The Review of DIABETIC STUDIES
Reprint from The Review of DIABETIC STUDIES
The Review Of
DIABETIC
STUDIES OPEN ACCESS

ML Integration In Robotic-Assisted Surgical Devices: Enhancing Precision And Reducing Human Error

Venudhar Rao Hajari

Independent Researcher, Nagpur University, India
venu.hajari@gmail.com

Abstract

The introduction of machine learning (ML) into robotic-assisted surgical machines is transforming modern surgery by adding more accuracy to it and reducing human error. Compared to traditional robotic systems, which offer mechanical stability and dexterity but lack cognitive support, machine learning (ML) introduces a transformative advantage. ML enables the system to analyse medical images, predict motion, and optimise workflow processes. These capabilities are grounded in data-driven analysis, allowing for more intelligent and efficient decision-making during robotic procedures. These characteristics allow robots to reason about complex anatomy, personalize surgical routes, and avoid risk during surgery. ML also helps the surgeons with predictive analytics, anomaly detection, and real-time decision aids in situations of high pressure. This paper introduces the idea of implementing ML in robotic surgery and compares it to the conventional and intelligent systems, algorithmic approaches to increased precision, and the effects on clinical safety. ML-based robotics is a fresh start in the sphere of surgery despite all the challenges related to the generalisation of data, ethics, and regulation.

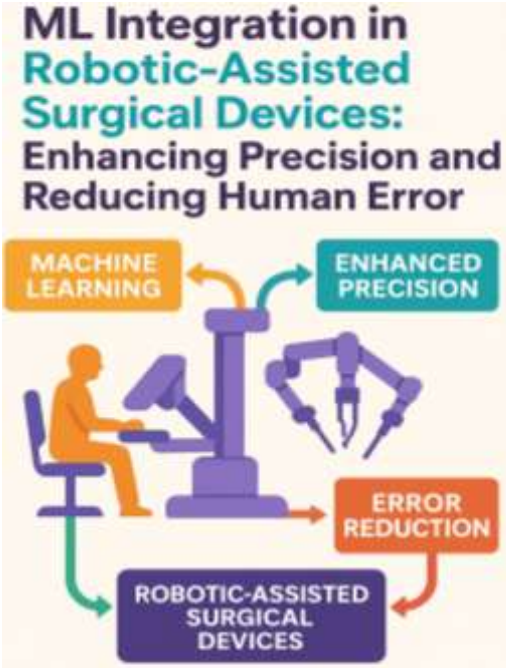
Keywords: Machine Learning; Robotic-Assisted Surgery; Surgical Precision; Human Error Reduction; Intelligent Automation.

1. Introduction

Machine learning (ML) implementation in robotically assisted surgical machines is an essential innovation in the field of contemporary medicine, which is supposed to transform surgical performance in terms of accuracy and minimise the error margin. Even the most advanced surgical techniques, refined over decades, are still susceptible to variability due to factors such as a surgeon's level of competence, fatigue, and decision-making ability. Robotic-assisted systems are already providing excellent dexterity and accessibility in difficult anatomical areas; however, the actual transformative potential is to provide intelligent algorithms capable of learning and adapting, and assisting in decision-making during surgery. The capacity of ML to manipulate large volumes of surgical data, identify trends, and forecast complications makes it a very valuable resource to robotic systems [1], [2], [3].

Moreover, the world trends, including but not limited to the growing popularity of minimally invasive surgeries, aging, and the growing number of chronic diseases, have hastened the evolution and use of smart surgical systems. They are no longer mechanical helpers but cognitive assistants (assessing real-time structured data, recommending instrument positioning, and even recommending the best procedural directions) [4, 5]. By introducing the use of supervised and unsupervised ML models, robotic-assisted equipment is emerging as more of an instrument of accuracy than an intelligent partner in the operating room. Notably, this integration not only enhances the outcomes of the procedures, but also lowers the variability in intraoperative and results of postoperative complications, which have been frequently associated with human error [6][7]. Building on these fundamental driving factors, it is essential to examine how ML tangibly enhances the functions of robotic-assisted surgery.

