning by observation to independently cut tissue as with the da Vinci Research Kit (*37*), whereas the LoA 3 (conditional autonomy) Smart Tissue Autonomous Robot (STAR) uses ML to track soft tissue deformation to execute the surgical plan of suturing (*38*). The LoA 4 (high autonomy) and LoA 5 (full autonomy) surgical systems are not yet feasible with today's technology, but their development is on the horizon.

There remain several technical, regulatory, and social challenges to solve before the highest levels of autonomy can be reached. Robots will need to better detect, process, and respond to unpredictable variations in the surgical field. These challenges will be magnified in soft tissue surgeries, where deep learning and AI will be necessary to predict, and react to, the changing surgical scene (*39*). The resulting technologies will face increased regulatory scrutiny because it is not clear how a system capable of practicing medicine would be regulated by the US Food and Drug Administration (FDA) or medical device regulators elsewhere. These systems will need to demonstrate safety that exceeds teleoperation and efficacy as good as the clinical standard of care. For AI algorithms, this means sensitivity and specificity at least as good as an expert surgeon's. Social pressures might also temper adoption as there is general resistance with using AI in medicine (*40*). To build public trust, autonomous robots will likely follow a stepwise approach to adoption, in which autonomous subtasks such as tissue identification, endoscope control, and suturing will be gradually introduced. These tasks will then be combined into a full procedure, paving the way for autonomous robotic surgery in the operating room of tomorrow.

# Rehabilitation robots to go

*By* **Krithika Swaminathan**[9] *and* **Conor J. Walsh**[10]

Rehabilitation needs to extend from the clinic into the community and home to provide patients with a continuum of care. Toward this goal, engineers, clinicians, and end users have developed wearable robots that allow people with mobility impairments to practice and experience better movement. Although these systems have historically been seen as assistive technologies, ongoing work is demonstrating that these portable and autonomous robots, and the data that they capture, can lead to fundamentally different rehabilitation approaches. One can imagine a future in which wearable robots are used in the clinic to reduce the physical burden on clinicians while learning patient-specific impairments, and are then sent to the patient's home to track their recovery with individualized ML algorithms.

Recent technological advances in hardware and software are facilitating this shift to real-world use (*41–44*). Innovative approaches for actuation hardware achieve higher specific powers (power per unit mass) through cable-driven (*45*) or pneumatically-driven mechanisms (*46*). Soft, apparel-based interfaces can be lightweight and nonrestrictive to the user and let a device smoothly transition between assisting motion, being mechanically transparent, and resisting motion for strength training. The increased modularity of these systems also allows for tailoring the technology to individual-specific impairments. Along with new mechanical designs, learning-based estimation algorithms now use wearable sensors to detect and quantify movements (*47*), and control strategies now bring users into the control loop to provide individualized intervention (*48*). These techniques further enable studying the rehabilitative potential of high-dosage and high-intensity training beyond the clinic (*49*).

Wearable cloud-connected robots will usher in the era of data-driven physical telerehabilitation. Integrated sensing can provide clinicians and users with feedback on important biomechanical and physiological metrics, similar to smart fitness trackers. However, optimally combining this feedback with clinical input to guide motor learning and encourage behavioral change remains an open challenge. Moreover, developing generalized data-driven ML and AI algorithms in clinical populations is particularly complex owing to the limited data available from any given individual and the large variability across individuals. Continuous movement assessments also increase the temporal resolution of characterizing a patient's progression, enabling more timely and accurate detection of performance degradation or improvement.

However, a challenge remains in developing estimation algorithms that are robust to noise across recovery timescales (months to years), owing to sensor drift, sensor placement, environmental changes, and day-to-day user variability. Validating these approaches is further complicated by the lack of ground-truth data in real-world settings. If successful, the corresponding data from the patients and robots can be used with ML techniques to identify who is most likely to benefit from a given device (*50*). Such categorization will enable efficient prescription of interventions, minimizing costs for clinicians and patients alike. The field will then have new opportunities to investigate how longitudinal data can inform new methods for individualization of training parameters, such as for biofeedback and device controller optimization.

Data from wearable robots worn in the real-world will inform the design of computational models and experimental validation of human-robot interaction during rehabilitation, ultimately leading to adaptive systems that better synergize with end users.

A soft robotic, cloud-connected glove facilitates high-dosage and high-intensity self-directed teletherapy for stroke survivors in the home.

PHOTO: HARVARD BIODESIGN LAB

# AI enables symbiotic robotic prosthetics

*By* **He (Helen) Huang**[11,12] *and* **I-Chieh Lee**[11,12]

Advanced robotic prosthetics, such as dexterous prosthetic hands and motorized prosthetic legs, have led to a paradigm shift to restore the mobility of individuals with limb loss (*51*, *52*). These modern prostheses have embedded AI into machine operation to enable adaptation to user intent, environments, and the user's physical condition. This is essential for human-prosthesis symbiosis—an intelligent prosthesis and a human user functioning seamlessly together as one system in daily life (*53*).

For example, AI has enabled neural control of prosthetic limbs. Controlling prosthetic limbs on the basis of user intent from the brain is a fascinating concept. This requires an effective neural decoder that can accurately interpret user intent through human neuromuscular signals for prosthetic limb control. ML algorithms, ranging from simple linear classifiers to deep learning regression models, have been powerful neural decoding methods for recognizing user intent regarding joint motions (e.g., wrist or knee flexion and extension), hand grasping patterns (e.g., fine pinch or power grip), or locomotion modes (e.g., sit-to-stand transition and level ground walking) (*54*, *55*). The ML decoder output is sent to the prosthesis controller to produce the user's intended limb motion to enable human-prosthesis symbiosis during task performance.

Human-prosthesis symbiosis through the implementation of AI allows adaptation to various environments and contexts. Human hands can dexterously interact with objects of different sizes and materials; human legs can adapt to various terrains while walking. Therefore, a symbiotic prosthetic limb should also be environmentally adaptive. Machine vision has been adopted to create environmental awareness for prosthesis control. Through deep learning algorithms applied to images captured by cameras mounted on a prosthetic hand, machine vision can recognize the intended grasping object, which allows the prosthesis arm to prepare the appropriate wrist posture and hand grasping pattern or force to facilitate grasping actions (*56*, *57*). Similarly, vision sensors mounted on prosthetic legs can recognize the terrain in front of the user, which autonomously adapts prosthesis control accordingly for seamless terrain transitions (*58*, *59*).

A symbiotic prosthesis needs to provide personalized assistance to each user owing to the large inter-amputee differences in their physical conditions and motor deficits. In current clinics, personalization of robotic lower-limb prosthesis control is performed manually and heuristically, which is inaccurate and time- and labor-intensive. To automate the process, researchers have developed RL algorithms and other data-driven optimization approaches, such as Bayesian optimization, to tune prosthesis control with the human-in-the-loop for personalized walking assistance (*60*). For RL-based algorithms, the prosthesis personalization procedure can be as short as 5 minutes, and the resulting smart AI tuning agent can continue producing user-adaptive control over different time frames (*61*).

Although AI in robotic prosthetics has shown great promise, AI needs to be more robust and safer for daily prosthesis control owing to having the human-in-the-loop. Additionally, it is an open question whether human users cognitively embody and trust AI-enabled prostheses. These challenges should direct future research efforts toward making AI-enabled symbiotic, robotic prostheses versatile, safe to use, and cognitively acceptable by users with limb amputations.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