Reinforcement Learning–Based Optimization of Postoperative Pain Management Following Peripheral Nerve Block for Knee Arthroscopy

Ethan J. Marshall
Department of Biomedical Informatics, University of Arkansas, Fayetteville, AR, USA.
ethan.marshall@uark.edu

Priya Nandakumar
Department of Industrial and Systems Engineering, University of North Texas, Denton, TX, USA.
priya.nandakumar@unt.edu

Tamuel Breene
Department of Health Systems Science, University of Vermont, Burlington, VT, USA.
tamuel.breene@uvm.edu

Abstract

Postoperative pain management remains a critical challenge in ambulatory orthopedic surgery despite substantial advances in regional anesthesia and multimodal analgesic strategies. Knee arthroscopy is among the most frequently performed minimally invasive orthopedic procedures, and peripheral nerve block techniques have significantly improved perioperative pain control. However, postoperative pain trajectories exhibit substantial heterogeneity across patients, making standardized analgesic protocols insufficient for achieving optimal outcomes. Recent developments in artificial intelligence, particularly reinforcement learning, provide opportunities to transform postoperative pain management from static guideline-based approaches into adaptive decision-making systems capable of continuously optimizing treatment recommendations according to patient-specific responses.

This study proposes a reinforcement learning–based framework for optimizing postoperative pain management following peripheral nerve block for knee arthroscopy. The research examines how sequential decision-making models can integrate clinical observations, patient-reported outcomes, physiological indicators, and healthcare resource constraints to generate personalized analgesic strategies. Beyond algorithmic performance, the study explores broader system-level considerations, including healthcare infrastructure requirements, model governance, fairness, explainability, regulatory compliance, and institutional deployment challenges. The analysis situates reinforcement learning within evolving digital health ecosystems characterized by electronic health record integration, clinical decision support systems, and data-driven perioperative management platforms.

The findings suggest that reinforcement learning offers significant potential to improve pain control effectiveness, reduce opioid exposure, enhance resource utilization, and support continuous learning healthcare systems. Nevertheless, successful implementation depends on robust governance mechanisms, interdisciplinary collaboration, transparent model development, and equitable deployment strategies. The study contributes a comprehensive systems perspective on the role of reinforcement learning in next-generation postoperative

pain management and highlights future directions for scalable, trustworthy, and sustainable clinical AI infrastructures.

Keywords

Reinforcement Learning; Clinical Artificial Intelligence; Knee Arthroscopy; Peripheral Nerve Block; Postoperative Pain Management; Healthcare Systems; Clinical Decision Support; Personalized Medicine.

1. Introduction

The growing complexity of modern healthcare systems has generated increasing interest in intelligent decision-support technologies capable of adapting to dynamic clinical environments. Among orthopedic procedures, knee arthroscopy represents one of the most commonly performed surgical interventions worldwide, encompassing diagnostic assessments, meniscal repair, ligament reconstruction, cartilage treatment, and various minimally invasive therapeutic procedures. Although advances in surgical techniques have reduced procedural invasiveness, postoperative pain remains a significant determinant of patient satisfaction, recovery quality, rehabilitation adherence, and healthcare resource utilization [3].

Peripheral nerve block techniques, particularly femoral, sciatic, and adductor canal blocks, have emerged as effective approaches for postoperative analgesia following knee arthroscopy [11]. These interventions can substantially reduce opioid consumption and improve immediate postoperative recovery. Nevertheless, substantial variability exists in patient responses to regional anesthesia, influenced by demographic factors, physiological characteristics, psychological conditions, surgical complexity, and perioperative care pathways [5]. Consequently, standardized postoperative analgesic protocols often fail to account for individual differences in pain trajectories.

Traditional clinical decision-making frameworks rely heavily on predefined guidelines and clinician experience. While such approaches remain valuable, they frequently lack the adaptability necessary to respond to continuously evolving patient conditions. Contemporary healthcare environments increasingly generate real-time clinical data through electronic health records, wearable monitoring devices, patient-reported outcome systems, and integrated perioperative information platforms [8]. These developments create opportunities for artificial intelligence systems capable of leveraging longitudinal patient data to support individualized treatment decisions.

