

The Use of Artificial Intelligence for Orthopedic Surgical Backlogs Such as the One Following the COVID-19 Pandemic

A Narrative Review

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Abstract

- The COVID-19 pandemic created a persistent surgical backlog in elective orthopedic surgeries.
- Artificial intelligence (AI) uses computer algorithms to solve problems and has potential as a powerful tool in health care.
- AI can help improve current and future orthopedic backlogs through enhancing surgical schedules, optimizing preoperative planning, and predicting postsurgical outcomes.
- AI may help manage existing waitlists and increase efficiency in orthopedic workflows.

Introduction: COVID-19 and the Surgical Backlog

COVID-19 was pronounced a global pandemic in March 2020, leading to significant stress on the US health care system¹. Resources were reallocated to treat infected patients and prevent further infection, causing a widespread limitation to elective surgical services². Every surgical field was affected, and over 28 million surgeries were estimated to be delayed or canceled worldwide secondary to the pandemic^{3,4}. Elective surgeries were drastically reduced, leading to numerous potential problems in the postpandemic health care landscape⁴.

Orthopedic surgeries were one of the most impacted surgical specialties with over 80% being canceled during the initial 3 months of the pandemic³. Although surgical volumes returned to prepandemic baselines⁵, delays in surgical care caused distress for patients and health care systems⁶. Jain et al. studied arthroplasty and spinal fusion cases in 2020, estimating 7 to 16 months to return to 90% of prepandemic surgical volumes, with over 1 million cases awaiting completion after episodic stoppages of elective surgery during 2 years of the pandemic⁷. Another 2020 study modeled a one-time, 3-month shutdown and predicted, the best case scenario, the health care system would require 16 months to clear the backlog on total knee arthroplasties (TKA) alone, with some of the approximately 300,000 deferred patients during the pandemic waiting over 6 months for a procedure, also leading to extended wait times for new surgical patients⁶. These quantitative models, while interesting, may not be generalizable to the entirety of orthopedics. More recently, a study using data through April 2021 found a backlog of 26,412 knee procedures and 26,412 shoulder procedures, a number that steadily increased despite return to prepandemic surgical volumes⁸. With demand for procedures such as arthroplasties projected to increase over the coming years⁹, these backlogs could worsen if not appropriately and quickly addressed. It is difficult for the current health care system and surgeons to increase surgical volume for delayed patients while also keeping pace with the needs of new patients.

The postpandemic backlog may also potentially cause significant health care distress. Cisternas et al. reviewed studies discussing potential consequences of increased surgical wait time on orthopedic patients, which include poorer postoperative outcomes¹⁰, potential for opiate dependence¹¹, and worsening of functional abilities and other comorbidities $6,12,13$. Patients suffering from canceled orthopedic procedures reported increased pain, analgesic use, and psychological distress¹⁴. In the United States, the estimated loss of net income for hospitals was between \$4 and 5.4 billion per month¹⁵, and surgical providers have reported increased stress¹⁶. The backlog strains the health care system, both from a provider and patient

Disclosure: The Disclosure of Potential Conflicts of Interest forms are provided with the online version of the article [\(http://links.lww.com/JBJSOA/A668\)](http://links.lww.com/JBJSOA/A668).

Copyright 2024 The Authors. Published by The Journal of Bone and Joint Surgery, Incorporated. All rights reserved. This is an open access article distributed under the terms of the [Creative Commons Attribution-Non Commercial-No Derivatives License 4.0](http://creativecommons.org/licenses/by-nc-nd/4.0/) (CCBY-NC-ND), where it is permissible to download and share the work provided it is properly cited. The work cannot be changed in any way or used commercially without permission from the journal. perspective, and will continue to until it can be addressed safely and efficiently.

The Rise of Artificial Intelligence in Orthopedic Surgery

A rtificial intelligence (AI) involves computer algorithms to
solve problems using pattern recognition¹⁷. Various subtypes exist. Machine learning (ML) allows computers to recognize patterns in data sets and can be either guided by human labeling and feedback (supervised) or permitted to repeatedly find patterns on their own (unsupervised)^{18,19}. Within ML, deep learning (DL) is a more complex system using many layers of algorithms, called artificial neural networks (ANNs), with many times the parameters of ML¹⁷.

Publications discussing AI and its applications in orthopedics have sharply increased recently¹⁸. Predicted uses include radiologic advances, data extraction from medical records, improved resident training, and algorithms predicting patient clinical courses²⁰. Although likely years away, AI may be used with robotics to improve the efficacy of surgery itself²¹. As outlined by Farhadi et al., AI may also afford health care systems increased efficiency, including improved workflow, postoperative complication prediction, and increased intraoperative precision 18 .

