

Forum

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Code, control, and cure: how automation is transformed modern medicine

Code, Steuerung und Therapie – Wie Automatisierung die moderne Medizin verändert

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Abstract: Over the past decades, automation technology has brought about profound changes in medicine. From the introduction of automated laboratory analyses and computer-assisted imaging to robot-assisted surgical procedures and Artificial Intelligence (AI)-supported diagnostics, medical care has undergone fundamental changes. The aim of this article is to illustrate how automation technology has developed in medicine since the 1950s and how selected applications have influenced diagnostics, therapy, efficiency, and patient safety. Selected examples of technological advances and future challenges will be presented in four areas of medicine.

Keywords: automation; medical technology; clinical laboratory; imaging

Zusammenfassung: In den vergangenen Jahrzehnten hat die Automatisierungstechnik tiefgreifende Veränderungen in der Medizin bewirkt. Von der Einführung automatisierter Laboranalysen und computergestützter Bildgebung bis hin zu robotergestützten chirurgischen Eingriffen und durch künstliche Intelligenz (KI) unterstützter Diagnostik hat sich die medizinische Versorgung grundlegend gewandelt. Ziel dieses Artikels ist es, zu veranschaulichen, wie sich die Automatisierungstechnik in der Medizin seit den 1950er Jahren entwickelt hat und wie ausgewählte Anwendungen die Diagnostik, Therapie, Effizienz und Patientensicherheit beeinflusst haben. Ausgewählte Beispiele für technologische Fortschritte und zukünftige Herausforderungen werden in vier Bereichen der Medizin vorgestellt.

Schlagwörter: Automatisierung; Medizintechnik; klinisches Labor; Bildgebung

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1 Introduction

Medicine has always been closely linked to technological progress, from Röntgen's discovery of X-rays to the introduction of objective measurement like clinical thermometry and Laennec's invention of the stethoscope in the early 19th century, each of which fundamentally changed diagnosis and treatment. Since the second half of the 20th century in particular, the rapid development of automation, information technology and computing has created new opportunities to make medical processes more efficient, precise, and safe. Automation technology refers to systems and processes that completely or partially replace human activities with machines, software, or control loops. Over the past 50 years, this development has affected almost all areas of medicine: from basic research to diagnostics and therapy to hospital organization. The increasing complexity of medical data and the growing demand for high-quality yet cost-effective healthcare make automation a key factor in innovation. Against this background, this article asks how automation has changed medical practice over the past decades: Which tasks have been automated, how have human roles changed, and to what extent has automation contributed to more efficient, precise, and safer healthcare? Rather than providing a comprehensive review, selected examples from diagnostics, therapy, surgery, rehabilitation, and intensive care are used to illustrate these developments and their broader implications.

2 Automation in medical diagnostics

2.1 Automated clinical laboratory analysis

One of the earliest and most significant applications of automation technology can be found in laboratory medicine. The concept of continuous flow analyzers combined with automatic titration encompassed coulometric, potentiometric, and photometric devices and discrete analyzers like the

Technicon AutoAnalyzer, as early as the 1950s and 1960s [1], [2]. In Germany, rapid growth of clinical chemistry and laboratory medicine hospitals and university centers after WW II, including widespread adoption of automated analyzers and the creation of specialized laboratories and professional societies (e.g., DGKL) pushed innovation [3]. Automated clinical chemistry analyzers replacing manual single-parameter measurement progressed from continuous-flow instruments to fully integrated total laboratory automation (TLA) systems that combine pre-, intra- and post-analytical steps with high throughput. The first automated clinical chemistry analyzers enabled automated measurement of core analytes like urea, glucose, albumin, total protein, chloride, carbon dioxide, sodium, potassium, glucose, urea nitrogen and calcium and significantly reducing manual workload, but faced challenges with hemolysis or lipemia [4]. It was Dr Masahide Sasaki who pioneered in Japan in the 1980s the world's first automated clinical laboratory with a belt line and introduced the term TLA. He described TLA as a setup of analytical instruments connected via a specimen transport track system. He led a trained team and industry partners to develop, commercialize, and publish widely on laboratory automation innovations [5]. Multi-channel analyzers with built-in computers (e.g., SMAC in 1974) enabled high-throughput clinical chemistry and subsequent integration into automated systems. During the 1990s modular systems were developed that combined clinical chemistry and immunoassay on integrated analyzers, with automated sample identification, sorting, and centrifugation [4]. Since 2000, the entire TLA product line has been expanded that link pre-analytical modules, core analyzers, post-analytical storage, and automated retrieval, with documented benefits in reduced turnaround time, error reduction, and improved productivity in routine laboratories [6]. These systems not only increase the speed of diagnostics, but also their reproducibility and accuracy. Sources of error such as manual pipetting errors or subjective evaluations have been significantly reduced. At the same time, standardized processes have enabled better comparability of measurement results worldwide. Today, modern laboratory systems can process thousands of samples per day with minimal human intervention. For the future of clinical laboratory automation, the following trends are predicted: deeper Artificial Intelligence (AI) integration, fully digital “smart labs,” and expansion of automation into microbiology and mass spectrometry [7]–[10]. Human roles shift from repetitive tasks to supervising workflows, interpreting data and validating AI, while real-time AI optimization improves reproducibility and reduces errors [9], [10]. Labs become tightly networked ecosystems linking TLA hardware, Laboratory Information Management Systems (LIMS), Electronic Medical Records (EMRs), Internet of Things