Reinforcement learning represents a particularly promising paradigm because it addresses sequential decision-making problems in which actions influence future outcomes. Unlike conventional predictive machine learning models that estimate risks or classify outcomes, reinforcement learning seeks to optimize long-term rewards through adaptive interactions with complex environments [2]. In the context of postoperative pain management, treatment recommendations made during one recovery period may significantly influence future pain severity, medication requirements, rehabilitation progress, and complication risks.

This paper investigates the application of reinforcement learning to postoperative pain management following peripheral nerve block for knee arthroscopy. Rather than focusing solely on algorithmic implementation, the study adopts a socio-technical systems perspective, examining clinical integration, infrastructure requirements, governance considerations, ethical implications, and deployment challenges associated with large-scale implementation.

2. Evolution of Postoperative Pain Management Systems

The management of postoperative pain has evolved considerably over recent decades. Earlier approaches relied predominantly on opioid-centered treatment paradigms, reflecting limited understanding of multimodal analgesia and patient-specific variability. While opioids remain important components of pain management, concerns regarding dependence, adverse effects, and public health consequences have motivated healthcare systems to pursue more sophisticated strategies [14].

The introduction of regional anesthesia techniques transformed perioperative pain management by providing targeted analgesia while reducing systemic medication exposure. In knee arthroscopy, peripheral nerve blocks have demonstrated favorable outcomes regarding pain reduction, functional recovery, and patient satisfaction [11]. Clinical evidence indicates that combining femoral and sciatic nerve block approaches may provide substantial analgesic benefits in selected patient populations undergoing arthroscopic procedures [17].

Despite these advancements, postoperative pain management remains characterized by significant uncertainty. Patients experiencing similar surgical interventions often exhibit markedly different recovery trajectories. Pain intensity may fluctuate over time due to inflammatory processes, psychological responses, medication adherence patterns, sleep quality, and rehabilitation participation. Such complexity challenges traditional protocol-based management approaches that assume relatively predictable patient responses.

The digital transformation of healthcare has created new possibilities for addressing these challenges. Electronic health records now capture extensive perioperative data, including medication administration histories, laboratory results, physiological measurements, clinical notes, and patient outcomes. Simultaneously, wearable technologies and remote monitoring systems provide increasingly granular information regarding recovery processes outside traditional clinical settings [6].

These developments have facilitated the emergence of learning healthcare systems, which continuously analyze clinical data to improve future care delivery. Within such systems, artificial intelligence technologies serve not merely as analytical tools but as components of adaptive infrastructures capable of supporting evidence generation, knowledge dissemination, and decision optimization. Reinforcement learning aligns particularly well with this vision because it emphasizes continuous learning from experience rather than static prediction based on historical data alone.

The transition toward intelligent pain management systems reflects broader changes in healthcare governance. Policymakers, clinicians, and healthcare organizations increasingly recognize the need for approaches that simultaneously improve patient outcomes, reduce costs, minimize opioid exposure, and support equitable care delivery. Reinforcement learning offers a potential mechanism for balancing these competing objectives within complex clinical environments.

3. Reinforcement Learning as a Framework for Personalized Analgesia

Reinforcement learning differs fundamentally from conventional supervised learning approaches because it focuses on optimizing sequences of actions rather than predicting isolated outcomes. In healthcare contexts, this distinction is particularly important because treatment decisions rarely occur independently. Instead, clinical interventions form interconnected pathways in which each action influences subsequent patient states and future decision opportunities [1].

Within postoperative pain management, the clinical environment can be conceptualized as a dynamic system characterized by evolving patient conditions. The patient's pain level, physiological status, medication history, functional capacity, and rehabilitation progress collectively define a continuously changing state. Clinicians select interventions based on these observations, including analgesic adjustments, monitoring strategies, rehabilitation recommendations, and escalation decisions. The resulting patient responses provide feedback regarding intervention effectiveness.

