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Enhancing Operating Room Surgical Efficiency through Artificial Intelligence: A Comprehensive Review

Alejandro Espaillat*

South Florida Eye Institute, Fort Lauderdale, Florida, USA.

[*]Correspondence:
Alejandro Espaillat, M.D., 6233 N. University Drive, Fort Lauderdale, FL 33321, Telephone: 954-721-0000.

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ABSTRACT

Operating rooms are critical in delivering healthcare services, yet they often face efficiency and resource management challenges. In recent years, integrating artificial intelligence (AI) technologies has shown great potential in optimizing operating room operations. This review article provides a comprehensive analysis of AI's latest advancements and applications in enhancing operating room efficiency in forecasting the duration of surgical cases, maximizing the allocation of resources in the post-anesthesia care unit, and identifying instances of surgical case cancellations. Various AI-enabled solutions such as predictive analytics, robotic surgery, and intelligent scheduling systems are discussed, as well as augmented reality, highlighting their impact on improving patient outcomes, reducing costs, and saving valuable time for healthcare professionals. Furthermore, challenges and future directions in AI-driven operating room management are also explored to provide insights for further research and implementation.

Keywords

Operating room efficiency, Artificial intelligence, Predictive analytics, Robotic surgery, Intelligent scheduling, Healthcare management, Augmented reality.

Introduction

The operating room (OR) is a crucial component of any healthcare facility, where complex surgical procedures are performed to treat various medical conditions. However, OR operations are often characterized by high costs, inefficiencies, and resource constraints, leading to challenges in delivering timely and cost-effective patient care [1]. In recent years, AI has emerged as a promising technology to address these challenges and enhance the efficiency of ORs [2,3]. By leveraging AI-driven solutions, healthcare providers can optimize surgical workflows, improve patient outcomes, and streamline resource allocation in the OR environment [4-6]. This review article aims to provide an in-depth analysis of how AI is transforming OR management and shaping the future of surgical care.

AI Fundamentals

AI is a field of computer science that involves using mathematical models to train computers to solve problems by simulating human thinking processes when the models are trained correctly [7]. Machine learning (ML) is a subset of AI that allows computers to make predictions using patterns in data, and deep learning (DL) is a form of ML [8,9]. In recent years, AI has been effectively utilized in medicine [11]. Surgical Data Science focuses on applying AI to surgical practice to enhance the quality of healthcare delivery through data collection, organization, analysis, and modeling [11]. AI can be used in surgery for various purposes, such as providing automated skill assessment during training [12], implementing automated procedures in robot-assisted surgery (RAS) [13], facilitating intra-operative navigation [14], and detecting errors early to improve patient outcomes [15].

- **AI and Surgical Workflow:** One crucial factor affecting surgical costs is the operative time (OT). Accurate prediction of OT can improve workflow. Zhao et al. developed an ML model to predict case duration for robotic surgery based on factors like patient characteristics, procedure type, robotic system model, and tableside assistant expertise [16]. Analyzing 424 robotic procedures, the model increased prediction accuracy by 16.8%, impacting OR resource utilization. Additionally, automated assessment of surgical skills and kinematic data showed predictive value for surgical outcomes, as demonstrated in a study by Hung et al. analyzing features from robotic surgery recordings [17]. ML models accurately predicted patient outcomes like OT and catheter duration, showing the potential role of metrics like camera manipulation in indicating robotic surgical expertise and optimizing logistics and workflow.

- **AI and Surgical Scheduling Optimization:** Scheduling operative procedures by averaging the last 10 case times often leads to 50% of cases running over time due to the variability in case durations [18]. This variability can create a domino effect of delays across ORs. An optimization model is proposed to address this issue with decision variables for each procedure type constrained by historical case time data. An OR is deemed to be running over time if the total of actual procedure times and changeovers surpasses the scheduled duration for the day, while it is considered to be running under time if procedures finish more than 15 minutes ahead of schedule [19].