(IoT) and dashboards for analytics and personalized diagnostics [9]. Sustainability gains (e.g. up to 30 % material savings) and standardized interfaces like Open Platform Communications Unified Architecture (OPC UA) and Standardization in Lab Automation (SiLA) further drive adoption [8], [11].

2.2 Imaging techniques and digital evaluation

Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) are prime examples of medical imaging techniques enabled by automation through computational reconstruction algorithms. Both imaging techniques require automated processing of vast datasets from multiple angles or gradients, infeasible manually due to mathematical complexity and data volume, enabling precise, volumetric visualization. Computed Tomography (CT) emerged in the early 1970s through the pioneering efforts of Godfrey Hounsfield [12], who built the first prototype scanner at EMI Laboratories in 1971, and Allan Cormack [13], whose mathematical reconstructions earned them the 1979 Nobel Prize in Physiology or Medicine. Magnetic Resonance Imaging (MRI) built on nuclear magnetic resonance principles. In 1977, Peter Mansfield and colleagues [14] created the first MRI reconstruction image of a live human body part at the University of Nottingham: The cross-section of a student's finger. Peter Mansfield received the 2003 Nobel Prize in Physiology or Medicine for MRI discoveries for advancing fast imaging techniques like echo-planar imaging and shared it with Paul Lauterbur who developed the key imaging method using magnetic field gradients. Both innovations revolutionized non-invasive diagnostics by enabling detailed cross-sectional body imaging. Other innovative inventions in medical imaging that require some intervention effort include Digital Subtraction Angiography (DSA) and Positron Emission Tomography (PET). PET uses automated coincidence detection and iterative reconstruction to handle probabilistic photon events from radioactive tracers, whereas DSA subtracts pre- and post-contrast frames pixel-by-pixel to isolate vessels, processing dynamic sequences rapidly. Over the past two decades, automated image analysis methods have increasingly been added, which can detect pathological changes with the help of pattern recognition and artificial intelligence to support physicians in the early detection of tumors, neurological and other diseases.

It is anticipated that future automated medical imaging will feature AI for diagnosis and prognosis, deeper workflow automation, multimodal patient modeling, and integration

with robotics [15]. Furthermore, it is predicted that systems will automate administrative and technical tasks, accelerating workflows and improving accuracy [16] and that AI reconstruction will enable faster, lower-dose imaging with high quality [17]. It is also forecasted that methods will predict outcomes using radiomics with clinical and genomic data and that generative models will augment data and translate modalities [17], [18]. Finally, digital twins and autonomous imaging robots are anticipated [18].

3 Automation in therapy and surgery

3.1 Robot assisted surgery

One particularly visible advance in automation technology is the use of surgical robot systems. Such systems have been in development to make minimally invasive procedures more precise and ergonomic. The surgeon controls the robot, which performs movements with high accuracy and tremor filtering. Robot-assisted systems enable smaller incisions, less blood loss, and faster postoperative recovery [19]. Despite their high cost, they have become established in urology, gynecology, and cardiac surgery in particular [20], [21]. Over the last 50 years, three major advances in robot-assisted surgery have markedly increased automation in medical therapy and surgery:

1. Early active and semi-autonomous robots like the PUMA 200 were used for CT-guided brain tumor biopsies [22], as one of the first documented robotic surgical procedures in humans. It showed that preoperative imaging and planning could be transferred into robot-executed drilling, cutting, or milling tasks with high accuracy, introducing true automated execution of well-defined surgical subtasks in humans.
2. Controller – remote system tele-operated platforms (like ZEUS, developed by Computer Motion, or ARTEMIS developed by the Forschungszentrum Karlsruhe) automated the “instrument handling” layer through motion scaling, tremor filtering, and constrained kinematics, enabling highly precise minimally invasive surgery in many specialties while the surgeon remained in full cognitive control.
3. Recent developments enhanced da Vinci tele-robot platforms with image-guided real-time computer vision, machine learning, and low-latency networks to automate perception, guidance, and discrete subtasks (e.g., camera control, path following, elements of suturing), moving from pure teleoperation toward shared control and increasing levels of autonomy within the surgical workflow [23], [24].

Expected future developments in robot-assisted surgery are expected to address several key areas, as highlighted in recent publications [19], [25]. Future surgical robotics will move beyond simple teleoperation toward greater autonomy, shifting to shared control and task-level automation such as automated suturing, camera guidance, and trajectory execution, while surgeons supervise and intervene when necessary. Deeper integration of artificial intelligence will enable real-time tissue and surgical phase recognition, risk prediction, and decision support, creating cognitive robotic systems that learn from large surgical datasets. Advances in intraoperative imaging, augmented reality, and patient-specific digital twins will further enhance precision and allow real-time adaptation to tissue changes. At the same time, the development of miniaturized and soft robotic systems will permit access to complex anatomical regions with less trauma. Finally, improved low-latency networks and telepresence technologies will support scalable telesurgery, remote mentoring, and wider global access to specialized surgical care [19], [23]–[25].

3.2 Automated therapy planning in radiation therapy

Automation has also become central to radiation therapy. Modern systems use imaging data to automatically calculate individual radiation plans that spare healthy tissue as much as possible, promoted as “Inverse planning” or “Intensity-modulated radiotherapy (IMRT)” [26]. Control technology ensures that the radiation dose is applied precisely, even if the patient moves, for example, due to breathing [27].

3.3 Decision support and diagnostics

Since the pioneering artificial intelligence (AI) diagnostic and consultation systems in the early 1970s, like MYCIN (infectious disease therapy assistant), CASNET (glaucoma), INTERNIST (internal medicine diagnosis), and PIP (Present Illness Program), all of which used explicit knowledge representations and were evaluated clinically, the use of AI has increased rapidly [28]. Machine learning enables the analysis of large amounts of data from electronic patient records, image data, or genetic information, resulting in clinical decision support systems (CDSS) that can assist physicians with diagnoses, therapy recommendations, or risk assessments [29]. The authors expect CDSS to become more widely used, more tightly integrated into routine workflows, and more powerful through data and AI, but only if key risks like bias and alert fatigue are actively managed.

3.4 Rehabilitation technology

Another key area of application for automation is Rehabilitation technology, as it supports the restoration of motor, sensory, and cognitive abilities after illness or injury. In recent decades, this field has evolved from simple mechanical aids to highly complex mechatronic and cyber-physical systems. A significant advance is the use of robot-assisted rehabilitation systems, particularly in neurological rehabilitation after strokes or spinal cord injuries, like the Lokomat [30]. Exoskeletons and automated gait trainers enable intensive, repetitive, and reproducible training that would be virtually impossible to achieve with manual therapy alone. Control and sensor technology allows the support provided to be adapted to the individual performance level of each patient. Lightweight exoskeletons like the Hybrid Assistive Limb (HAL) incorporated bioelectric signals for shoulder and gait rehab, as shown in case studies for post-surgical palsy. Functional electrical stimulation (FES) and early brain-computer interfaces gained traction for neuro-rehabilitation [31]. Automated feedback and assistance systems also play an important role. By integrating force, position, and biosignal sensors (e.g., EMG), movement sequences can be analyzed and corrected in real time. In combination with virtual reality, interactive training environments are created that have been proven to improve motivation and therapeutic success. Automation thus contributes not only to increased efficiency but also to the individualization of rehabilitative measures. Ottobock, commercialized the C-Leg, the first microprocessor knee joint for amputees in 1997, after Canadian engineer Dr. Kelly James presented a prototype at the ISPO World Congress in Chicago in 1992. Sensors and real-time computing automate gait adaptation across terrains, simulating natural walking. This prosthetic breakthrough enhanced mobility automation for over a million users worldwide. From 1999 on a multiarticulated prosthetic hand was developed by researchers from the Forschungszentrum Karlsruhe [32] that uses fluidic actuation and an anthropomorphic design (see Figure 1). Multi-jointed fingers made with flexible materials conform to object shapes, minimizing grip force for stable holding and adaptive grasping with optional tactile feedback. The multiarticulated prosthetic hand was successfully commercialized in 2010 as the VINCENT evolution hand.