A reinforcement learning framework can model these interactions by treating analgesic management as a sequential optimization problem. Rather than recommending treatments solely according to population-level averages, the system learns which interventions produce favorable long-term outcomes for specific patient profiles. Importantly, optimization objectives can incorporate multiple dimensions simultaneously, including pain reduction, opioid minimization, adverse event prevention, patient satisfaction, and healthcare resource efficiency [4].

The value of reinforcement learning becomes particularly evident when considering the temporal dynamics of postoperative recovery. Immediate pain reduction does not necessarily correspond to optimal long-term outcomes. Excessive opioid administration may provide short-term relief while increasing risks of adverse effects, delayed rehabilitation, or prolonged medication use. Conversely, insufficient analgesia may hinder mobility, impair sleep, and negatively affect recovery experiences. Reinforcement learning can theoretically identify balanced strategies that maximize overall recovery quality rather than focusing on isolated clinical metrics.

Another advantage lies in the ability to adapt recommendations as new information becomes available. Recovery trajectories often diverge substantially from initial expectations. Patients demonstrating unexpectedly rapid recovery may require reduced intervention intensity, whereas individuals experiencing complications may benefit from more aggressive management. Adaptive learning systems can respond to such changes more effectively than rigid protocol-based frameworks.

From a systems engineering perspective, reinforcement learning also facilitates integration across multiple layers of healthcare delivery. Data generated within surgical units, post-anesthesia care facilities, outpatient clinics, telehealth platforms, and home monitoring systems can contribute to a unified decision-making ecosystem. This capability supports continuity of care and enables optimization across organizational boundaries that traditionally fragment postoperative management.

4. System Architecture for Reinforcement Learning–Enabled Pain Management

The successful deployment of reinforcement learning within postoperative pain management requires comprehensive technological infrastructures extending far beyond algorithm development. Healthcare organizations must establish integrated architectures capable of supporting data collection, model training, decision support, monitoring, governance, and continuous improvement.

At the foundational level, data integration mechanisms are essential. Reinforcement learning systems depend upon comprehensive representations of patient states. Relevant information may include demographic characteristics, surgical details, anesthesia records, medication histories, pain assessments, physiological measurements, rehabilitation progress indicators, and patient-reported outcomes. These data sources frequently reside within separate

information systems, creating interoperability challenges that must be addressed through standardized data architectures [7].

Clinical decision-support interfaces constitute another critical component. Reinforcement learning recommendations must be presented in forms that support clinician understanding and workflow integration. Excessively complex interfaces may increase cognitive burden and reduce adoption rates. Conversely, oversimplified presentations may obscure important contextual information. Effective design therefore requires careful balancing of transparency, usability, and informational richness.

Model lifecycle management represents an additional architectural consideration. Clinical environments continuously evolve due to changing patient populations, treatment protocols, healthcare policies, and organizational practices. Reinforcement learning systems must therefore incorporate mechanisms for performance monitoring, model updating, validation, and auditing. Continuous evaluation helps ensure that recommendations remain aligned with current clinical realities rather than becoming degraded by distributional shifts [10].

Healthcare cybersecurity considerations further complicate deployment. Reinforcement learning systems depend upon large-scale data flows across interconnected platforms. These infrastructures create potential vulnerabilities related to unauthorized access, data breaches, model manipulation, and operational disruptions. Robust security frameworks are therefore essential components of sustainable implementation strategies.

Beyond technical architecture, organizational infrastructure plays an equally important role. Successful deployment requires collaboration among clinicians, data scientists, health informaticians, administrators, ethicists, and regulatory specialists. Interdisciplinary governance structures help ensure that technological development remains aligned with clinical priorities and patient interests.

Furthermore, institutional readiness significantly influences implementation outcomes. Healthcare organizations vary considerably regarding digital maturity, workforce capabilities, resource availability, and cultural attitudes toward innovation. Reinforcement learning deployment strategies must therefore accommodate heterogeneous organizational contexts rather than assuming uniform infrastructure capabilities.

