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Artificial intelligence and robotic surgery in clinical medicine: progress, challenges, and future directions

Salih Beyaz, Alaaddin Levent Özgözen, Necmettin Turgut and Hakkı Can Ölke

Orthopedics and Traumatology Department, Adana Turgut Noyan Research and Training Centre, Baskent University, Adana, Türkiye

ABSTRACT

Technological innovations in medicine are increasingly expected to replicate the diagnostic, decision-making, and procedural skills of experienced physicians. This review explores the evolution, current status, and limitations of artificial intelligence (AI) and robotic surgery in clinical practice. Radiology and pathology have led the way in digital transformation, enabling AI applications through standardized datasets and electronic health records. However, limitations such as algorithmic opacity, legal-ethical uncertainties, and fragmented digital infrastructures continue to hinder broader implementation. In robotic surgery, soft tissue procedures have not yet demonstrated significant advantages over conventional laparoscopy in terms of cost or operative efficiency. Orthopedic applications, particularly in arthroplasty, are promising but still lack long-term validation. Importantly, for any technology to create true value in healthcare, its benefits must clearly outweigh its costs. As healthcare systems face mounting pressure from aging populations and rising procedural demand, particularly for cholecystectomy, prostatectomy, and arthroplasty, the development of efficient and scalable technologies becomes inevitable. While neither AI nor robotic surgery has yet fulfilled its transformative promise, historical trends suggest that innovation will persist toward overcoming these barriers.

ARTICLE HIGHLIGHTS

- The most successful applications of artificial intelligence (AI) in medicine are found in image processing, with radiology and pathology emerging as the leading specialties in clinical implementation.
- AI is accelerating digital transformation in healthcare and is expected to reshape decision support systems, particularly through the integration of large language models (LLMs) in the near future.
- The widespread clinical adoption of AI and robotic systems remains limited; for these technologies to deliver value, their benefits must demonstrably outweigh their financial and operational costs.
- Robotic surgery has yet to reach optimal standards in terms of operative duration and cost-effectiveness, with its clinical superiority over conventional techniques still under debate.
- Key barriers to the widespread adoption of robotic surgery include high initial investment costs, expensive disposable instruments, and complex preoperative preparation requirements.
- The rising and aging global population serves as a major driving force behind the pursuit of cost-effective technological innovations in modern healthcare systems.

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1. Introduction

The integration of artificial intelligence (AI) and robotic surgery into medicine has emerged as one of the most striking technological transformations of the 21st century. Although these concepts may appear relatively recent, the notion that technology could support clinical decision-making was first proposed in 1970 by William B. Schwartz. He envisioned that computers would revolutionize healthcare, yet also emphasized that this transformation would face significant psychological, organizational, and legal barriers [1].

For many years, the limited processing power and insufficient volume of digital data prevented this vision from becoming a practical reality. However, the evolution of deep learning algorithms, increased access to

CONTACT Salih Beyaz sbeyaz@baskent.edu.tr Orthopedics and Traumatology Department, Adana Turgut Noyan Research and Training Centre, Baskent University, Adana, Turkey.
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large-scale datasets, and significant advancements in CPU and GPU technologies during the 2000s have collectively accelerated the transformation of healthcare technologies. AI-based clinical decision support systems and robotic surgical applications have since entered routine clinical practice, marking the beginning of a revolutionary shift in the delivery of healthcare services.

This technological transformation is framed within the broader concept of Health 4.0. Health 4.0 refers to the systematic integration of digital technologies—such as artificial intelligence, robotic systems, big data analytics, the Internet of Things (IoT), and augmented reality—into patient care processes as well as diagnostic and therapeutic approaches [2]. This vision encompasses not only the deployment of individual technological tools, but also the comprehensive digital transformation of the entire healthcare ecosystem. This comprehensive digital transformation can be conceptualized as a "digital (r)evolution" in healthcare, reflecting both the gradual evolution and the disruptive revolution brought about by emerging technologies.

However, for novel technologies to gain widespread acceptance in clinical practice, they must demonstrate clear and meaningful advantages over traditional approaches. These advantages include enhanced diagnostic and therapeutic efficacy, reduced procedure times, improved cost-effectiveness, and significant improvements in patient outcomes. Moreover, successful integration also requires these technologies to be scalable, user-friendly, and approved by regulatory authorities.