3.5 Hemodialysis

Another example of a therapy that was only made widely possible through automation is hemodialysis for patients

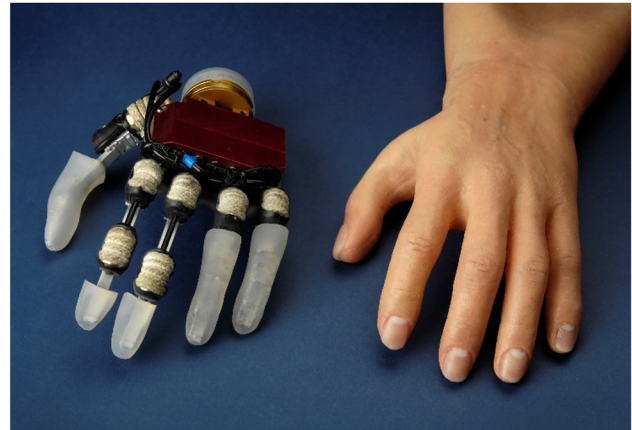


Figure 1: Early prototype of a multiarticulated fluidic actuated hand. © Stefan Schulz/FZK.

with chronic or acute renal failure. By using control loops that monitor real-time both, patient-specific parameters and system parameters, safety, precision, and long-term stability for controlled blood detoxification are ensured and cardiovascular stress is minimized [33]. Projected future developments in hemodialysis include a shift toward increased automation and the use of algorithm-driven, self-adapting dialysis systems integrated with cloud-based analytics and electronic health records. In parallel, the expansion of tele-dialysis and remote monitoring is expected to facilitate self-management and promote the adoption of home-based dialysis modalities. Furthermore, the growing use of digital health technologies, including artificial intelligence-based decision support systems, wearable devices, and educational platforms, will enable personalized therapy, enhance patient autonomy, and assist caregivers through data driven clinical decision making [34].

3.6 Intensive care medicine and artificial ventilation

Intensive care units (ICU) are one of the most technically demanding fields of application for automation technology. Patients here are often in life-threatening conditions that require continuous monitoring and immediate response to physiological changes. A key example is artificial ventilation. There was a gradual change from the 1950s to the 1970s from negative-pressure ‘iron lungs’, widely used during polio epidemics, to positive-pressure ventilators in intensive care units, following the first successful use of positive-pressure ventilation by Bjørn Ibsen in Copenhagen in 1952–1953. In the 1980s, the introduction of microprocessor-based ventilators further improved the precision, flexibility, and

monitoring of real-time control in ICU ventilators and became standard in the management of acute respiratory failure [35]. Modern ICU ventilators now employ advanced algorithms to continuously adjust airway pressure, tidal volume, and oxygen fraction to optimize oxygenation and minimize ventilator-induced lung injury. Building on this tradition of automated feedback control, newer ventilation modes synchronize support with patients' spontaneous breathing efforts using real-time analysis of respiratory signals. In parallel, automated monitoring systems integrate multiple vital parameters and alarm logic to detect clinical deterioration early and to drive semi-autonomous closed-loop interventions, including automated oxygen or sedation titration. Despite these advances, intensivists remain essential, because automation is designed to reduce workload and enhance patient safety rather than replace expert clinical assessment and decision-making. For the future [36], predict that AI-based algorithms will transform respiratory care to enable more personalized treatment plans, early detection of conditions, remote real-time monitoring, and optimized mechanical ventilation to improve outcomes and reduce complications.