5. Governance, Fairness, and Clinical Trust in Adaptive Analgesic Systems

The introduction of reinforcement learning into postoperative pain management raises important governance challenges that extend beyond technical performance. Healthcare decision-making operates within highly regulated environments where patient safety, accountability, transparency, and ethical responsibility must be carefully balanced against innovation objectives. Consequently, reinforcement learning systems designed for analgesic optimization should be viewed not merely as computational tools but as socio-technical infrastructures embedded within broader institutional governance frameworks.

One of the most significant concerns involves clinical trust. Healthcare professionals are unlikely to adopt recommendations generated by systems they do not understand or cannot justify. Traditional evidence-based medicine emphasizes transparency regarding treatment rationale, whereas reinforcement learning policies often emerge through complex optimization processes that may not be immediately interpretable. This tension highlights the necessity of explainable artificial intelligence mechanisms capable of translating model recommendations into clinically meaningful reasoning structures [9]. Explanations should not

simply describe algorithmic outputs but should contextualize recommendations within observable patient characteristics, historical treatment responses, and expected outcome trajectories.

Fairness constitutes another critical governance dimension. Historical healthcare datasets frequently contain embedded inequities reflecting differences in access to care, socioeconomic status, demographic representation, and institutional practices. Reinforcement learning systems trained on such data may inadvertently perpetuate or amplify existing disparities if fairness considerations are not explicitly incorporated into development and monitoring processes [15]. For example, differential treatment recommendations across demographic groups may emerge due to historical prescribing patterns rather than genuine clinical need.

The issue of fairness becomes particularly relevant in pain management because pain perception, reporting behavior, and treatment access are influenced by complex social and cultural factors. Research has documented disparities in pain assessment and analgesic prescribing among various patient populations [16]. Therefore, reinforcement learning systems should undergo continuous auditing to evaluate whether recommendations remain equitable across age groups, genders, racial populations, socioeconomic categories, and geographic regions.

Accountability frameworks must also evolve alongside intelligent decision-support technologies. Traditional clinical responsibility structures assume that treatment decisions originate primarily from healthcare professionals. The integration of adaptive algorithms introduces new questions regarding responsibility allocation when adverse outcomes occur. Effective governance models require clear delineation of roles among clinicians, healthcare organizations, technology developers, and regulatory authorities. Reinforcement learning systems should function as decision-support mechanisms rather than autonomous decision-makers, preserving meaningful human oversight throughout clinical workflows [12].

Regulatory agencies worldwide are increasingly examining adaptive artificial intelligence technologies. Unlike static software systems, reinforcement learning models may change over time as they incorporate new information and update decision policies. Such adaptability challenges conventional regulatory approaches based on fixed system validation. Emerging governance models increasingly emphasize lifecycle oversight, continuous monitoring, and real-world performance evaluation as mechanisms for ensuring long-term safety and effectiveness [13].

Institutional governance committees can play an important role in overseeing deployment activities. These multidisciplinary bodies may evaluate ethical considerations, monitor performance metrics, review adverse events, and coordinate improvement initiatives. Such structures help establish organizational trust while supporting responsible innovation within clinical environments.

6. Infrastructure Sustainability and Health System Integration

The long-term value of reinforcement learning–enabled pain management depends heavily upon infrastructure sustainability. Many healthcare artificial intelligence projects demonstrate promising results during pilot phases yet encounter significant challenges when transitioning to routine clinical operations. Sustainable implementation requires attention to technical, financial, organizational, and policy dimensions that collectively determine system viability.

From a technical perspective, reinforcement learning systems require continuous access to high-quality data streams. Data incompleteness, inconsistent documentation practices, missing observations, and interoperability limitations can significantly reduce model effectiveness. Therefore, healthcare organizations must invest in data governance infrastructures capable of supporting standardized collection, validation, and integration processes [7]. Such investments often produce benefits extending beyond pain management applications by strengthening broader digital health capabilities.