Rozario et al. applied an ML algorithm to optimize OR booking times using a custom Python script and the OR-Tools software from Google AI (a division of Alphabet Inc.). This approach led to a personalized model that improved OR efficiency, reducing nursing overtime by 21% and potentially saving $469,000 over three years [19]. Predicting operative booking times at a lower cost is essential for maximizing OR efficiency. In upcoming models, real-time predictions could be implemented to anticipate changes in case completion times due to factors like intraoperative complications [20]. Surgeon estimations of case times are often inaccurate, and relying on historic mean times does not account for the variability of cases and can lead to inefficiencies. An average of only 10 cases can introduce errors due to the small sample size, and outlier cases can skew booking times.

In contrast, an ML model considers average case times, variability, procedure types, and surgeon-specific data to calculate scheduling times that optimize OR efficiency. As more data is integrated into the model, estimates of case times are expected to become even more precise, free of bias, and based on objective evidence. Adopting this method may require programming knowledge and acceptance from all involved parties.

- **AI and Streamlining of Resource Allocations:** Bellini et al. [21] systematically reviewed the literature to explore the impact of new technologies on OR management and administration in the perioperative period. The review focused on studies involving adult patients from 2015 to February 2019. Out of 19 papers reviewed, it was found that ML shows promise in enhancing OR organization. ML accurately predicts surgical case durations, enabling more efficient scheduling and resource utilization. ML can support complex models to coordinate multiple spaces simultaneously, such as ORs and post-anesthesia care units. Certain types of AI algorithms can help address the issue of surgery cancellations by identifying high-risk cases using methods like Random Forest, allowing for preventive measures to be planned. While the current literature on the subject is limited, the potential for ML in optimizing OR organization is significant, but further research is needed to understand its full impact in perioperative medicine.

- **AI and Surgical Skill Assessment:** The need for proper surgeon training and evaluation has increased due to concerns about surgeon proficiency and the rise of robotic surgery [22,23]. New training models have been developed to address the specialized skills required for robotic techniques [24]. These models incorporate various methods such as dry lab, wet lab, mentoring, and actual clinical practice under experienced supervision [25]. However, current assessment methods need more objectivity and consistency, highlighting the need for objective evaluation metrics to provide unbiased assessments of trainees' performances [26].

An automated and quantitative assessment of surgical skills can be achieved using ML algorithms that analyze motion, energy, and force. These tools can provide feedback during a surgeon's learning process and for periodic credential evaluations. Fard et al. conducted a study using ML to analyze the robotic surgery skills of eight surgeons, showing that the algorithm could accurately differentiate between novice and expert surgeons [23]. Another study by Wang et al. used a DL model based on artificial neural networks (ANN), achieving over 90% accuracy in assessing robotic surgical skills within seconds [27]. More research is needed to validate these models on a larger scale. Ershad et al. introduced a new ML approach skills assessment focused on analyzing surgeons "movement style." They gathered kinematic data from 14 surgeons of varying experience levels in robotic surgery, tracking movements during simulator training tasks [28]. The surgeons' movement styles were categorized based on descriptive adjectives and then used to train a classifier model. This method significantly increased skills level classification accuracy compared to raw kinematic data analysis. Considering qualitative motion features that are surgeon-specific rather than task-specific, this approach offers a potential advantage in skill assessment without requiring expert surgical interpretation.

AI systems can assist experienced surgeons by enhancing the visualization of anatomical structures during surgery through augmented reality technology [17]. When 3D reconstructions of the surgical site are accurately overlaid onto the patient's anatomy, it improves the understanding and navigation of the surgical field [29].