This review discusses how these and other applications of AI might be leveraged to ease the surgical backlog of orthopedic procedures caused by COVID-19. Applying this technology may also provide new workflows to help surgeons accommodate the increasing need for orthopedic procedures in our aging population.

Improved Surgical Scheduling

Wumerous studies have sought to optimize surgical sched-
willing and decrease operating room (OR) delays²²⁻²⁵. Financially, hospitals desire improved efficiency because the OR generates substantial revenue. A large 2023 study found over 60% of elective surgeries were scheduled for longer durations than needed, with a median overestimation of 29 minutes. In addition, 37% of surgeries were scheduled for shorter durations than needed, with a median underestimation of 30 minutes 26 . Both affect workflow, with overestimation leading to inefficient OR usage and underestimation causing case cancelations and rescheduling.

Inputting procedural characteristics with patient and surgeon profiles within AI could allow more accurate predictions of surgical operating times. Zaribafzadeh et al. developed a ML program with this technique²⁷. They analyzed a large set of surgical case data to develop historical norms using numerous variables, including age, sex, surgeon-predicted case length, and relative value units of the case. They then developed a 3-step similarity cascade to compare new cases with existing data and predict future operating times. The ML model was used conjunctively by surgical schedulers and allowed 4.3% fewer underpredicted cases and a 3.4% increase in cases scheduled within 20% of the actual length, with just a 1% increase in overpredicted cases. While the improvements now are small, AI's effectiveness in scheduling may increase with time.

Other studies have similarly used ML to generate improved surgical scheduling²⁸⁻³¹. Jiao et al. found their ANNs made lower time error than a Bayesian approach, an established statistical method of making updated decisions based on new information³¹. Another study created 2 ML programs and found the surgeon-specific scheduler was more accurate than the specialty-specific scheduler, indicating individual surgeons may be more important in estimating case time than specialty grouping²⁸. Although likely well known in the surgical community, AI may provide tools to better analyze it and correctly adjust scheduling to improve OR utilization. Although many of these ML programs are still in infancy, their precision may continue to improve as they are provided with and respond to more data.

With both TKA and total hip arthroplasty (THA) being removed from the Medicare inpatient-only list, there is increased focus on day surgery arthroplasty procedures at ambulatory surgical centers. Appropriate selection of patients for outpatient arthroplasty surgery could minimize complications and increase case volume. Lopez et al. developed a ML model for selecting patients based on numerous modifiable and nonmodifiable factors and achieved relatively high predictive and discriminative value for same-day discharge³². As an increasing proportion of surgeries are now performed outpatient settings, identifying patients well-suited for same-day discharge could ensure more efficient scheduling of surgeries.

The practical concern is whether this will truly allow additional case volumes. Improved OR turnover time is not always significant enough to enable an additional case in a day³³. Despite a paucity of data to prove AI will increase scheduled surgeries, the technology should become more efficient and grow in its applications. As AI further develops, it may also be applied to resource allocations and aid surgeons inside and out of the OR.

In addition, ML programs may dynamically adjust to changes in scheduling better than manual schedulers, providing rapid responses to the unpredictable nature of the OR. Finally, significant benefit may simply exist in preventing cancelations. Over 11% of orthopedic cases are canceled with over half citing lack of time as the primary reason³⁴. Preventing case cancelation through improved scheduling itself could help improve the backlog.

Preoperative Planning

Considerable time and resources are spent planning or-
thopedic surgeries. First, the patient must be clinically evaluated to determine if operative treatment is warranted. ML has been used to accurately determine whether a patient should undergo surgery in hip complaints using the hospital data³⁵. While AI should not replace provider judgment and caution is necessary to avoid a biased clinical assessment, it could prove a valuable tool in increasing efficiency in clinic visits, allowing providers to assess more patients.

Once surgical necessity is determined, imaging is often used to plan component size and position³⁶. Allowing AI to help draft, preoperative plans could optimize the planning process. Lambrechts et al. found preoperative AI-generated TKA plans required 39.7% fewer adjustments by the surgeon compared with standard manufacturer-provided plans³⁷, allowing surgeons to develop patient-specific surgical plans more quickly. Adjacently, considerable interest surrounds using patient-specific instrumentation (PSI) in arthroplasties to decrease waste and provide more personalized prostheses. Overall, PSI has not been shown to be cost-effective and can be time-consuming both developmentally and intraoperatively if changes are necessary³⁸⁻⁴⁰. In 2023, Li et al. used neural network structures to accurately interpret computed tomography (CT) images and provide more accurate specifications for PSI for TKA without increasing preoperative time⁴¹. By quickly providing accurate PSI measurements, AI could decrease time spent in the OR trialing different component sizes.