2. Methodology

This narrative review was conducted using the PubMed database to identify relevant English-language literature published between 2005 and 2025. The search strategy involved combining the keyword *"artificial intelligence"* with discipline-specific terms (e.g., *radiology, pathology, dermatology, ophthalmology, orthopedics*) to capture a wide range of AI applications across medical fields. For robotic surgery, the search included combinations such as *"robotic surgery AND [specialty/procedure]"* (e.g., *prostatectomy, cholecystectomy, arthroplasty*), with a particular focus on review and systematic review articles that compared robotic surgery to conventional surgical techniques.

Filters were applied to include only English-language *reviews* and *systematic reviews*. Articles were selected based on their relevance to clinical implementation, methodological rigor, and availability of outcome data. Priority was given to studies offering comparative analyses, meta-analyses, or critical evaluations of AI or robotic systems. Meta-analytic effect sizes, heterogeneity indices, and reported limitations were especially noted in robotic surgery literature to provide a comprehensive synthesis of current evidence.

3. Artificial intelligence

Artificial intelligence (AI) is rapidly transforming clinical medicine by offering faster, more consistent, and personalized solutions across diagnosis, treatment, and follow-up. Rather than being viewed solely as an automation tool, AI is now regarded as a "clinical co-pilot" that enhances medical insight and supports informed decision-making. To provide conceptual clarity, we categorize AI applications into three primary domains: (1) image-based algorithms for visual diagnostics (e.g., radiology, pathology), (2) large language models (LLMs) used in natural language processing and clinical documentation, and (3) clinical decision support systems (CDSS) integrated into electronic health records (EHRs). Each category presents unique technical and regulatory considerations in practice.

3.1. Image processing

Image processing represents one of the most successful domains of artificial intelligence (AI) applications. Radiology was the first medical specialty to adopt image-based diagnosis, and the field saw its first digital imaging technology emerge in the early 1970s. Specifically, digital imaging was first introduced into medicine in 1972 with the invention of computed tomography (CT) by British engineer Godfrey Hounsfield [3]. While working at EMI, Hounsfield revolutionized medical imaging and was later awarded the Nobel Prize in 1979 for this groundbreaking innovation.

By the 1990s, the widespread adoption of Picture Archiving and Communication Systems (PACS) enabled efficient digital management of radiologic images. The availability of large volumes of digitized data became

a driving force behind AI research in medical imaging. The initial applications of AI to digital medical images began in the 1980s with rule-based expert systems and early computer-aided diagnosis (CAD) software. In the 1990s, artificial neural networks (ANNs) and machine learning techniques were introduced into mammography and general radiologic image analysis. Since the 2010s, convolutional neural networks (CNNs) have led to substantial advances in medical image analysis. Today, AI-based systems have received FDA and CE approvals and are actively utilized in clinical settings as radiologic decision support tools.

While image analysis in pathology has not progressed as rapidly as in radiology, recent developments have significantly advanced the field. Until the early 1990s, pathology slides were evaluated analogically under a microscope. The digital transformation of pathology began in 1999 when Dr. Ronald S. Weinstein introduced the concept of Whole Slide Imaging (WSI), enabling microscopic slides to be digitized and reviewed electronically [4] Companies such as Leica, Aperio, and Hamamatsu contributed to the widespread adoption of digital pathology in the early 2000s by developing commercial WSI scanners. A major milestone was reached in 2017 when the Philips digital pathology system became the first of its kind to receive FDA approval, accelerating its integration into clinical workflows.

Unlike radiologic images, digital pathology images are significantly higher in resolution and can occupy up to 100 times more storage space. As a result, alternative data storage solutions are required, and PACS systems are generally inadequate for this purpose. Consequently, the development of AI applications in this domain has lagged behind. Nevertheless, AI-assisted digital pathology systems are now increasingly used to enhance diagnostic accuracy through the objective analysis of cellular morphology, tissue architecture, staining patterns, and proliferative activity. Quantifiable parameters—such as nuclear size, mitotic index, glandular irregularities, and immunohistochemical marker expressions—can be assessed by AI algorithms, providing pathologists with standardized and reproducible decision support.