Figure 1: Illustration of machine learning integration in robotic-assisted surgical devices, highlighting its role in enhancing surgical precision and reducing human error.



2. Enhancing Precision through Machine Learning

As surgical procedures demand increasing levels of accuracy, ML plays a pivotal role in elevating the precision of robotic-assisted devices. One of the primary applications of ML in this context is in real-time image analysis. During operations, high-resolution imaging modalities such as MRI, CT, and intraoperative ultrasound provide crucial data. ML algorithms trained on thousands of annotated images can detect subtle anatomical differences, identify tumour margins, and guide the robotic instruments with sub-millimetric accuracy. This significantly reduces the risk of healthy tissue damage and increases the likelihood of complete pathological removal [8][9].

The accuracy of surgery can be enhanced through ML with dynamic motion prediction and adaptive control. Surgical environments are changing in nature since the organs move due to breathing, heartbeat, or body movements. The other robotics systems are manually compensated, and the systems with ML rely on the past patterns of the movements to predict them and adjust the robotic movements in real-time so that they never miss their targets. This is an adaptive characteristic that accelerates stability and reliability during laparoscopic tumour resection and cardiac ablation operations [10][11]. ML is increasingly being applied in complex surgical procedures, particularly to assist in surgical path planning. In such cases, ML algorithms help identify the optimal surgical route that minimizes tissue movement and potential damage. For instance, in neurosurgery, advanced systems analyse brain scans to determine the safest possible trajectory. These systems are designed to avoid critical structures such as major blood vessels. Moreover, the ML component learns from previous surgical outcomes. By analysing the results of past interventions, the system continuously improves its predictive capabilities, thereby enhancing the safety and effectiveness of future procedures [12][13]. Deep reinforcement learning allows surgery robots to learn through simulation and complete thousands of virtual surgeries to achieve mastery of their procedures without harming any patients [14][15]. The better a robot measures intraoperative parameters, the more they are constantly corrected by the ML algorithms, which show the immediate accuracy and long-term procedural optimization within the institutions [16][17]. As a combination of robotic dexterity and cognitive learning, ML-based systems create a goal of a continuous improvement feedback loop, which assists in bridging the gap between action and adaptive decision making. This preconditions the comparative description of the traditional and ML-integrated robotic systems as far as the capabilities that relate to precision are concerned.

Table 1: Comparison of Traditional vs ML-Integrated Robotic-Assisted Surgical Systems

Criteria	Traditional Robotic Systems	ML-Integrated Robotic Systems
Real-Time Image Processing	Static processing, limited enhancement	Adaptive, real-time segmentation
Tissue Differentiation Accuracy	Surgeon-dependent	Algorithm-enhanced precision
Instrument Path Optimization	Manual planning	AI-driven trajectory prediction
Motion Compensation (e.g., breathing)	Manual or pre-set motion filtering	Predictive modeling using live data
Learning from Past Surgeries	Non-adaptive	Continuous model refinement via feedback
Intraoperative Decision Support	Minimal	Real-time alerts and suggestions
Adaptability to Patient Variance	Limited	Highly trained on diverse datasets

As seen in this comparative table, the dynamic benefits of ML-driven systems are specifically in the capacity to learn by experience and change according to patient-specific situations. The transition of the passive aids to smart ones is a serious move in the direction of the precision of the surgery and individualisation. As we move beyond the realm of improving precision and begin to deal with the problem of human error, it is worth considering the mechanisms by which ML systems detect and correct non-standard surgical processes. This leads to the second part on the reduction of human error.