Will increased efficiency in preoperative planning translate to more procedures and a decreased surgical backlog, though? Prior analyses have generally found approximately a 5 minute reduction in surgical time when using PSI compared with standard instrumentation^{38,39,42,43}. This change alone would likely not be sufficient to add additional surgical cases. The previously mentioned study using CT imaging found their model took approximately 3.74 ± 0.82 minutes for the CT interpretation and 35.10 ± 3.98 minutes for the PSI design, compared with a respective 128.88 ± 17.31 minutes and 159.52 $±$ 17.14 minutes for standard methods⁴¹. This represents a significant reduction in time to generate PSI. Hopefully, as AI models improve, surgeons' preoperative planning time will continue to decrease, and intraoperative time will decrease as implants become more precise and require fewer adjustments. Together, this may become efficient enough to increase weekly surgical volumes.

Predicting Postsurgical Outcomes

 $\bigcup_{\text{supery, and the risk of potential complications has been}$ excellently summarized by several review articles^{18,20,44,45}. This can be useful for identifying which patients may require planned, extensive care or control of comorbidities. ML has been used to effectively predict improvement after THA using partially modifiable risk factors, which could help providers optimize patient health before surgery⁴⁶. Failure to improve postoperatively or readmission both divert resources from future surgeries and may be minimized by appropriate planning and risk reduction. Another application of ML includes studies predicting length of hospital stay for arthroplasty patients^{47,48}. Valid estimates of length of stay translate to more efficient hospital scheduling and optimization of procedural volume. Overall prognosis and morbidity are important, too, not just for hospital efficiency but also for patient safety. ML models were used retrospectively to demonstrate superior prediction of mortality and adverse events following spine surgery⁴⁹. These models may even identify patients at too high risk for adverse events from surgery. AI could prevent poor surgical candidates from being scheduled and increase availability for better candidates that will benefit from surgery.

Numerous complications of orthopedic surgery can occur and may require dedicated follow-up⁵⁰. Revision arthroplasty is often time-consuming with significant resource burden⁵¹. ML programs have predicted major complications from THA more effectively than current risk calculators⁵⁰. Similarly, programs have accurately predicted the risk of postoperative falls, allowing for implementation of fall prevention measures⁵². Postsurgical falls represent a significant resource burden and can result in complications such as pain, wound dehiscence, dislocation, and fracture⁵²⁻⁵⁵. Fall prevention measures are economically beneficial⁵⁶ and will decrease the need for additional office visits, revision surgery, or fracture care, allowing orthopedists to focus on new elective procedures.

The effectiveness of predicting postsurgical outcomes on overall case volume is difficult to report. However, it makes intuitive sense that hospitals that are well-planned for potential complications can achieve greater efficiency with their resources. Predicting length of stay particularly could work in conjunction with AI-influenced surgical scheduling to improve OR efficiency.

Managing Waitlists

The surgical waitlist itself could be a target for AI. Researchers in China developed an AI-assisted module to help patients order necessary laboratory and imaging tests automatically based on their symptoms before the clinical evaluation⁵⁷. This algorithm used DL to analyze medical records and develop likely diagnostic classifications based on patient clinical features. While this incurs the risk of burdening the system with unnecessary testing and should not replace a clinical visit, similar modules could be helpful for primary care physicians and mid-levels to improve the workup for orthopedic referrals. These modules could help providers work through an orthopedic-specific workflow, guiding them through an algorithm for orthopedic visits akin to one used in orthopedic office visits and better identify surgical candidates. This could reduce nonoperative visits for orthopedists and allow them to see more surgical patients.

With a waitlist, prioritizing patients appropriately is important to minimize harm and maximize resources. Considerable research involves ethical methods of prioritizing elective surgical candidates⁵⁸. This has been of increasing interest to countries like the United Kingdom that have dealt with ongoing waitlists worsened following the COVID-19 pandemic⁵⁹. Researchers from the United Kingdom undertook a pilot study with their augmented intelligence system, COMPASS, to aid in prioritizing surgical candidates⁵⁹. Although only 29 patients were included, they found significantly decreased rates of complications and mortality using their program. Similar methods could feasibly be used to manage US orthopedic waitlists to prioritize the appropriate patients. Table I summarizes key applications of AI to address the orthopedic surgical backlog.