Another promising application of AI in pathology is content-based image retrieval (CBIR). This tool enables pathologists to search large histopathology databases for images similar to a query image. CBIR supports diagnostic decision-making in rare and complex cases by retrieving images based on both visual resemblance and shared histopathological characteristics. As a result, it serves as a valuable tool for facilitating faster and more accurate diagnoses in challenging scenarios [5,6].

Despite its promise, digital pathology still faces several challenges. High implementation costs, technical compatibility issues, and data management complexities remain significant barriers to full integration. Nonetheless, given its educational value and potential cost-efficiency in the long term, the widespread adoption of digital pathology appears inevitable.

In dermatology, the digital transformation began in the early 1990s with the shift from analog photography to digital imaging. Around the same time, the emergence of digital dermoscopy enabled the high-resolution capture of skin lesion images by the early 2000s, catalyzing a wave of AI-driven research in this field. The integration of machine learning into digital dermatology gained momentum in the 2010s, culminating in a landmark 2017 study from Stanford University, which demonstrated that an AI algorithm could diagnose malignant melanoma with an accuracy comparable to that of expert dermatologists [7].

In ophthalmology, optical coherence tomography (OCT)—introduced in the 1990s—revolutionized digital imaging by enabling high-resolution cross-sectional analysis of retinal structures. The early 2000s saw the expansion of tele-ophthalmology applications, facilitating remote evaluation of conditions such as diabetic retinopathy and glaucoma. In 2018, the FDA approved IDx-DR, the first AI-powered diagnostic system for eye diseases, officially marking the entry of AI into clinical ophthalmology [8]. Today, algorithms developed by technology companies such as Google Health and DeepMind have demonstrated diagnostic accuracy in retinal screening that rivals ophthalmologists. Furthermore, mobile ophthalmology platforms and smartphone-based retinal screening tools offer cost-effective and accessible diagnostic options, thereby extending eye care services to underserved populations.

In the early stages of image-based artificial intelligence (AI) development, research centers typically relied on locally constructed datasets to train and test their algorithms. However, concerns regarding the accuracy of data labeling, the reliability of annotators, legal and ethical issues, and the limited generalizability of models trained in one institution to external data from other centers highlighted critical limitations of this approach. As a result, efforts were initiated to develop standardized, well-annotated reference datasets that could be used across research institutions. For example, the Multicenter Osteoarthritis Study (MOST) is widely used for knee osteoarthritis staging [9], the NIH Chest X-ray dataset for pulmonary imaging [10], The Cancer Genome

Atlas (TCGA) for pathology [11], the International Skin Imaging Collaboration (ISIC) dataset for dermatology [12] and the EyePACS dataset for diabetic retinopathy diagnosis in ophthalmology [13]. These publicly available datasets have enabled researchers not only to develop new algorithms but also to benchmark their own data and models against standardized references. Consequently, the clinical applicability and generalizability of AI models have improved significantly, leading to the development of more reliable and standardized systems.

3.2. Large language model

Large Language Models (LLMs) are artificial intelligence systems trained on extensive textual datasets using deep learning techniques and Transformer-based architectures. By leveraging the attention mechanism, these models are capable of understanding contextual relationships between words, enabling them to perform language-based tasks such as text generation, summarization, and analysis with high accuracy.

LLMs have a broad range of applications in medicine, from synthesizing rapidly expanding scientific literature into evidence-based insights, to analyzing electronic health records for predicting complications. A major turning point in this field occurred on November 30, 2022, with the public release of ChatGPT by OpenAI. Although not specifically designed for medical use, studies have shown that ChatGPT possesses medical knowledge sufficient to pass board-level exams in various specialties and can provide postoperative patient responses with accuracy comparable to expert physicians [14].

One of the most significant limitations of LLMs, however, is their tendency to generate inaccurate or non-factual content. This phenomenon—commonly referred to in the literature as "hallucination" or "confabulation"—poses a serious concern in clinical contexts, as it can undermine trust in AI tools and lead to potentially harmful medical decisions [15].

These models are not held accountable for the information they generate, and the reliability of their outputs must be supported by external source verification. A meta-analysis conducted by Omar et al. demonstrated that while LLMs performed well in diagnosing various psychiatric disorders, they tended to underestimate risk in cases of suicidal depression [16]. This finding highlights the limitations of LLMs in delivering patient-specific, ethically sound, and clinically reliable recommendations.