3. Reducing Human Error via Intelligent Automation

Some of the factors that contribute to human error in surgery include fatigue, poor hand visualisation, lapses of judgement, and tremors in the hands. The solution to these weaknesses is ML integration, which provides intelligent automation and decision-support facilities so that robotic systems may become safety nets. The anomaly detection algorithms are able to identify the difference in the designed protocols or the unwanted anatomy features and offer warning or prevention methods, including halting or redirecting a robotic tool to an unwanted target [18][19]. ML also optimises the preoperative planning procedures by looking into the data that is specific about the patient, like imaging, surgical history, and comorbidities, which allows individualised surgical plans and reduces the chances of complications [20][21]. All intricate visual and sensor data are refined and prioritized in operations by giving real-time suggestions, which help in intra-surgical decision-making. In orthopaedic surgery, e.g., ML can suggest optimal drilling pressure or path based on bone density and minimise risks of microfractures [22][23]. Predictive insights and cognitive support can reduce uncertainty and enable humans to reduce it, which may decrease the likelihood of uncertainty in surgery, reduce human error, and increase surgical safety and efficiency.

Robotic systems integrated with ML also contribute to surgical training and simulation. Novice surgeons can perform simulated surgeries in virtual environments where ML algorithms monitor their actions, provide feedback, and flag potential errors. This leads to better preparedness and reduces the incidence of errors in actual procedures. Additionally, post-surgical analysis supported by ML helps identify patterns of error across different procedures, thereby informing training modules and system improvements [24][25]. Another critical aspect is fatigue-related error prevention. Surgeons performing long procedures may experience physical and mental exhaustion, which is a leading cause of mistakes. ML-assisted robots, however, do not suffer from fatigue and maintain consistent performance. They can take over repetitive tasks, monitor physiological signals of the surgeon (e.g., tremors or hesitations), and prompt breaks or interventions when necessary [26][27]. Such systems ensure that surgical performance remains optimal throughout the procedure, regardless of human limitations. By acting as a cognitive extension and providing an intelligent buffer against known risk factors, ML-enabled robotic systems serve to significantly lower the margin of human error in the operating room. With both precision and safety improved, the future of robotic surgery appears increasingly autonomous and efficient.

To further complement the discussion on mitigating surgical errors, it is essential to examine the specific ML techniques employed in detecting and correcting different types of errors during surgery. The table below presents a classification of ML algorithms based on their functional application in surgical environments.

Table 2: Machine Learning Techniques for Minimizing Human Error in Robotic-Assisted Surgeries

ML Technique	Primary Function	Surgical Application Example
Convolutional Neural Networks (CNNs)	Image recognition & tissue classification	Identifying tumor margins during laparoscopic oncology
Support Vector Machines (SVMs)	Classification of abnormal patterns	Differentiating between healthy and ischemic tissues
Reinforcement Learning (RL)	Decision-making under uncertainty	Adaptive tool path correction during neurosurgery
Recurrent Neural Networks (RNNs)	Temporal sequence prediction	Predicting patient vitals deterioration intraoperatively
Anomaly Detection Algorithms	Real-time detection of procedural deviations	Alerting tool misalignment or incorrect tissue targeting
Natural Language Processing (NLP)	Understanding surgeon commands & notes	Automatic transcription of intraoperative decisions

This table shows the variety of ML applications outside the general area of automation and highlights the importance of specialized algorithms to minimize technical and cognitive errors. All these models have their role in creating a safer and smarter surgical setting, detecting and reducing divergences before they become harmful. It is now possible to discuss these technical improvements and error-reducing measures, as they allow addressing the greater implications, challenges, and future possibilities of ML-driven surgical robotics.

