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Review Article

Revolutionizing Post Anesthesia Care Unit with Artificial Intelligence: A Narrative Review

Shahnam Sedigh Maroufi[1], Maryam Sarkhosh[1]*, Maryam Soleimani Movahed[2], Ali Behmanesh[2], Azar Ejmalian[3]

[1]*Department of Anesthesia, Faculty of Allied Medical Sciences, Iran University of Medical Sciences, Tehran, Iran.*

[2]*Education Development Center, Iran University of Medical Sciences, Tehran, Iran.*

[3]*Department of Anesthesiology, School of Medicine, Iran University of Medical Sciences, Tehran, Iran.*

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ABSTRACT

Artificial intelligence (AI) is increasingly being utilized in Post-Anesthesia Care Units (PACUs) to improve patient monitoring and care. This narrative review explores the current use of AI in PACUs and discusses the potential benefits and challenges associated with its implementation and highlights how AI technologies such as predictive analytics, machine learning algorithms, and robotics can enhance patient safety, reduce human error, and improve outcomes in the PACU setting. Overall, this narrative review provides insights into the evolving role of AI in PACUs and offers recommendations for future research and practice in this area.

Introduction

Artificial Intelligence (AI) and Machine Learning (ML) have increasingly been merged with various medical fields, demonstrating significant potential to enhance patient outcomes and operational efficiency. In anesthesiology, much of the research and application have focused on preoperative assessments, intraoperative management, and intensive care units (ICUs) [1-8]. These studies have showcased AI and ML's capabilities in predicting patient outcomes, optimizing anesthesia administration, and managing intraoperative complications [9-11]. However, there remains a notable gap in the literature concerning the specific application of these technologies in Post-Anesthesia Care Units (PACUs). This narrative review aims to address this gap by exploring the current and potential roles of AI and ML in PACUs, evaluating existing evidence, and identifying areas for future research. By focusing on the unique challenges and opportunities within the recovery room setting, this review seeks to provide a comprehensive understanding of how AI and ML can improve patient care during the critical post-operative period.

Artificial Intelligence

The origins of artificial intelligence can be traced back to the period preceding the 1950s when researchers sought to simulate and replicate human cognitive abilities [12]. Prior to this period, individuals such as Aristotle, René Descartes, Alan Turing, and John von Neumann proposed theories and concepts that later became foundational to the field of AI [13-14]. In the 1940s, formal research in AI commenced, marked by the construction of the first electromechanical computing device by Warren McCulloch and Walter Pitts in 1943 [15]. The term "Artificial Intelligence" was first used by Dartmouth College and MIT in 1946, establishing it as a new domain within computer science [16].

Throughout the 1950s, pioneers such as John McCarthy, Herbert Simon, and Allen Newell, among others, continued to advance research in AI [17]. Alan

The authors declare no conflicts of interest.
*Corresponding author.
E-mail address: maryamsarkhosh1999@gmail.com

Turing's contributions to the field through his introduction of key concepts in AI and computational theory were also notable during this period [18].

Subsequent to the 1950s, research AI expanded significantly, incorporating new areas such as machine learning, neural networks, and natural language processing [19]. The ensuing decades witnessed substantial progress in AI, solidifying its status as a key technology across diverse disciplines [20].

Machine Learning

Machine learning is a subset of artificial intelligence that concentrates on the development of algorithms and statistical models enabling computers to learn and enhance their performance through experience, rather than relying solely on explicit programming [21]. The history of ML dates back to the 1950s, with the development of early neural networks and perceptrons [22]. Over the years, advancements in computational power and the availability of large amounts of data have led to significant progress in the field, with ML algorithms now being widely used in various industries and applications [23].

Machine learning algorithms can be classified into three categories: supervised learning, unsupervised learning, and reinforcement learning. [24]. Supervised learning employs labeled data to discern the relationship between inputs and outputs, while unsupervised learning identifies patterns within unlabeled data. In contrast, reinforcement learning emphasizes decision-making aimed at achieving a specific objective through a process of trial and error. [25]. Additional approaches, such as semi-supervised learning, active learning, and transfer learning, are also applied in particular contexts [26-28].

The main objective of implementing AI-based systems in PACUs is to provide the computer with access to patient data and medical literature in order to analyze and extract valuable information [29]. However, two major obstacles include the difficulty of integrating data from disparate EHR systems and the high development costs associated with these systems [30-31].