Financial sustainability represents another important consideration. Developing and maintaining reinforcement learning systems involves substantial costs associated with software development, cloud infrastructure, cybersecurity, workforce training, compliance activities, and performance monitoring. Healthcare administrators must therefore evaluate whether anticipated clinical benefits justify implementation expenditures. Economic assessments should incorporate both direct outcomes, such as reduced medication utilization and shortened recovery periods, and indirect benefits, including improved patient satisfaction, enhanced clinician efficiency, and reduced complication rates.

Workforce development constitutes a frequently overlooked component of sustainability. Effective deployment requires clinicians who understand the capabilities and limitations of artificial intelligence systems. Similarly, data scientists and engineers working within healthcare environments must appreciate clinical workflows, regulatory requirements, and patient safety priorities. Educational programs that promote interdisciplinary competencies can help bridge these knowledge gaps and facilitate successful implementation.

Integration with existing healthcare infrastructures is equally important. Reinforcement learning systems should complement rather than disrupt established clinical workflows. Excessive workflow complexity may generate resistance among healthcare professionals and reduce adoption rates. Consequently, successful implementations often emphasize seamless integration with electronic health records, computerized physician order entry systems, telehealth platforms, and patient engagement applications [8].

The growing adoption of remote monitoring technologies creates additional opportunities for reinforcement learning–based pain management. Wearable devices can provide continuous information regarding physical activity, mobility patterns, sleep quality, and physiological indicators. Patient-reported outcome platforms can capture subjective experiences that are often unavailable within traditional clinical records. Together, these technologies support more comprehensive representations of recovery processes and enable decision-making beyond hospital boundaries.

At a policy level, sustainability also depends upon reimbursement mechanisms and regulatory support. Healthcare systems are more likely to adopt advanced analytics technologies when incentives align with improved outcomes and value-based care objectives. Policymakers may therefore play a significant role in facilitating broader implementation through reimbursement reforms, interoperability standards, and innovation support programs.

7. Comparative Perspectives and Future Healthcare Ecosystems

The application of reinforcement learning to postoperative pain management reflects broader transformations occurring across healthcare sectors. Similar approaches have been explored in critical care, chronic disease management, treatment personalization, resource allocation, and precision medicine initiatives [1][2]. Examining these parallel developments provides

valuable insights regarding opportunities and challenges relevant to orthopedic perioperative care.

In intensive care medicine, reinforcement learning has been investigated as a mechanism for optimizing treatment strategies involving fluid administration, vasopressor management, and sepsis care. These applications share important characteristics with postoperative pain management, including dynamic patient states, sequential interventions, and competing clinical objectives. Lessons from critical care research highlight the importance of rigorous validation, clinician engagement, and cautious deployment strategies [4].

Precision oncology offers another relevant comparison. Cancer treatment increasingly relies upon individualized decision-making informed by complex data sources, including genomic information, treatment histories, and patient-specific characteristics. Similar principles underpin reinforcement learning–based analgesic optimization, where personalized recommendations emerge from continuous evaluation of evolving patient conditions. Both domains illustrate the transition from population-based protocols toward adaptive care pathways tailored to individual circumstances.

The emergence of digital twins may further enhance reinforcement learning capabilities within postoperative care environments. Digital twin technologies create dynamic computational representations of patients that evolve in response to real-world observations. When combined with reinforcement learning, such systems may enable simulation-based evaluation of alternative treatment strategies before clinical implementation. This capability could improve safety while supporting more sophisticated personalization approaches.

Federated learning architectures represent another promising direction. Healthcare organizations often face constraints regarding data sharing due to privacy regulations and institutional policies. Federated learning enables collaborative model development across multiple institutions without requiring centralized data aggregation. Such approaches may support broader reinforcement learning deployment while preserving patient privacy and organizational autonomy [18].