4. Comparative Studies: Human vs Robotic Surgery

Several comparative studies have assessed the performance differences between human surgeons and robotic-assisted systems across various surgical disciplines. While robotic surgery offers enhanced precision, stability, and consistency through machine learning integration, human-performed surgeries continue to demonstrate advantages in adaptability, tactile feedback, and intuitive decision-making. Clinical trials and retrospective studies show that robotic-assisted surgeries generally result in reduced intraoperative blood loss, shorter hospital stays, and lower complication rates for specific procedures like prostatectomy, hysterectomy, and cardiac valve repair [28, 29]. On the other hand, manual surgeries performed by experienced surgeons tend to have shorter operative times, particularly in routine or straightforward procedures where robotic setup and docking add time overhead. Moreover, human surgeons possess haptic sensitivity, which remains absent in most robotic systems, allowing better discrimination of tissue characteristics and subtle anatomical cues during complex or exploratory surgeries [30, 31]. A notable limitation in comparative studies is the learning curve associated with robotic surgery. While robotic systems reduce hand tremors and enable precise motion scaling, outcomes can vary significantly based on surgeon proficiency and institutional experience. In many comparative studies, results improve markedly after the first 20-40 robotic cases, suggesting that outcomes are closely tied to user expertise. Economic evaluations have also been included in comparative research. Robotic procedures are consistently more expensive due to high capital costs, maintenance, and consumables. For instance, a study found that robotic hysterectomies cost approximately $2,000 more per case than laparoscopic equivalents, without consistently superior clinical outcomes. In terms of decision-making, human surgeons currently outperform ML-driven robotic systems in real-time improvisation. Robotic systems, while excellent at following structured pathways and adjusting for known variables, struggle when confronted with unexpected anatomical variations or intraoperative complications requiring rapid judgment [32, 33]. Overall, comparative studies suggest that robotic surgery offers measurable advantages in specific areas of precision, recovery time, and ergonomics, while human-performed surgeries retain strengths in tactile responsiveness, decision-making flexibility, and cost-effectiveness. The most effective surgical outcomes often arise from a hybrid approach, combining human expertise with robotic precision and AI-driven insights.

5. Technological Advancements in Robotic-Assisted Surgery

Recent years have witnessed substantial technological progress in robotic-assisted surgery, largely driven by the integration of machine learning (ML), computer vision, advanced sensor systems, and cloud-based data platforms. These developments have not only enhanced the capabilities of surgical robots but have also redefined the surgeon-machine relationship, enabling a transition from mechanical assistance to intelligent surgical collaboration.

One of the most notable advancements is the incorporation of real-time image-guided navigation, powered by ML algorithms trained on large datasets of annotated surgical images. These systems can now segment organs, track surgical instruments, and recognize pathological features with sub-millimetric accuracy. Technologies such as augmented reality overlays further enhance intraoperative visualization by integrating 3D anatomical reconstructions into the surgeon's view. Another significant advancement is the implementation of reinforcement learning (RL) and simulation-based training environments. Surgical robots can now learn through thousands of virtual procedures, optimizing their decision-making without patient risk. These simulation environments also aid in training human surgeons, offering adaptive feedback, error detection, and performance analytics [34, 35]. Robotic systems are increasingly incorporating such intelligent feedback loops. Advances in force-sensing technologies and haptic interfaces have aimed to overcome one of the core limitations of robotic systems, the lack of tactile feedback. While not yet universal, some robotic platforms now include sensorized instruments that provide resistance data and simulate the sensation of touch, allowing surgeons to better assess tissue properties during procedures.

Furthermore, the integration of cloud-based surgical data repositories allows robotic systems to continuously learn and update models based on outcomes across institutions. This federated learning approach ensures that robotic systems are not limited to a single training environment, improving the generalizability of ML algorithms without compromising patient privacy. Robotics has also benefited from advances in miniaturization and modularity [36]. Modern robotic platforms are more compact, allowing easier setup in crowded operating rooms, and are increasingly modular, enabling customizable configurations based on procedural needs. These hardware innovations are accompanied by improved cybersecurity protocols, essential as surgical systems become more connected via hospital networks and cloud platforms. In sum, these technological advancements are driving robotic surgery toward a new era of autonomous assistance, predictive intelligence, and human-machine synergy, fundamentally reshaping how surgery is planned, executed, and evaluated.