- **AI and Robotic Surgery:** In the medical field, DL has shown success in tasks like predicting cardiovascular risk from retinal images [30], classifying skin lesions [31], and detecting breast cancer from mammograms [32]. However, the full potential of AI in surgery has not been realized due to unique challenges [33]. Unlike static image analysis, surgery involves dynamic procedural data in an environment with various components like the patient, devices, sensors, and the surgical team, requiring domain knowledge and real-time processing. The need for large annotated datasets for training DL models poses a challenge, especially in surgery. Surgical data science aims to enhance interventional healthcare quality using AI methods for tasks such as decision support, context-aware assistance, and cognitive robotics along the surgical path [34].

Operating theaters today contain numerous sources of information. Before surgery, images and planning data show lesion locations and the intended procedure. Various medical devices report status updates, such as suction systems, operating lights, and anesthesia monitors. Intraoperative imaging tools like microscopes, endoscopes, and ultrasounds capture real-time data on the patient and ongoing processes in the OR. These diverse sensors provide essential information for understanding the surgery's progress and offering timely assistance, known as "context-aware assistance [35]." This approach aims to prevent information overload and reduce cognitive strain, especially in high-pressure and complex OR environments. A sensor-enhanced OR (SensorOR) is necessary to enable this assistance, where all devices are interconnected to gather their data efficiently.

AI has the potential to revolutionize robot-assisted surgery by moving towards cognitive-surgical robotics. While current surgical robots are mainly controlled by surgeons without autonomous capabilities, research has shown advancements in automatic needle insertion, suturing, and bowel anastomosis using robotic systems [36,37]. However, these systems need a deeper understanding of the surgical environment and need to adjust to the surgical workflow. Further developments in surgical scene understanding and workflow analysis are necessary to enable cognitive surgical robots to perform tasks like controlling cameras or conducting complex surgical procedures autonomously. Once robots can comprehend their surroundings and learn from experience using AI technology, they can enhance their performance and efficiency in the OR.

- **AI and Augmented Reality**: Augmented reality (AR) is a technology that enriches the real-world environment with computer-generated information in real time, utilizing all senses, including sight, hearing, smell, and touch [29,38]. In addition to overlaying virtual elements onto the physical environment, AR applications can also involve modifying or altering real-world objects, known as mediated reality or diminished reality [39]. Unlike virtual reality (VR), which transports users into entirely virtual environments, AR integrates digital information into the natural world to enhance the user's perception and interaction with reality. AR has advanced quickly and found applications in diverse fields such as medicine and cultural heritage [40]. The healthcare sector, in particular, has embraced AR for various uses, including medical education, surgical navigation, and gastrointestinal endoscopy [41,42]. Ophthalmology, which heavily relies on visual perception, is closely associated with AR technology. AR shows great promise in treating ocular diseases causing visual field defects, color vision deficiency, low vision, blindness, nyctalopia, amblyopia, and metamorphopsia, offering non-invasive and user-friendly alternatives for patients who cannot undergo traditional medical or surgical procedures [43-48]. Apart from therapy, AR is also used for education, clinical support, and surgery in ophthalmology [49].

Traditional ocular surgery has long relied on monocular and binocular ophthalmic surgical microscopes dating back to the early 20th century. While the quality of microscopes has steadily improved over time, the core imaging technology has mainly remained the same. In recent years, there have been significant advancements in three-dimensional (3D) digital visualization platforms that are alternatives to traditional microscopes [50]. These systems offer improved resolution, magnification, and depth of field, contributing to enhanced surgical precision, surgeon comfort, and expanded teaching opportunities [51]. However, existing heads-up systems require specific viewing conditions and lack the immersive experience of standard microscopes. A newer 3D digital visualization ophthalmic exoscope platform, equipped with a surgeon-worn AR/VR surgical headset named Beyeonics One, is also commercially available. (*Beyeonics Vision in Haifa, Israel*). This advanced system offers a binocular visual field comparable to that seen through a traditional optical microscope while also providing digital enhancements, improved ergonomics, and augmented reality functionalities [49,52,53] (Figure 1). The 3D digital ophthalmic exoscope comprises critical components: the surgical headset unit for a 3D surgical view, which adjusts to the surgeon's head size and utilizes motion sensors for precise head control of images; the main suite housing ultra high-definition 4K cameras, a semi-robotic arm unit, and a processing unit with a touchscreen display; and a foot pedal with programmable buttons and standard microscope controls (Figure 2). This system allows for two surgical headsets to be used simultaneously for the surgeon and assistant/observer to view surgery in 3D, with the option of adding supplemental screens for additional observers (Figure 3).