4 Discussion: how automation has transformed medicine

The examples presented in this article illustrate a fundamental transformation in modern medicine. Automation has evolved from replacing repetitive manual tasks toward increasingly integrated systems that combine sensing, computation, decision support, and physical action. This development can be observed across laboratory medicine, medical imaging, surgery, rehabilitation, radiation therapy, dialysis, and intensive care. One important change is the transition from manual work to automated processes. Laboratory automation and medical imaging demonstrate how repetitive and standardized tasks can be performed by machines and software with high throughput and reproducibility. Automation has thereby increased efficiency and reduced variability in many clinical processes. A second major change is the transition from isolated measurements to continuous feedback and control. Modern medical systems increasingly measure physiological or technical parameters and use these data to adapt their operation. This principle is evident in mechanical ventilation, dialysis, radiation therapy, and rehabilitation. Medical technology has therefore progressed from measurement toward active control of therapeutic processes. A third transformation concerns the role of automation in therapy and surgery.

Robotic and rehabilitation systems increasingly move beyond simple assistance and can perform defined subtasks with a certain degree of autonomy. In surgical robotics, automation is developing from pure teleoperation toward shared control, while the healthcare professional remains responsible for the overall procedure. Finally, artificial intelligence, automated image analysis, and clinical decision support systems are changing how medical decisions are prepared. These technologies can process large amounts of data and support diagnosis, risk assessment, and treatment planning. At the same time, appropriate human oversight remains essential because of challenges such as data quality, bias, and transparency. Automation has therefore transformed medicine not simply by replacing manual work with machines, but by changing the relationship between measurement, decision making, and action. The most important transformation is not the replacement of healthcare professionals, but the emergence of increasingly interconnected human machine systems. Future medical automation will depend on the effective integration of technical capabilities with human expertise, clinical responsibility, and patient needs.

Acknowledgments: Prof. Georg Bretthauer made significant contributions to the integration of modern automation and mechatronics into medical technology (Figure 2). His research addressed mechatronic and biomechanical systems, model-based control, learning algorithms, and optimization methods for technical systems interacting closely with humans, particularly in medical devices and assistive technologies. He also advanced precision measurement and automation



Figure 2: Professor Georg Bretthauer. © Stefan Schulz/FZK, 1999.

techniques that improved the safety and accuracy of computer-assisted and robotic medical procedures. In collaboration with interdisciplinary partners, he contributed to innovations such as an artificial accommodation system for intraocular lenses [37], sensor-based orthotic and neuro-rehabilitation devices [38], eye-movement guidance systems for ophthalmology [39], and compliant medical robotics using flexible fluidic actuators [40] and automated image analysis for high-throughput screening [41]. Beyond technical developments, Prof. Bretthauer helped institutionalize automation-oriented medical technology through academic program development, interdisciplinary collaboration, and extensive patenting and community-building activities. We would like to express our sincere appreciation for his many years of dedicated support in advancing visionary goals in medical technology, and we wish him continued good health and vitality.

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Use of Large Language Models, AI and Machine Learning