3.3. Clinical decision support systems

Artificial intelligence–enabled Clinical Decision Support Systems (CDSS) are computer-based tools designed to assist physicians in diagnostic reasoning, treatment planning, and disease management by analyzing patient data. The conceptual foundation of CDSS can be traced back to the development of Bayesian Decision Theory in Medicine in 1959 [17]. One of the earliest practical implementations of CDSS in the medical field was the MYCIN system, introduced in 1978 to provide antibiotic recommendations for infectious diseases [18]. However, these rule-based systems lacked flexibility and were not easily generalizable beyond the specific clinical scenarios for which they were designed.

In 1986, Harvard University developed DXplain, a more advanced CDSS that offered diagnostic suggestions based on patient symptoms [19]. A notable example of AI-based CDSS was developed by IBM Watson in 2011, specifically tailored to assist diagnostic and therapeutic decision-making in oncology [20]. More recently, in 2016, Google DeepMind developed deep learning–based algorithms that marked a significant advancement in predicting clinical conditions such as eye diseases and kidney failure [21,22].

One of the major limitations of these systems is the lack of transparency in their decision-making processes, commonly referred to as the "black box" problem. Since deep learning models do not reveal the specific criteria upon which clinical decisions are based, physicians are unable to directly audit these systems, making it difficult to use them confidently in clinical practice. From a patient safety perspective, the verifiability of clinical decisions is of paramount importance. Therefore, the effective use of CDSS requires that electronic health records (EHRs) be complete, accurate, and up-to-date.

Despite the development of AI-based CDSS, several critical challenges remain unresolved. These include the objectivity of data sources, legal accountability in the event of incorrect decisions, the adaptation of healthcare professionals to the use of such tools, and broader ethical concerns. The integration of CDSS into healthcare systems must be approached not only from a standpoint of technical accuracy but also through careful consideration of legal frameworks.

3.4. The impact of artificial intelligence on health informatics

The advancement of AI-based image processing systems in healthcare has not only improved diagnostic workflows but also acted as a catalyst for transforming digital health record systems. In order for AI to deliver effective and reliable results, it requires high-quality, structured, and accessible data, thereby underscoring the need for more organized data management in clinical settings. Historically, patient records were maintained on paper; however, the integration of AI-driven analyses into clinical decision-making has prompted a transition toward more standardized, analyzable, and digitized formats.

The widespread adoption of electronic health records (EHRs) has facilitated data sharing across institutions and accelerated the development of AI-powered clinical decision support systems. This integration has enabled the combination of diagnostic data with longitudinal patient histories, paving the way for more comprehensive and personalized healthcare decision-making. Consequently, the success of AI algorithms in medical imaging has not only contributed to clinical diagnostics, but also intensified the demand for digital transformation in health informatics, leading to more systematic, reliable, and accessible record-keeping systems

For AI algorithms to be effectively utilized in daily clinical practice, they must be integrated into existing healthcare systems, and medical personnel must be adequately trained in their use. Variations in hospital infrastructure necessitate customized solutions for each institution, often resulting in efficiency challenges in terms of both cost and time. It is critically important that AI systems remain under the control of healthcare professionals, allowing for manual intervention in the event of errors. Furthermore, transparency and interpretability in decision-making mechanisms enhance the traceability and accountability of clinical recommendations.

For AI technologies to evolve meaningfully, they must be systematically integrated into clinical workflows, and insights gained from real-world applications should be used to refine these systems and accelerate their adaptation [23]. In recent years, systematic reviews conducted across various medical specialties have evaluated both the clinical benefits and methodological limitations of AI applications from an interdisciplinary perspective (Supplementary Table 1) [24–37].