- **AI and Improvement of Patient Surgical Outcomes**: Postoperatively, AI technology can significantly enhance patient management. Deciding when patients can be safely discharged is complex, often requiring simultaneous analysis of multiple variables. Accurate identification of the most vulnerable patients is crucial to tailor monitoring strategies. Mišic et al. [54] introduced an ML model predicting the risk of 30-day readmission post-surgery, demonstrating vital performance metrics with area under the curve values between 0.85 and 0.87. Remarkably, these predictions can be made within the first 36 hours post-surgery while the

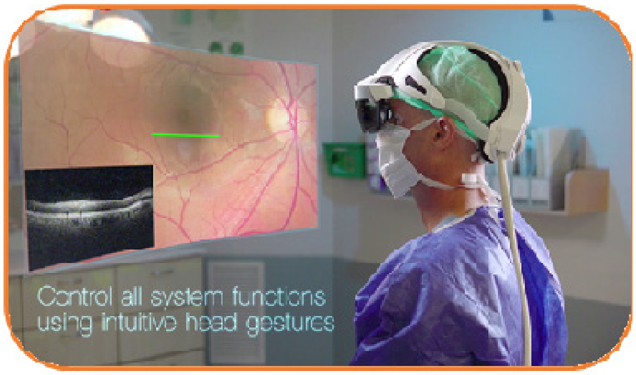

Figure 1: Augmented reality system delivering binocular visual field similar to a traditional optical microscope, enhanced with digital features, improved ergonomics, and augmented reality capabilities (Beyeonics One. Beyeonics Vision in Haifa, Israel).

Figure 2: Ophthalmic Exoscope Platform Overview (Beyeonics One. Beyeonics Vision in Haifa, Israel).

Figure 3: The Ophthalmic Exoscope system enables the surgeon and assistant/observer to view surgery in 3D via individual head units, with optional supplemental screens for additional viewers. (Images courtesy of R. Weinstock, MD, A. Lowenstein, MD).

patient is still hospitalized. AI can also re-evaluate discharge timings, as Yang et al. [55] showed that nighttime intensive-care-unit discharges may increase hospital mortality risk. In postoperative care, AI applications can identify safe discharge criteria and predict surgical and non-surgical complications that preoperative assessments cannot foresee. The accuracy of these predictive models improves with more comprehensive data inputs from preoperative, intraoperative, and postoperative phases [56].

- **AI and Hospital Postoperative Readmission Reduction:** Unplanned hospital readmissions that could have been prevented significantly burden patients and the healthcare system [57]. Estimated to cost $41.3 billion annually, reducing these readmission rates is a top priority [57]. In 2012, the Centers for Medicare and Medicaid Services (CMS) introduced the Hospital Readmissions Reduction Program (HRRP) in response to a push for higher healthcare quality [58]. Through this program, hospitals face penalties in the form of reduced Medicare reimbursement rates based on their 30-day readmission rates. This has prompted hospitals and researchers to dedicate considerable efforts to identifying and addressing factors within their control that contribute to readmissions [59]. ML involves computer programming that enables automatic learning and enhancement of data interpretations without direct human intervention. These sophisticated computing techniques offer the ability to rapidly process extensive data sets and determine optimal predictive features. The widespread use of big data and ML enables healthcare professionals to utilize these analytical tools to comprehend intricate relationships better and identify predictive elements that can be applied to upcoming patients [60,61]. Prior research has examined how ML algorithms impact the forecasting of hospital readmission within 30 days following posterior spinal fusion surgery [62]. Their deep neural network (DNN) predicted 60% of the readmissions and presented novel findings relevant to the HRRP. The model was robustly able to predict the patients who would not require readmission but struggled to predict which patients with borderline characteristics would need readmission accurately.