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References

- [1] L. T. Skeggs and H. Hochstrasser, "Multiple automatic sequential analysis," *Clin. Chem.*, vol. 10, no. 10, pp. 918–936, 1964.
- [2] J. B. Levine, "Recent advances in automated lipid analysis," *J. Am. Oil Chem. Soc.*, vol. 44, no. 2, pp. 95–98, 1967.
- [3] D. Meissner and W. Jaross, "Aspects of the development of clinical chemistry and laboratory medicine in the former East Germany," *Clin. Chem. Lab. Med.*, vol. 40, no. 4, pp. 411–418, 2002.
- [4] K. Olsen, "The first 110 years of laboratory automation: Technologies, applications, and the creative scientist," *J. Lab. Autom.*, vol. 17, no. 6, pp. 469–480, 2012.
- [5] M. Sasaki, T. Kageoka, K. Ogura, H. Kataoka, T. Ueta, and S. Sugihara, "Total laboratory automation in Japan: Past, present and the future," *Clin. Chim. Acta*, vol. 278, no. 2, pp. 217–227, 1969.
- [6] Y. A. Al Naam, S. Elsafi, M. H. Al Jahdali, R. S. Al Shaman, B. H. Al-Qurouni, and E. M. Al Zahrani, "The impact of total automaton on the clinical laboratory workforce: A case study," *J. Healthc. Leader*, vol. 14, pp. 55–62, 2022.
- [7] J. Y. Park and L. J. Kricka, "One hundred years of clinical laboratory automation: 1967–2067," *Clin. Biochem.*, vol. 50, no. 12, pp. 639–644, 2017.
- [8] F. Biermann, J. Mathews, B. Nießing, N. König, and R. H. Schmitt, "Automating laboratory processes by connecting biotech and robotic devices – an overview of the current challenges, existing solutions and ongoing developments," *Processes*, vol. 9, no. 6, p. 966, 2021.
- [9] Y. Nam and H. D. Park, "Revolutionizing laboratory practices: Pioneering trends in total laboratory automation," *Ann. Lab. Med.*, vol. 45, no. 5, pp. 472–483, 2025.
- [10] K. Thurow, "Strategies for automating analytical and bioanalytical laboratories," *Anal. Bioanal. Chem.*, vol. 415, no. 21, pp. 5057–5066, 2023.
- [11] M. Đorđević *et al.*, "Effects of automation on sustainability of immunohistochemistry laboratory," *Healthcare*, vol. 9, no. 7, p. 866, 2021.
- [12] G. N. Hounsfield, "Historical notes on computerized axial tomography," *J. Can. Assoc. Radiol.*, vol. 27, no. 3, pp. 135–142, 1976.
- [13] A. M. Cormack, "Representation of a function by its line integrals, with some radiological applications," *J. Appl. Phys.*, vol. 34, no. 9, pp. 2722–2727, 1973.
- [14] P. Mansfield, P. G. Morris, R. J. Ordidge, I. L. Pykett, V. Bangert, and R. E. Coupland, "Human whole body imaging and detection of breast tumours by NMR," *Philos. Trans. R. Soc. Lond. B Biol. Sci.*, vol. 289, no. 1037, pp. 503–510, 1980.
- [15] R. K. Samala *et al.*, "AI and machine learning in medical imaging: Key points from development to translation," *BJR Artif. Intell.*, vol. 1, no. 1, p. ubae006, 2024.
- [16] J. Potočník, S. Foley, and E. Thomas, "Current and potential applications of artificial intelligence in medical imaging practice: A narrative review," *J. Med. Imag. Radiat. Sci.*, vol. 54, no. 2, pp. 376–385, 2023.
- [17] A. Barragán-Montero *et al.*, "Artificial intelligence and machine learning for medical imaging: A technology review," *Phys. Med.*, vol. 83, pp. 242–256, 2021.
- [18] Y. Yang, L. Ye, and Z. Feng, "Application of artificial intelligence in medical imaging: Current status and future directions," *Iradiology*, vol. 3, no. 2, pp. 144–151, 2025.
- [19] J. C. R. Burbano, N. I. Ruiz, G. A. R. Burbano, J. S. G. Inca, C. A. A. Lezama, and M. S. González, "Robot-assisted surgery: Current applications and future trends in general surgery," *Cureus*, vol. 17, no. 4, 2025, <https://doi.org/10.7759/cureus.82318>.
- [20] Y. E. Hong, H. Shim, and M. Shin, "Costs and cost-effectiveness of robotic-assisted surgery in South Korea: A systematic review and meta-analysis," *Front. Public Health*, vol. 13, 2025, <https://doi.org/10.3389/fpubh.2025.1683482>.
- [21] H. Sadri, M. Fung-Kee-Fung, B. Shayegan, P. Y. Garneau, and P. Pezeshki, "A systematic review of full economic evaluations of robotic-assisted surgery in thoracic and abdominopelvic procedures," *J. Robot. Surg.*, vol. 17, no. 6, pp. 2671–2685, 2023.
- [22] Y. S. Kwok, J. Hou, E. A. Jonckheere, and S. Hayati, "A robot with improved absolute positioning accuracy for CT guided stereotactic brain surgery," *IEEE Trans. Biomed. Eng.*, vol. 35, no. 2, pp. 153–160, 1988.
- [23] Y. Li, N. Raison, S. Ourselin, T. Mahmoodi, P. Dasgupta, and A. Granados, "AI solutions for overcoming delays in telesurgery and