6. Future Implications and Challenges

In this section, the focus is placed on the future implications, possible challenges, and the main considerations to integrate ML into robotic-assisted surgical systems. This knowledge can help inform research, clinical adoption, and policy creation, as well as to maximize the benefits of ML-based robotics, improve surgical precision, safety, and workflow efficiency, and mitigate ethical, regulatory, and operational challenges [28] [29] [30].

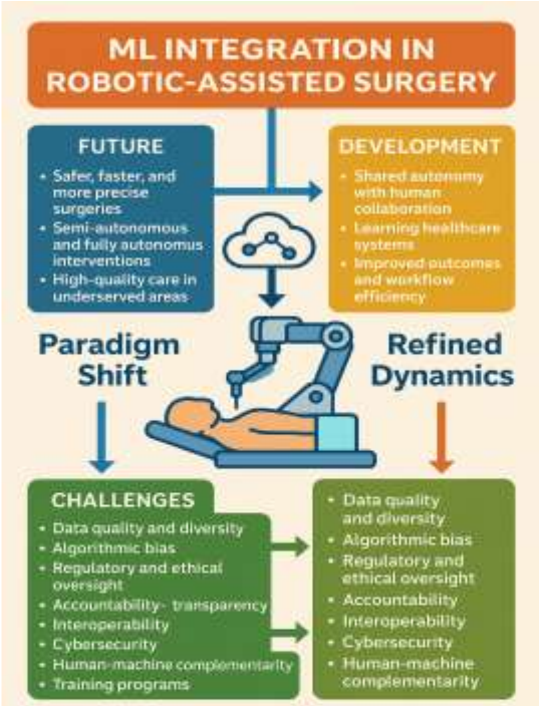


Figure 2: Color-coded infographic summarizing the integration of machine learning in robotic-assisted surgery, highlighting future opportunities, developmental advances, and key challenges such as data quality, regulatory oversight, and human-machine collaboration.

The key future implications and challenges related to ML-enabled surgical robotics are summarised in Table 3.

Table 3: Future Implications and Challenges of ML-Integrated Robotic Surgery

Category	Detailed Description	Examples / Applications	Potential Impact
Semi-/Fully Autonomous Surgery	ML-enabled robots capable of performing routine tasks or complete procedures under supervision	Automated suturing, laparoscopic tissue dissection, and catheter placement	Expands access to high-quality surgical care, especially in regions with few expert surgeons; reduces surgeon workload
Shared Autonomy	A collaborative framework where human surgeons and ML systems share decision-making and task execution	Real-time trajectory adjustment during neurosurgery; predictive alerts in cardiac ablation	Optimizes workflow efficiency, reduces cognitive burden, improves procedural safety, and improves outcomes

Data Quality & Diversity	Requirement for large, representative, high-quality datasets for algorithm training	Multi-institutional imaging datasets, diverse patient demographics	Reduces algorithmic bias, ensures generalizability, and enhances predictive accuracy across patient populations
Regulatory & Ethical Oversight	Continuous validation, monitoring, and compliance with evolving regulatory standards	FDA/CE-approved ML models, real-time audit logs	Ensures patient safety, maintains public trust, and balances innovation with ethical practice
Accountability & Transparency	Clear delineation of responsibility for decisions made or actions executed by ML-enabled systems	Decision traceability, error reporting systems	Mitigates legal and ethical risks; supports clinician oversight and informed consent
Interoperability	Integration with hospital IT infrastructure, electronic health records (EHRs), and imaging systems	DICOM-compatible imaging, HL7-compliant data streams	Enables seamless operation, avoids delays, and reduces operational errors
Cybersecurity	Protection of networked surgical systems against unauthorized access or malicious attacks	Encrypted data transmission, secure firmware updates	Safeguards patient data, prevents system manipulation, and maintains operational integrity
Human-Machine Hybrid Intelligence	Combining ML-driven automation with human expertise, judgment, and contextual decision-making	Surgeon oversight during robotic-assisted tumor resection, ML-assisted robotic orthopedic drilling	Preserves clinical intuition, enhances precision, and creates a feedback loop of continuous improvement
Continuous Learning & Feedback	ML algorithms update and refine models based on cumulative surgical data	Postoperative outcomes feeding into trajectory optimization	Improves procedural efficiency and safety over time; fosters institutional knowledge sharing