Several ML models have been created to address specific clinical inquiries using a comprehensive dataset such as using preoperative data to predict recovery time after general anesthesia [32]. The accuracy and precision of these models are contingent upon the credibility and approach of the research method they are built upon [33]. Additionally, anesthesiologists may struggle to grasp how these predictions are generated [34]. Today, PACUs are increasingly looking to implement AI technologies for tasks such as predicting recovery time and determining treatment plans [35]. Computers are becoming essential for providing support and guidance in PACU and aiding in decision-making processes [36].

Application of Artificial Intelligence in Post Anesthesia Care Unit

Recovery Time Prediction

In the peri-operative management process, it is important to consider the length of stay in the PACU when making decisions about scheduling surgeries and staffing. It is crucial to allow enough time for patients to safely recover and be discharged on schedule [37]. Operational decisions, such as case scheduling and OR staffing, are often made well in advance, but it can be challenging to perfectly allocate cases within appropriate time blocks [38]. ML has shown great potential in optimizing operating room management by improving accuracy in enhancing recovery room management as multiple studies have highlighted. Different ML algorithms are getting used for the prediction of PACU length of stay [35,39-40]. Most studies so far have utilized supervised algorithms to forecast the length of patients' recovery stays, such as Logistic Regression, KNN, ANN, XGBoost, Decision Trees, and Random Forests. These studies investigated that predictive analytics can assist clinical staff in identifying high-risk delayed emergence patients early on, leading to reduced peri-operative risk and shorter PACU stays. By forecasting the duration of patients' stays in the Post-Anesthesia Care Unit (PACU), administrative personnel can enhance staff management and improve bed turnover rates in both the operating room and the PACU [35].

Determining Factors Influencing Patient Discharge

It is imperative for anesthesiologists to accurately identify and document key features involved in a patient's discharge from the recovery room. These features, such as vital signs, level of consciousness, pain management, ambulation ability, and post-operative instructions or medications, play a critical role in ensuring a smooth transition to the next phase of care [41]. By identifying these factors, anesthesiologists can assess the patient's stability and readiness for discharge, as well as identify any necessary support or interventions before they leave the recovery room. This identification not only promotes the patient's well-being but also contributes to a positive recovery process [42]. Recent developments in AI and ML have empowered researchers to undertake studies focused on identifying critical features that significantly influence the discharge of patients from recovery. Various methodologies, including Stepwise Multilinear Regression, Bayesian Ridge, Random Forest, Support Vector Regression (SVR), and XGBoost, have been utilized to analyze and predict the factors affecting the patient discharge process [43]. These advanced algorithms provide an evidence-based framework for enhancing decision-making processes in healthcare environments, ultimately resulting in more efficient and effective strategies for patient care [44]. Through these studies, researchers can harness the power of AI to enhance the discharge planning process and improve patient outcomes [43].

Pain Management in PACU

PCA, or patient-controlled analgesia, has become increasingly popular among patients and anesthesiologists. However, despite expectations of significant analgesic efficacy, one notable drawback of traditional PCA systems is their decentralized nature [45]. This indicates that patient-controlled analgesia (PCA) devices are generally situated in inpatient wards, lacking direct or immediate access to medical staff. Patients must familiarize themselves with the operation of the pre-programmed PCA equipment after receiving a brief instructional session from healthcare providers. [46]. While this setup may work well when the equipment functions properly, any mechanical issues or the need for analgesic adjustments can lead to compromised pain management efficiency if there is a delay in medical staff response [47].

Currently, wireless intelligent patient-controlled analgesia (Wi-PCA) systems are available that incorporate features such as remote monitoring, intelligent alarm systems, analysis and evaluation of PCA equipment, and the automatic recording and storage of essential information in a wireless environment [48]. The implementation of the Wi-PCA system showed significant advantages, including a marked/ reduction in the incidence of substantial to severe postoperative pain and related adverse effects, as well as a decrease in hospital length of stay and improved patient satisfaction regarding postoperative pain management [49].