4. Robotic surgery

Robotic surgery is expected to reduce operative time, lower the risk of complications such as infection and bleeding, shorten hospital stays, and decrease overall healthcare costs. In addition, it holds the potential to standardize surgical procedures, ensuring consistent quality of care across patients. obotic systems can eliminate hand tremors during surgery, allowing for greater precision and control. As a result, these systems aim to minimize errors and, when used effectively, may achieve outcomes comparable to those of highly experienced surgeon

4.1. Historical development

The first robotic surgical procedure was performed in 1985 using the PUMA 560 robot during a stereotactic brain biopsy. In the 1990s, specialized robotic systems such as PROBOT (for prostate surgery) and ROBODOC (for orthopedic procedures) were developed [38] However, the first commercially available robotic surgical system to receive FDA approval for clinical use was the da Vinci Surgical System (Intuitive Surgical, Inc., Sunnyvale, CA, USA), approved in 2000. Initially adopted in only a few specialties, robotic surgery has gained broader popularity since 2015, driven by increased computational power, reduced costs, growing demand for minimally invasive procedures, and advancements in 3D imaging technologies.

According to a literature search conducted in PubMed, the number of publications related to robotic surgery has increased significantly between 2014 and 2024 (Supplementary Table 2). This table presents the number of articles published annually across different surgical specialties, based on a manual search using the keywords “robotic surgery” in combination with procedure-specific terms (e.g., prostatectomy, nephrectomy, arthroplasty). While this dataset does not directly reflect clinical utilization rates, it provides insight into the academic interest surrounding robotic surgery and suggests which fields have likely experienced greater integration into clinical practice. High publication volumes in areas such as prostate surgery and arthroplasty point to more widespread adoption of robotic systems in these specialties.

4.2. Clinical applications by discipline

In soft tissue surgeries involving systems like the da Vinci robot, the surgeon performs the procedure remotely by operating robotic arms from a console separate from the patient. Unlike conventional laparoscopy, robotic surgery offers up to tenfold magnification, reduced hand tremor, three-dimensional visualization, and improved ergonomics for the surgeon [39]. Robotic surgery is most commonly applied in standardized elective procedures. Examples include arthroplasty (hip and knee replacements) in orthopedics; prostatectomy and nephrectomy in urology; cholecystectomy and pyeloplasty in general surgery; and lobectomy in thoracic surgery.

A common feature of these procedures is that they are typically performed in patients over the age of 60. According to the World Health Organization, by 2050, 16% of the global population will be aged 65 and older, indicating a rising demand for surgical interventions related to degenerative diseases [40]. An increase is expected both in the total number and the relative proportion of procedures such as hip and knee arthroplasty, spinal surgeries, prostatectomy for benign prostatic hyperplasia, cholecystectomy for gallstones, and arthroplasty for gonarthrosis and coxarthrosis.

4.3. Economic and operational challenges

The rising cost of healthcare associated with population aging is expected to place a significant burden on social security systems and insurance providers. Robotic surgery is increasingly being considered as a potential strategy to mitigate this burden. Due to its minimally invasive nature, robotic procedures may promote faster patient recovery and shorter hospital stays, thereby contributing to a reduction in overall healthcare expenditures. As a result, the expansion of robotic surgery across multiple disciplines may not remain merely an innovation but could become a necessity for future healthcare systems.

As with any emerging technology, robotic surgery has faced several challenges in its early stages. Prolonged operative times and higher complication rates initially raised concerns among clinicians. Surgeons performing robotic procedures were typically experienced in conventional techniques, as their expertise was critical in managing intraoperative complications—particularly when reverting to traditional methods became necessary. In orthopedic surgery, one operational challenge has been the need to keep all conventional instrument sets available in the operating room, which has hindered the expected pace of cost reduction.

Studies based on early-stage, limited case series have generally concluded that robotic surgery is not cost-effective in fields such as urology, gynecology, and general surgery [41–45]. Kulayat et al. reported that, in pediatric cholecystectomy cases, robot-assisted cholecystectomy was 40% more expensive and had a 24% longer operative time compared to laparoscopic cholecystectomy [46]. They noted that the primary advantage of robotic surgery over laparoscopy lies in the ability to perform the procedure through a single port.

Similarly, Simianu et al. found that the cost-effectiveness of robotic surgery depends on factors such as operative time and length of hospital stay. Their analysis revealed that robotic proctectomy was $497 more expensive than laparoscopy, and the associated improvement in quality of life did not fully justify the cost difference. From a healthcare system perspective, robotic surgery was reported to incur an additional $983 in costs compared to laparoscopy, with a high cost-effectiveness ratio of $1,485,139 per quality-adjusted life year (QALY). These findings suggest that for robotic surgery to become cost-effective, either the cost of disposable instruments must be reduced below $1,496 or postoperative hospital stays must be shortened to less than 2.9 days [47].