Similarly, their DNN initially was able to claim roughly a 60% true positive rate of readmission for the given cutoff values while still boasting no false positives. These findings suggested that while difficult to predict in overall terms, up to 60% of all hospital readmissions were evident to the model and were easily separated from the non-readmitted patients. Only 40% of readmitted patients were, in turn, left to have questionable characteristics that may be difficult to classify by their predictive metrics. These findings suggested that a high percentage of patients who require readmission have poor prospective predictability. While most patients were identified with their ML algorithm, those not recognized by the algorithm may present difficulty in management, as there may need to be a logical way to stratify them by risk. As a result, rather than penalizing hospitals for the readmission rates of all patients, it may be more prudent to separate those who have an identifiable risk profile for complications from those who do not (nonidentifiable risk profile) before imposing penalties (as their model was able to expect 60% of readmissions without any false positives accurately) [62].

The current payment model incentivizes hospitals to limit or even avoid admitting high-risk patients to minimize penalties and high readmission rates. Legislation that would change the current penalties for readmission could allow treatment of this specific high-risk subset, further ensuring that these patients receive the appropriate care and discharge plan. Instead of penalizing hospitals for any readmission, it may be possible to penalize only those readmissions predicted to be extremely unlikely. Therefore, it eliminates adverse selection as a reason for bias in surgical patient care.

Challenges and Future Directions

While AI promises to improve OR efficiency, several challenges must be addressed to ensure successful adoption and implementation. Data privacy and security concerns, regulatory hurdles, interoperability issues, and limited access to high-quality data are critical challenges healthcare organizations may face when integrating AI solutions into OR operations. Furthermore, ensuring seamless integration of AI technologies with existing healthcare systems and workflows requires careful planning, technical expertise, and stakeholder engagement.

In the future, continued research and development in AI-driven OR management will be essential to unlocking the full potential of these technologies. Advancements in ML, NLP, computer vision, and robotics will further enhance the capabilities of AI systems in optimizing surgical workflows, predicting patient outcomes, and improving decision-making processes in the OR environment. Collaborations between healthcare providers, technology companies, researchers, and regulatory bodies are crucial to driving innovation, addressing challenges, and fostering the widespread adoption of AI in OR operations.

Conclusion

Big data analytics is expected to save between $300 billion and $450 billion annually in the US healthcare system, incentivizing the integration of AI and big data into various healthcare aspects [63]. Surgeons can play a crucial role in driving these innovations. Surgeons should expand their involvement in clinical data registries at different levels to enhance AI's predictive capabilities. Improving data cleaning techniques can further link registries, broadening their utility and increasing access to diverse data types. Surgeons partnering with data scientists can capture and interpret new clinical data forms, using their clinical expertise to guide data-driven questions and solutions. This collaboration can improve global surgical practices and patient outcomes by leveraging AI to aggregate surgical knowledge akin to genomics efforts. Ultimately, big data can help develop a "collective surgical consciousness," providing technology-augmented real-time clinical decision support.

In conclusion, AI offers tremendous opportunities to enhance the efficiency of ORs and improve the overall quality of surgical care. By leveraging AI-driven solutions such as predictive analytics, robotic surgery, and intelligent scheduling systems, healthcare providers can optimize resource allocation, streamline surgical workflows, and deliver high-quality care to patients. While challenges exist in implementing AI technologies in the OR environment, ongoing research and collaboration efforts hold the key to realizing the full potential of AI in transforming OR operations. As technology evolves, healthcare organizations must stay abreast of the latest developments in AI and embrace innovation to drive positive changes in surgical care delivery.

Author Contribution

Writing, editing, reviewing, conceptualization, and supervision, AE.

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