The future healthcare ecosystem will likely involve increasingly interconnected networks of intelligent systems operating across perioperative pathways. Reinforcement learning–based analgesic management may interact with predictive risk models, rehabilitation planning systems, remote monitoring platforms, and clinical communication tools. These interconnected infrastructures could support continuous optimization across the entire patient journey rather than focusing solely on isolated treatment episodes.

Nevertheless, the expansion of intelligent healthcare ecosystems also introduces new risks. Excessive dependence on automated recommendations may reduce clinician autonomy or contribute to skill degradation. Algorithmic errors may propagate across interconnected systems, amplifying unintended consequences. Therefore, future healthcare architectures should emphasize resilience, redundancy, transparency, and human-centered design principles that preserve meaningful professional oversight [10].

Importantly, evidence from regional anesthesia literature demonstrates that effective perioperative pain management depends upon coordinated integration of procedural techniques and postoperative care strategies [17]. Reinforcement learning systems should therefore be viewed as complementary enhancements to established clinical expertise rather than replacements for evidence-based regional anesthesia practices.

8. Strategic Implications for Orthopedic Surgery and Perioperative Medicine

The integration of reinforcement learning into postoperative pain management has implications extending beyond individual patient encounters. At a strategic level, such technologies may contribute to broader transformations in orthopedic surgery, perioperative medicine, and healthcare delivery systems.

For orthopedic practices, adaptive pain management systems offer opportunities to improve patient experiences while addressing concerns regarding opioid stewardship. Healthcare organizations increasingly face pressure to demonstrate high-quality outcomes alongside responsible medication utilization. Reinforcement learning may support these objectives by facilitating individualized treatment strategies that balance analgesic effectiveness with safety considerations.

Perioperative medicine programs may also benefit from enhanced continuity across care transitions. Traditional postoperative management often involves fragmented communication among surgeons, anesthesiologists, nurses, rehabilitation specialists, and primary care providers. Reinforcement learning platforms integrated within shared digital infrastructures could support coordinated decision-making throughout recovery pathways [6].

The strategic significance extends to population health management as well. Aggregated data generated through reinforcement learning systems may provide valuable insights regarding treatment effectiveness, resource utilization, and recovery patterns across diverse patient populations. Such information can inform quality improvement initiatives, policy development, and healthcare planning activities.

Furthermore, healthcare systems increasingly recognize the importance of learning-oriented organizational cultures. Reinforcement learning embodies the concept of continuous adaptation through experience, aligning closely with the principles of learning health systems. Organizations capable of effectively integrating adaptive intelligence technologies may gain advantages regarding innovation capacity, operational efficiency, and patient-centered care delivery.

The long-term evolution of orthopedic perioperative care will likely involve increasing convergence among artificial intelligence, digital health infrastructure, regional anesthesia innovations, and personalized medicine frameworks. Reinforcement learning represents one component of this broader transformation, offering mechanisms for translating expanding data resources into actionable clinical intelligence.

9. Conclusion

Reinforcement learning offers a promising framework for optimizing postoperative pain management following peripheral nerve block for knee arthroscopy. Unlike traditional protocol-driven approaches, reinforcement learning enables adaptive, personalized, and sequential decision-making that reflects the dynamic nature of postoperative recovery. By integrating clinical observations, patient-reported outcomes, physiological indicators, and healthcare system constraints, these models have the potential to improve analgesic effectiveness, reduce opioid exposure, enhance patient satisfaction, and support more efficient resource utilization.

However, successful implementation depends upon more than algorithmic performance. Sustainable deployment requires robust digital infrastructures, interdisciplinary governance mechanisms, fairness auditing processes, cybersecurity protections, regulatory compliance

strategies, and clinician-centered design approaches. Reinforcement learning systems must be integrated into broader healthcare ecosystems that prioritize transparency, accountability, and patient safety.

As healthcare continues its transition toward data-driven and learning-oriented models of care, reinforcement learning may become an important component of future perioperative management infrastructures. The greatest value will emerge not from replacing clinical expertise but from augmenting human decision-making through adaptive intelligence capable of continuously learning from real-world patient experiences. Through responsible development and governance, reinforcement learning can contribute to more personalized, equitable, and effective postoperative pain management systems for knee arthroscopy and beyond.