Currently, artificial intelligence (AI) algorithms are utilizing brain imaging techniques to detect pain and predict opioid dose responses through biomarkers. Images are collected from individuals undergoing functional magnetic resonance imaging (fMRI) during both painful and non-painful thermal stimuli. Machine learning (ML) methods have been employed to analyze the differences and similarities in these images, indicating that examining brain images is more effective for identifying pain than concentrating on specific brain regions associated with nociception [29]. PainChek™, an AI tool specifically designed to detect pain in dementia patients within the field of Geriatric medicine [50]. Additionally, Gram et al. conducted an analysis on electroencephalography signals from 81 patients using ML techniques, achieving a 65% accuracy in predicting which patients would respond to post-operative opioid therapy [51].

Ultrasound Guided Blocks in PACU

The use of regional anesthesia for managing acute postoperative pain is increasingly gaining popularity. Ultrasound is being utilized to aid in performing regional blocks, improve the success rate of procedures, and lower the risk of complications. ScanNav™, an AI-powered device developed by Intelligent Ultrasound in Cardiff, UK generates a color overlay on live ultrasound images to emphasize specific anatomical structures [52]. AI technology could be beneficial in identifying anatomical landmarks, potentially lowering the risk of complications. AI-driven solutions have the potential to enhance detection in the enhancement and analysis of sonographic images, improve the visualization of needle positioning, and assist in the administration of local anesthetics for pain relief [53].

Ataxic Breathing Detection in PACU

Traditionally, opioid-induced respiratory depression is identified through the evaluation of respiratory rate, pulse oximetry readings, and mental status. Researchers have investigated ataxic or irregular respiratory patterns and created an ML algorithm (Support Vector Machine) to quantify these patterns, aiming to enhance the prediction of respiratory depression during the post-operative phase [54].

Delirium Prediction in PACU

Post-Operative Delirium (POD) is a condition that manifests as an acute mental disorder following surgery, marked by disruptions in consciousness, attention, and cognition [55]. ML, a significant subset of AI, offers the benefit of creating models with enhanced stability and precision in prediction. Consequently, it is increasingly being employed in clinical settings for tasks such as predicting POD and recognizing its risk factors to mitigate their occurrence [56]. Various AI algorithms are being utilized for this purpose to enhance prediction accuracy and aid in preventive measures. The utilization of these models would involve the automated, real-time assessment of delirium risk in order to enhance the peri-operative care of surgical patients who are prone to POD [57].

Complication Prediction in PACU

Accurately evaluating pre-operative risk can enhance hospital resource utilization and decrease morbidity and mortality rates in high-risk surgical patients [58]. A tool known as the Surgical and Medical Post-operative Complications Prediction Tool (SUMPOT) utilizes An Artificial Neural Network to identify patients at risk of post-operative complications [59]. The Artificial Neural Network demonstrated strong predictive capabilities for determining the likelihood of post-operative complications, indicating its potential usefulness in managing surgical patients during the peri-operative period. Additional clinical research is necessary to validate its effectiveness in everyday clinical settings [32].

Ileus Prediction in PACU

An increasing number of studies are concentrating on predicting postoperative intestinal obstruction, with risk prediction playing a vital role in clinical decision-making. The incorporation of AI algorithms offers promising prospects for improving risk assessment and developing customized predictive strategies [60]. ML algorithms within AI are instrumental in analyzing medical data and can help identify relevant variable characteristics. By applying ML techniques, new perspectives and methodologies are introduced to the study of post-operative intestinal obstruction in the PACU, leading to an enhanced comprehension of the condition and providing robust backing for clinical decision-making [61].

Hypotension Prediction Algorithm

Hypotension is also a common complication in PACUUs and ICUs and is linked to negative patient outcomes [62]. The Hypotension Prediction Index (HPI) algorithm is currently considered a closed system, utilizing undisclosed calculations with proprietary variables. It underwent validation both internally and externally in PACU patients. Multiple research studies have consistently HPI serves as a reliable predictor of hypotension and its occurrence in different patient groups and in different peri-operative and post-anesthesia care settings [63].

Conclusions

In summary, the integration of AI in the PACUs presents significant potential for improving patient care and outcomes. By utilizing AI technologies for tasks such as identifying anatomical landmarks, enhancing sonographic image quality, visualizing needle placement, predicting complications, and managing pain, anesthesiologists can effectively reduce complications, increase operational efficiency, and elevate the overall quality of care within the PACU environment. As AI technology continues to evolve and become more embedded in clinical practice, further research and implementation of AI-driven solutions in the PACU are essential to fully harness the advantages and possibilities offered by this innovative technology in postoperative care.

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