Training & Skill Development	Surgeons require education in ML systems, data analytics, and human-machine interaction	Simulation-based training, ML system tutorials, and augmented reality guidance	Ensures safe and effective adoption of ML-assisted surgery; enhances surgeon confidence and competence

7. Limitations of Robotic Surgery

While robotic-assisted surgery integrated with machine learning offers notable advancements in precision, efficiency, and safety, several limitations persist that hinder its universal adoption and optimal performance. Current robotic platforms typically do not provide tactile sensation, reducing a surgeon's ability to assess tissue resistance or texture. This deficiency can compromise delicate maneuvers and increase reliance on visual cues, thus elevating the risk of inadvertent injury. Furthermore, the steep learning curve associated with robotic surgery requires extensive training, often delaying full integration into clinical practice. From a technical standpoint, robotic systems are not immune to malfunctions. Mechanical failures, software bugs, and hardware errors can lead to intraoperative disruptions or even endanger patient safety. Machine learning models used within these systems also depend heavily on the quality and diversity of training data. Inadequate or biased datasets can lead to poor generalization, limiting effectiveness in diverse patient populations or unusual anatomical scenarios. Ethical and legal challenges also emerge with the integration of autonomy in surgical decision-making. Issues related to accountability, whether errors stem from human input, robotic systems, or AI algorithms, remain unresolved. Additionally, cybersecurity risks are heightened as these systems become increasingly interconnected, making them potential targets for data breaches or manipulation. Lastly, despite technological promise, clinical superiority over traditional surgical techniques is not universally established. In certain procedures, outcomes with robotic systems are comparable to laparoscopic alternatives, raising questions about cost-effectiveness. Overall, while ML-driven robotic surgery marks a substantial technological milestone, these limitations must be addressed to ensure equitable, reliable, and safe clinical integration.

8. Conclusion

To sum up, implementing machine learning in robotic-assisted surgery machines is one of the major technological advances in the contemporary world of medicine. ML makes robotic systems like intelligent partners instead of tools of a passive device because it increases accuracy and minimizes human errors. The advantages are evident: better accuracy of surgical operations, fewer complications, and more efficient workflows. Nonetheless, to achieve the maximum potential of such integration, it will be necessary to overcome the difficulties associated with data, regulation, interoperability, and ethics. With careful planning and interdisciplinary cooperation, ML-enabled robotic surgery can transform the standards of care and guarantee safe and efficient results for patients in the global community.

References

[1] Hussain, S. M., Brunetti, A., Lucarelli, G., Memeo, R., Bevilacqua, V., & Buongiorno, D. (2022). Deep learning based image processing for robot assisted surgery: a systematic literature survey. IEEE Access, 10, 122627-122657.

[2] Ardila, C. M., & González-Arroyave, D. (2024). Precision at scale: Machine learning revolutionizing laparoscopic surgery. World Journal of Clinical Oncology, 15(10), 1256.

[3] Guni, A., Varma, P., Zhang, J., Fehervari, M., & Ashrafian, H. (2024). Artificial intelligence in surgery: the future is now. European Surgical Research, 65(1), 22-39.

[4] Wang, Y., Jiang, Z., Kwon, S. H., Ibrahim, M., Dang, A., & Dong, L. (2025). Flexible Sensor-Based Human–Machine Interfaces with AI Integration for Medical Robotics. Advanced Robotics Research, 202500027.