References

1. Komorowski, M., Celi, L. A., Badawi, O., Gordon, A. C., & Faisal, A. A. (2018). The Artificial Intelligence Clinician learns optimal treatment strategies for sepsis in intensive care. Nature Medicine, 24(11), 1716–1720.
2. Sutton, R. S., & Barto, A. G. (2018). Reinforcement learning: An introduction (2nd ed.). MIT Press.
3. Thorlund, J. B., Juhl, C. B., Roos, E. M., & Lohmander, L. S. (2015). Arthroscopic surgery for degenerative knee: Systematic review and meta-analysis of benefits and harms. BMJ, 350, h2747.
4. Yu, C., Liu, J., Nemati, S., & Sun, J. (2019). Reinforcement learning in healthcare: A survey. ACM Computing Surveys, 55(1), 1–36.
5. Gan, T. J. (2017). Poorly controlled postoperative pain: Prevalence, consequences, and prevention. Journal of Pain Research, 10, 2287–2298.
6. Topol, E. (2019). Deep medicine: How artificial intelligence can make healthcare human again. Basic Books.
7. Adler-Milstein, J., Holmgren, A. J., Kralovec, P., Worzala, C., Searcy, T., & Patel, V. (2017). Electronic health record adoption in US hospitals. Health Affairs, 36(7), 1273–1277.
8. Bates, D. W., Cohen, M., Leape, L. L., Overhage, J. M., Shabot, M. M., & Sheridan, T. (2001). Reducing the frequency of errors in medicine using information technology. Journal of the American Medical Informatics Association, 8(4), 299–308.
9. Doshi-Velez, F., & Kim, B. (2017). Towards a rigorous science of interpretable machine learning. arXiv Preprint arXiv:1702.08608.
10. Amann, J., Blasimme, A., Vayena, E., Frey, D., & Madai, V. I. (2020). Explainability for artificial intelligence in healthcare. NPJ Digital Medicine, 3(1), 1–13.
11. Abdallah, F. W., & Brull, R. (2011). Is sciatic nerve block advantageous when combined with femoral nerve block for postoperative analgesia following knee surgery? Regional Anesthesia and Pain Medicine, 36(5), 493–498.
12. Goodman, K. W. (2020). Ethics, medicine, and information technology: Intelligent machines and the transformation of health care. Cambridge University Press.

13. U.S. Food and Drug Administration. (2021). Artificial Intelligence/Machine Learning (AI/ML)-Based Software as a Medical Device Action Plan. FDA.

14. Chou, R., Gordon, D. B., de Leon-Casasola, O. A., Rosenberg, J. M., Bickler, S., Brennan, T., et al. (2016). Management of postoperative pain: A clinical practice guideline. The Journal of Pain, 17(2), 131–157.

15. Rajkomar, A., Hardt, M., Howell, M. D., Corrado, G., & Chin, M. H. (2018). Ensuring fairness in machine learning to advance health equity. Annals of Internal Medicine, 169(12), 866–872.

16. Anderson, K. O., Green, C. R., & Payne, R. (2009). Racial and ethnic disparities in pain: Causes and consequences of unequal care. The Journal of Pain, 10(12), 1187–1204.

17. 金子, 吴川, 王秀丽, & 刘朋. (2014). 股神经联合坐骨神经阻滞用于膝关节镜诊治术. 实用医学杂志, 30(4), 666-667.

18. Rieke, N., Hancox, J., Li, W., Milletari, F., Roth, H. R., Albarqouni, S., et al. (2020). The future of digital health with federated learning. NPJ Digital Medicine, 3(1), 119.

19. Friedman, C. P., Rubin, J. C., & Sullivan, K. J. (2017). Toward an information infrastructure for global health improvement. Yearbook of Medical Informatics, 26(1), 16–23.

20. Berwick, D. M. (2003). Disseminating innovations in health care. JAMA, 289(15), 1969–1975.