The cost-effectiveness of robotic surgery is also influenced by the income level of the countries in which it is implemented. Bejrananda et al. published a meta-analysis including 13 studies and 17 comparisons that evaluated the cost-effectiveness of robot-assisted radical prostatectomy (RARP) compared with open (ORP) and laparoscopic (LRP) approaches. The study reported that RARP was not cost-effective compared to ORP in either high- or middle-income countries. When compared with LRP, RARP was found to be potentially cost-effective only in high-income countries, although this difference was not statistically significant. In middle-income countries, RARP was determined to be less cost-effective than LRP [48].

4.4. Technical and workflow differences across surgical disciplines

Robotic surgery is not used with the same objectives across all surgical disciplines, as each field has its own unique dynamics. In soft tissue surgeries—such as those in urology, general surgery, and gynecology—the

primary goal of robotic systems is to perform minimally invasive procedures that reduce tissue damage, enhance visualization of the surgical field, and accelerate postoperative recovery. For example, in procedures like prostatectomy and cholecystectomy, robotic systems such as the Da Vinci Surgical System leverage the benefits of minimally invasive approaches to provide enhanced visibility, enable smaller incisions, and reduce complication rates.

In contrast, robotic systems used in orthopedic surgery—such as MAKO (Mako Surgical Corp. [Stryker) and ROSA (Zimmer Biomet, Warsaw, USA)—adopt a fundamentally different approach. The primary aim in orthopedics is not soft tissue preservation but rather the precise execution of bone cuts and the accurate placement of prosthetic components. In arthroplasty procedures (e.g., hip and knee replacements), robotic assistance allows surgeons to adhere more closely to preoperative planning, position implants more optimally, and potentially achieve improved long-term patient outcomes.

The surgical robots currently in use are haptic-type systems, meaning they remain under the control of the surgeon and are manually manipulated. In soft tissue surgeries, such as those performed with the da Vinci system, robotic procedures typically do not require additional preoperative imaging. In contrast, orthopedic surgical robots—used primarily for bone cutting—often require preoperative computed tomography (CT) scans to precisely determine the locations of planned osteotomies.

Unlike soft tissue robots, orthopedic robotic systems do not aim to be minimally invasive. One of the most time-consuming aspects of robotic procedures in orthopedics is the preoperative setup of the robotic system. In soft tissue surgeries, time is primarily affected by the need to prepare and drape the robot in a sterile manner. In orthopedic procedures, however, additional steps are required, including registration of the surgical field, placement of navigation pins, and surface mapping, all of which contribute to extended operative times.

In abdominal surgeries, the main alternative to robotic surgery is laparoscopy, whereas in thoracic procedures it is video-assisted thoracoscopic surgery (VATS). Numerous studies have demonstrated the advantages of laparoscopic surgery over open procedures. While laparoscopic abdominal operations are typically performed using two or three ports, robotic surgery offers the capability for single-port procedures. However, aside from improved cosmetic outcomes, no significant clinical benefit of reducing the number of ports has been definitively established.

In orthopedic surgery, the situation is markedly different. Robotic systems are currently used exclusively in arthroplasty, and can only be compared with conventional techniques within that domain. Although some studies have reported improved early outcomes with robotic-assisted arthroplasty, there remains a lack of sufficient data regarding long-term revision rates—one of the most critical factors influencing the overall cost-effectiveness of these procedures.

4.5. Meta-analytic findings

In comparative studies of robotic surgery, intra-abdominal procedures are most commonly evaluated against open and laparoscopic approaches. Numerous studies comparing laparoscopic to open surgery have confirmed expected benefits such as reduced blood loss and shorter hospital stays. Consequently, robotic-assisted procedures in abdominal surgery should primarily be compared with laparoscopic techniques, while in thoracic surgery, video-assisted thoracoscopic surgery (VATS) serves as the appropriate comparator.