[5] Wagner, M., Bodenstedt, S., Daum, M., Schulze, A., Younis, R., Brandenburg, J., ... & Speidel, S. (2022). The importance of machine learning in autonomous actions for surgical decision making. Artificial Intelligence Surgery, 2(2), 64-79.

[6] Kassahun, Y., Yu, B., Tibebu, A. T., Stoyanov, D., Giannarou, S., Metzen, J. H., & Vander Poorten, E. (2016). Surgical robotics beyond enhanced dexterity instrumentation: a survey of machine learning techniques and their role in intelligent and autonomous surgical actions. International journal of computer assisted radiology and surgery, 11(4), 553-568.

[7] Dey, R., & Mahajan, R. A. Real-Time Support-System for Decision-Making in Robotic-Surgery Using IoT Sensors and Predictive-Analytics. safety, 13, 23.

[8] Raza, H. (2024). Artificial Intelligence in Surgical Robotics: Enhancing Precision and Reducing Risk. AI Medical Nexus, 1(2), 23-34.

[9] Tanzi, L., Piazzolla, P., Porpiglia, F., & Vezzetti, E. (2021). Real-time deep learning semantic segmentation during intra-operative surgery for 3D augmented reality assistance. International Journal of Computer Assisted Radiology and Surgery, 16(9), 1435-1445.

[10] Qin, Y., Feyzabadi, S., Allan, M., Burdick, J. W., & Azizian, M. (2020, October). davincinet: Joint prediction of motion and surgical state in robot-assisted surgery. In 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (pp. 2921-2928). IEEE.

[11] Rivero-Moreno, Y., Echevarria, S., Vidal-Valderrama, C., Pianetti, L., Cordova-Guilarte, J., Navarro-Gonzalez, J., ... & Avila, G. L. D. (2023). Robotic surgery: a comprehensive review of the literature and current trends. Cureus, 15(7).

[12] Ball, T., González-Martínez, J., Zemmar, A., Sweid, A., Chandra, S., VanSickle, D., ... & Wu, C. (2021). Robotic applications in cranial neurosurgery: current and future. Operative Neurosurgery, 21(6), 371-379.

[13] Dundar, T. T., Yurtsever, I., Pehlivanoglu, M. K., Yildiz, U., Eker, A., Demir, M. A., ... & Duru, N. (2022). Machine learning-based surgical planning for neurosurgery: artificial intelligent approaches to the cranium. Frontiers in Surgery, 9, 863633.

[14] Qian, C., & Ren, H. (2025). Deep reinforcement learning in surgical robotics: Enhancing the automation level. Handbook of Robotic Surgery, 89-102.

[15] Munawar, A., Wu, J. Y., Fischer, G. S., Taylor, R. H., & Kazanzides, P. (2022). Open simulation environment for learning and practice of robot-assisted surgical suturing. IEEE Robotics and Automation Letters, 7(2), 3843-3850.

[16] Kumar, A. (2025). Reinforcement Learning for Robotic-Assisted Surgeries: Optimizing Procedural Outcomes and Minimizing Post-Operative Complication. Int. J. Res. Publ. Rev, 6, 5669-5684.

[17] Andras, I., Mazzone, E., van Leeuwen, F. W., De Naeyer, G., van Oosterom, M. N., Beato, S., ... & Mottrie, A. (2020). Artificial intelligence and robotics: a combination that is changing the operating room. World journal of urology, 38(10), 2359-2366.

[18] Zhuang, W., Masui, K., Kume, N., & Nakao, M. (2025). Unsupervised Anomaly Detection of Forceps Force by Localizing the Region of Interest. IEEE Access.

[19] Tsapin, D., Pitelinskiy, K., Suvorov, S., Osipov, A., Pleshakova, E., & Gataullin, S. (2024). Machine learning methods for the industrial robotic systems security. Journal of Computer Virology and Hacking Techniques, 20(3), 397-414.