TABLE I Summary of 4 Key AI Applications to Reduce the Orthopedic Surgical Backlog: Surgical Scheduling, Preoperative Planning,

Anesthesia and Anesthetic Time

The effectiveness of AI in anesthesia may be similar to prior areas of focus, including improved preoperative analysis to determine the difficulty of the airway and postoperative programs to calculate the risk of patient mortality $60,61$. There has also been considerable focus on closed loop systems and pharmacological algorithms, as summarized by Singh and Nath, that provide more precise release of anesthetic medications, vasopressors, and paralytics 62 . It is impossible to measure a quantitative impact of these programs with current data, but more precise medication doses theoretically could prevent wait time due to overshooting of medication and thus increase OR efficiency. Although speculative, AI could help with anesthesia coordination to decrease time between cases and improve time allotted to preoperative blocks.

Future of AI in Orthopedics

Undoubtedly, AI will aid extensively in radiographic inter-pretation. Studies have reported AI's ability to accurately diagnose musculoskeletal trauma, degenerative disease, and musculoskeletal tumors^{18,20,63-67}. We chose not to focus on this area because it seems unlikely to significantly affect the current backlog.

AI is likely to manage robotic-assisted surgeries to improve procedural safety and efficiency⁴⁴. Li et al. demonstrated DL's effectiveness in robotic-assisted TKA by generating 3D models from CT scans⁶⁸. Someday AI-directed robotics may even operate autonomously, aiding surgeons in the $OR⁶⁹$. The future may also see advances in regenerative orthopedics with AI programming, including tissue regeneration, stem cell technology, and genomics/epigenomics⁷⁰. Although these developments will influence surgical procedures and patient care, their widespread implementation will not come in time to deal with the current backlog. Table II summarizes likely future AI applications.

Limitations and Challenges

 \blacksquare his study is limited by the lack of long-term data on AI use \perp in health care. Most studies involving AI in orthopedics have been published recently¹⁸ and involve ML applications at single institutions. No data exist, to our knowledge, of AI applications across multiple health care systems for an

TABLE II Summary of 4 Future Applications in the Field of Orthopedics: Radiographic Interpretation, Robotic-Assisted Surgery, Autonomous Operations, and Regenerative Orthopedics

extended time. Systematic reviews and meta-analyses are also lacking. Thus, modeling how much AI can reduce the surgical backlog is challenging. While AI can improve efficiency, its effectiveness within surgical backlogs is presently only speculative and cannot provide definitive or quantitative conclusions. Furthermore, the correction of the surgical backlog will likely require a multidisciplined approach involving many factors beyond AI, including systemic, institutional, and provider factors. This review therefore exists to commentate on how advances in AI could be useful in decreasing the surgical backlog but cannot provide quantitative estimates. This review is also not intended to be exhaustive for potential uses of AI in orthopedics.

More broadly, AI implementation faces logistical challenges. While AI has been projected to save health care systems' considerable capital long term 71 , its initial application could prove expensive and labor intensive^{$72,73$}. These factors could prevent many health care systems from adopting AI use until costs decrease. Many technologies drastically decrease in cost over time, though, such as genome sequencing falling from tens of millions of dollars to around 1,000 dollars over just 2 decades⁷⁴. We are hopeful that AI costs will similarly become less expensive in time.

Questions also exist concerning the generalizability of AI in health care¹⁸. ML algorithms designed in one location with specific patient populations may not be as accurate in other locations. Ultimately, clinicians must note the limitations of AI's effectiveness and treat it as an adjunctive tool in diagnosis and not a replacement for their expertise⁷⁵.

Finally, public response to AI implementation must be considered. Privacy is a concern when dealing with large data sets, and we are cognizant that advances in AI are outpacing regulatory oversight⁷⁶. Health care systems must proceed cautiously to avoid protected patient information exposure and consider that the public might view AI in health care with mistrust, particularly should any large-scale data leak occur. Indeed, many patients are concerned about potential loss of confidentiality, biases in algorithms, and communication barriers AI may create between them and their physician⁷⁷. Efforts must be made to maintain security and trust amidst these coming changes.

Conclusion

Thopedic surgery was highly affected by the COVID-19 pandemic due to its high rate of elective procedures^{3,6,7}. There now exists a persistent backlog of many procedures as patients are waitlisted to receive care⁸. AI has emerged as a powerful potential tool with numerous applications in orthopedic surgery¹⁸. Several demonstrated uses could prove helpful in improving the current backlog: improved surgical schedul ing^{27-31} , efficient and precise preoperative planning^{35,37,41}, accurate postsurgical predictions^{46-50,52}, and management of surgical waitlists^{57,59}. We are optimistic that AI's use in orthopedic surgery will evolve and help the health care system while being mindful that AI's implementation faces numerous challenges71-73,76,77. In addition, the technologies developed and implemented will likely play an important role in managing future surgical backlogs that may occur. This review, to our knowledge, is the first exploring the applications of AI in orthopedic surgery in the context of the current surgical backlog. \blacksquare

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