While these trends suggest limited short-term advantages, it is crucial to consider domain-specific outcome priorities. In soft tissue surgeries, short-term metrics such as blood loss or hospital stay dominate cost-benefit analyses. However, in orthopedic surgery—particularly arthroplasty—long-term prosthesis survival, alignment precision, and the potential for cementless implantation carry significant weight. With a growing population of younger patients undergoing joint replacement, robotic systems may offer strategic value in achieving durable outcomes. Nevertheless, the absence of high-quality, long-term comparative studies continues to restrict definitive conclusions regarding their cost-effectiveness and clinical superiority in this domain. A detailed overview of comparative meta-analyses across various surgical disciplines—highlighting robotic surgery's clinical performance relative to conventional techniques—is summarized in Supplementary Table 3 [49–58].

Robotic surgical systems remain far from fulfilling their promises of reducing operative time and delivering higher-quality surgery at a lower cost. Nonetheless, it is important to acknowledge that these systems have significantly evolved compared to the early prototypes introduced over 30 years ago [38]. Whether current

haptic systems will eventually transition into fully autonomous platforms remains to be seen. At present, however, robotic surgery does not yet offer a viable solution to the escalating healthcare costs associated with an aging global population.

5. Results

5.1. Achievements and limitations in the field of AI

The success of artificial intelligence (AI) in image processing serves as a reference point for its potential in clinical medicine. However, comparable progress has not yet been achieved in clinical decision support systems. The primary reason for this gap is the limited degree of digitalization and standardization of data structures in this domain. Unlike imaging data, text-based clinical data are largely unstructured, heterogeneous, and often incomplete, posing significant challenges for model development and practical implementation.

In addition to diagnostic applications, AI has demonstrated utility in administrative healthcare functions such as automated documentation, clinical summarization, and coding. In surgical practice, AI is beginning to contribute to intraoperative guidance and postoperative monitoring, although these applications remain in their infancy and are largely experimental.

Despite these advances, AI implementation still faces significant barriers. The opaque, "black box" nature of many algorithms hampers interpretability and trust. Furthermore, the absence of standardized validation frameworks complicates regulatory approval and clinical integration. Key issues—including data privacy, algorithmic bias, and the assignment of medico-legal responsibility—remain unresolved and hinder the broad adoption of AI systems in routine practice.

5.2. Clinical contributions and limitations of robotic surgery

In robotic surgery, the path toward full autonomy for systems currently used in standardized surgical tasks is likely to be considerably longer. Key limitations—such as high costs, lengthy setup times, and the inability to significantly reduce operative duration—remain unresolved. The development trajectory of robotic surgery closely mirrors that of autonomous electric vehicles; however, the evolution is markedly slower due to stricter regulatory constraints. Having a human hand on the controls—whether it be a steering wheel in a car or a joystick in surgery—still provides a greater sense of security.

At present, the adequacy of robotic surgery must be assessed individually for each specialty. In soft tissue surgeries, where laparoscopy is already a well-established and highly effective technique, competing with conventional methods remains challenging. In contrast, in orthopedic surgery, where long-term implant survival and precision are critical, the clinical advantages of robotic systems may become more evident in the future as high-quality longitudinal studies are conducted.

5.3. Shared challenges: cost, regulation, and data accessibility

Meanwhile, the volume of data generated in the medical field continues to grow exponentially, making it increasingly difficult for human clinicians to interpret this information unaided. The cognitive capacity of physicians is being stretched to its limits in the effort to generate meaningful and personalized insights during clinical decision-making. Rather than viewing these developments solely through the lens of artificial intelligence, a broader and more forward-looking perspective would include the integration of data from wearable technologies, genetic testing, and other tools supporting personalized medicine.

In this context, AI systems and robotic surgery are no longer merely technological innovations—they are becoming essential components for ensuring the sustainability of modern healthcare services. Viewed from this perspective, the promises of emerging technologies appear compelling; however, the financial burden and ambiguity surrounding who will bear the cost remain critical barriers. It seems unlikely that these expenses can be shouldered solely by patients or insurance providers. A more feasible approach may involve the equitable distribution of additional costs among stakeholders, including government subsidies, outcome-based reimbursements, or public-private partnerships that align incentives across the healthcare ecosystem.