[20] Senders, J. T., Zaki, M. M., Karhade, A. V., Chang, B., Gormley, W. B., Broekman, M. L., ... & Arnaout, O. (2018). An introduction and overview of machine learning in neurosurgical care. Acta neurochirurgica, 160(1), 29-38.

[21] Banbhrani, S. K., Akhter, M. N., Noureen, F., & Talpur, M. S. H. (2025). How AI is revolutionizing healthcare: from personalized medicine and diagnostic tools to drug discovery and robot-assisted surgery. Social Science Review Archives, 3(1), 2693-2709.

[22] Wong, S. W., & Crowe, P. (2024). Cognitive ergonomics and robotic surgery. Journal of Robotic Surgery, 18(1), 110.

[23] Budhiparama, N. C., Kort, N. P., Kort, R., & Lumban-Gaol, I. (2025). The future outlook for data in orthopedic surgery: A new era of real-time innovation. Journal of Orthopaedic Surgery, 33(1), 10225536251331664.

[24] Mirchi, N., Bissonnette, V., Yilmaz, R., Ledwos, N., Winkler-Schwartz, A., & Del Maestro, R. F. (2020). The Virtual Operative Assistant: An explainable artificial intelligence tool for simulation-based training in surgery and medicine. PloS one, 15(2), e0229596.

[25] Qian, C., & Ren, H. (2025). Deep reinforcement learning in surgical robotics: Enhancing the automation level. Handbook of Robotic Surgery, 89-102.

[26] Paul, R. A., & Pandya, A. (2025). A System for Surgeon Fatigue Monitoring in Robotic Surgery. Robotics, 14(4), 40.

[27] Costa, M. (2019). Detecting driver's fatigue, distraction and activity using a non-intrusive ai-based monitoring system. Journal of Artificial Intelligence and Soft Computing Research, 9(4), 247-266.

[28] Childers, C. P., & Maggard-Gibbons, M. (2018). Estimation of the acquisition and operating costs for robotic surgery. Jama, 320(8), 835-836.

[29] Barbash, G.I. and Glied, S.A., 2010. New technology and health care costs—the case of robot-assisted surgery. New England Journal of Medicine, 363(8), pp.701–704.

[30] Boutros, C. S., Kim, M. J., & Diasty, M. E. (2025). The learning curve of robotic cardiac surgery: a scoping review. Journal of Robotic Surgery, 19(1), 476.

[31] Lenihan, J.P., Kovanda, C. and Cammarano, C., 2008. What is the learning curve for robotic assisted gynecologic surgery? Journal of Minimally Invasive Gynecology, 15(5), pp.589–594.

[32] Wright, J. D., Ananth, C. V., Lewin, S. N., Burke, W. M., Lu, Y. S., Neugut, A. I., & Hershman, D. L. (2013). Robotically assisted vs laparoscopic hysterectomy among women with benign gynecologic disease. JAMA, 309(7), 689–698.

[33] Bergholz, M., Ferle, M., & Weber, B. M. (2023). The benefits of haptic feedback in robot assisted surgery and their moderators: a meta-analysis. Scientific Reports, 13(1), 19215.

[34] Xie, X., Tian, Y., Huang, J., Luo, Q., & Chen, T. (2025). Surgery without distance: will 5G-based robot-assisted telesurgery redefine modern surgery?. Translational Lung Cancer Research, 14(5), 1821.

[35] Jamjoom, A. A., Jamjoom, A. M., Thomas, J. P., Palmisciano, P., Kerr, K., Collins, J. W., ... & iRobotSurgeon Collaboration. (2022). Autonomous surgical robotic systems and the liability dilemma. Frontiers in Surgery, 9, 1015367.

[36] Schreuder, H. W., Wolswijk, R., Zweemer, R. P., Schijven, M. P., & Verheijen, R. H. (2012). Training and learning robotic surgery, time for a more structured approach: a systematic review. BJOG: An International Journal of Obstetrics & Gynaecology, 119(2), 137-149.