- telementoring to enhance surgical practice and education,” *J. Robot. Surg.*, vol. 18, no. 1, p. 403, 2024.
- [24] J. E. Knudsen, U. Ghaffar, R. Ma, and A. J. Hung, “Clinical applications of artificial intelligence in robotic surgery,” *J. Robot. Surg.*, vol. 18, no. 1, p. 102, 2024.
- [25] J. N. K. Wah, “The rise of robotics and AI-assisted surgery in modern healthcare,” *J. Robot. Surg.*, vol. 19, no. 1, p. 311, 2025.
- [26] A. L. Boyer *et al.*, Of the Intensity Modulated Radiation Therapy Collaborative Working Group, “Intensity-modulated radiotherapy: Current status and issues of interest,” *Int. J. Radiat. Oncol. Biol. Phys.*, vol. 51, no. 4, pp. 880–914, 2001.
- [27] P. J. Keall *et al.*, “The management of respiratory motion in radiation oncology: Report of AAPM task group 76,” *Med. Phys.*, vol. 33, no. 10, pp. 3874–3900, 2006.
- [28] C. A. Kulikowski, “An opening chapter of the first generation of artificial intelligence in medicine: The first rutgers AIM workshop, June 1975,” *Yearb. Med. Inf.*, vol. 24, no. 1, pp. 227–233, 2015.
- [29] R. T. Sutton, D. Pincock, D. C. Baumgart, D. C. Sadowski, R. N. Fedorak, and K. I. Kroeker, “An overview of clinical decision support systems: Benefits, risks, and strategies for success,” *NPJ Digit. Med.*, vol. 3, no. 1, p. 17, 2020.
- [30] B. Husemann, F. Muller, C. Krewer, S. Heller, and E. Koenig, “Effects of locomotion training with assistance of a robot-driven gait orthosis in hemiparetic patients after stroke: A randomized controlled pilot study,” *Stroke*, vol. 38, no. 2, pp. 349–354, 2007.
- [31] Y. Sankai, “HAL: Hybrid assistive limb based on cybernics,” in *Robotics Research: The 13th International Symposium ISRR*, Berlin, Heidelberg, Springer, 2010, pp. 25–34.
- [32] S. Schulz, C. Pylatiuk, M. Reischl, J. Martin, R. Mikut, and G. Bretthauer, “A hydraulically driven multifunctional prosthetic hand,” *Robotica*, vol. 23, no. 3, pp. 293–299, 2005.
- [33] R. K. Samala *et al.*, “AI and machine learning in medical imaging: Key points from development to translation,” *BJR Artif. Intell.*, vol. 1, no. 1, 2024, <https://doi.org/10.1093/bjrai/ubae006>.
- [34] B. Canaud *et al.*, “Digital health support: Current status and future development for enhancing dialysis patient care and empowering patients,” *Toxins*, vol. 16, no. 5, p. 211, 2024.
- [35] L. Reisner-Sénélar, “The birth of intensive care medicine: Björn Ibsen’s records,” *Intensive Care Med.*, vol. 37, no. 7, pp. 1084–1086, 2011.
- [36] S. Al-Anazi *et al.*, “Artificial intelligence in respiratory care: Current scenario and future perspective,” *Ann. Thorac. Med.*, vol. 19, no. 2, pp. 117–130, 2024.
- [37] M. Bergemann, U. Gengenbach, G. Bretthauer, and R. F. Guthoff, “Artificial accommodation system – a new approach to restore the accommodative ability of the human eye,” in *World Congress on Medical Physics and Biomedical Engineering 2006, IFMBE Proc.*, vol. 14, Berlin, Heidelberg, Springer, 2007, https://doi.org/10.1007/978-3-540-36841-0_75.
- [38] C. Pylatiuk, A. Kargov, I. Gaiser, T. Werner, S. Schulz, and G. Bretthauer, “Design of a flexible fluidic actuation system for a hybrid elbow orthosis,” in *Proc. IEEE Int. Conf. Rehabilitation Robotics (ICORR)*, 2009, pp. 167–171.
- [39] B. Köhler *et al.*, “EyeGuidance – a computer controlled system to guide eye movements,” *Curr. Dir. Biomed. Eng.*, vol. 2, no. 1, pp. 433–436, 2016.
- [40] S. Schulz, C. Pylatiuk, and G. Bretthauer, “A new ultralight anthropomorphic hand,” in *Proc. IEEE Int. Conf. Robotics and Automation (ICRA)*, vol. 3, Seoul, South Korea, 2001, pp. 2437–2441.
- [41] R. Alshut *et al.*, “Automatische Klassifikation von Bildzeitreihen für toxikologische Hochdurchsatz-Untersuchungen,” *Automatisierungstechnik*, vol. 59, no. 5, pp. 259–268, 2011.

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