5.4. Clinical benefits of technological advancements for patients

The primary aim of technological advancement is to enhance human life and contribute to overall well-being. In clinical practice, the evolution of artificial intelligence (AI) and robotic surgery is not only focused on optimizing surgical procedures but also on improving patient safety, enhancing clinical outcomes, and increasing access to care. In a world with limited resources, AI technologies will play an increasingly vital role in ensuring the sustainability and efficiency of healthcare systems. To truly create value in healthcare, however, technological innovations must offer clinical benefits that clearly outweigh their costs [59]. Achieving this balance requires enabling access to safe, effective, and clinically meaningful solutions, while also preventing the adoption of ineffective or high-risk products.

These innovations enable earlier diagnosis and the delivery of personalized, data-driven treatment strategies tailored to each patient's clinical profile. AI systems can integrate medical history, imaging, laboratory values, and even genetic information to support individualized decision-making. Moreover, by simplifying complex analyses and reducing reliance on specialist availability, these systems promote more equitable access to healthcare services, especially in underserved or remote regions.

Emerging platforms such as the Metaverse may further support patient engagement and education by providing immersive experiences that help patients understand their conditions and participate actively in decision-making [60]. In cancer care, technologies like augmented reality (AR) and virtual reality (VR) enhance treatment planning by enabling physicians and patients to better visualize surgical strategies and therapeutic options. Ultimately, the true value of these technologies lies not only in clinical efficiency, but in their potential to deliver accessible, personalized, and ethically grounded care that places the patient at the center of innovation.

5.5. Current status and future perspectives

We are still far from a world in which decisions made by artificial intelligence are autonomously executed by robotic systems. The true achievement of current technological advancements lies in initiating the digital transformation of healthcare. Digitalization enables hospital systems to adapt to computerized platforms and allows data to be processed and interpreted by algorithms. This transformation facilitates the systematic collection of data, which, in turn, can generate feedback to improve future clinical outcomes. Looking ahead, the convergence of artificial intelligence with virtual and augmented reality, as well as with next-generation autonomous robotic systems, holds the potential to further revolutionize clinical workflows. Although these innovations remain largely experimental, ongoing research continues to explore their integration into routine healthcare practice.

Undoubtedly, every emerging technology is initially expensive, difficult to access, and limited in functionality. These limitations are largely driven by high research and development costs, restricted production capacity, and complex regulatory processes. However, history has shown that truly beneficial technologies eventually overcome these barriers. In our view, although these innovations have not yet fully delivered on their promises, there is no realistic alternative to advancing in this direction. To achieve a more efficient, equitable, and sustainable model of healthcare delivery, continued investment in AI and robotic surgery is essential. These systems may be far from perfect—but the path to perfection lies in their rational, ethical, and scientifically grounded development.

To provide a concise summary of the key challenges and opportunities discussed throughout the manuscript, we present Supplementary Table 4.

6. Conclusion

Each emerging technology is introduced with the promise of addressing the limitations of its predecessors. In healthcare, both artificial intelligence (AI) and robotic surgery have followed this trajectory, offering theoretical improvements in diagnostic accuracy, surgical precision, and decision-making. However, the translation of these theoretical successes into routine clinical practice remains limited, primarily due to cost-related and infrastructural challenges.

Despite these constraints, the most significant contribution of these technologies may lie in accelerating the digital transformation of healthcare systems. Our review demonstrates that clinical departments with established digital workflows are more readily able to integrate AI and robotic technologies into their practice. Nevertheless, the current trajectory of adoption falls short of the vision for equitable and sustainable healthcare. The use of these advanced technologies remains largely confined to high-income countries. For broader global integration, achieving cost-effectiveness is not optional—it is essential.

Author contributions

S.B. conceived and designed the study, supervised the research, and led the manuscript writing. A.L.Ö. conducted the literature review and contributed to data collection. N.T. prepared the tables and figures and assisted in manuscript formatting. H.C.Ö. critically reviewed the final draft and provided essential revisions. All authors read and approved the final manuscript.

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ORCID

Salih Beyaz http://orcid.org/0000-0002-5788-5116
Alaaddin Levent Özgözen http://orcid.org/0000-0002-0479-3074
Necmettin Turgut http://orcid.org/0000-0003-4994-5059
Hakkı Can Ölke http://orcid.org/0000-0002-4743-0169

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