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COMMENTARY

# Automation of Anesthesiology – Will Artificial Intelligence Replace Clinicians

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As technology continues to evolve at an exponential rate, conversations about its innovative promise become increasingly prominent in every sphere of life. Medicine and the field of anesthesiology are no exceptions to this trend. Discussions surrounding the topic of artificial intelligence (AI) elicit a mixture of feelings, ranging from excitement about its potential for enhancing patient care to uncertainty about the impact it may have on the future of the profession among current and prospective practitioners alike [1]. Amidst these feelings of ambivalence, one aspect of technological advancement is nearly universally agreed upon – emerging innovations will inevitably impact the practice of anesthesiology.

Historically, anesthesiologists have established a track record of being the "early adopters" of technology. Beginning with the development of positive pressure mechanical ventilation in the 1951 during the polio epidemic in Copenhagen, the practice of anesthesia has been consistently shifting towards automation [2]. In addition to widespread emergence of ventilators, the 1950s were marked by the first attempts to automate anesthesia monitoring and administration [1]. The early anesthetic robots would measure the depth of anesthesia using data derived from the electroencephalograph (EEG) signal and respond with pre-programmed, rule-based feedback [1].

These devices were developed in a top-down manner, meaning they relied on pre-set algorithms to account for a multitude of clinical scenarios when executing their function [3]. This design limited the usefulness of human-programmed machines to the setting of simple and constrained systems, as they lacked the flexibility of a human anesthesiologist to manage the demands of complex clinical environments.

Recent decades have been marked by the emergence of machine learning - a highly promising subfield within the domain of AI. Machine learning enables the computer to develop its function based on an ongoing data input, in a bottom-up fashion, without the need for explicit programming [1]. This self-teaching capacity allows the system to continuously adjust to the new incoming data, greatly enhancing its ability to function in complex and dynamic clinical settings. There are several sub-types of machine learning algorithms, many of which are making their way into the field of anesthesia [4].

Regardless of whether the underlying algorithm was manually developed or emerged from machine learning, robots in anesthesia can be categorized into two major classes - closed loop systems and clinical decision support (CDS) systems. Closed loop systems are based on the principle of feedback control, where the machine continuously measures the variable of interest, compares it to the desired target, and adjusts its output accordingly [3]. The ultimate advantage of closed loop systems is their capacity to consistently maintain the variable of interest near the target value. As such, these algorithms became the basis for the development of pharmacologic robots used in anesthetic delivery and hemodynamic management [5].

To execute their function, pharmacologic robots need to be capable of accurately assessing the depth of anesthesia and establishing a reliable control of

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medication delivery rate. Anesthesia depth is typically monitored via parameters derived from the EEG tracings such as bispectral index classically, along with the more sophisticated measures in recent years [4]. Current research indicates that the area of anesthesia depth monitoring has significantly benefited from machine learning methods, with newer systems achieving the accuracy of 88-93% in discriminating between awake versus anesthetized patients - a notable improvement compared to the results yieded via traditional methods [4].

Target control infusion (TCI) systems represent the earliest approach towards the automation of medication administration. Predating the development of closed-loop systems, TCIs are programmed to target selected drug plasma concentration and manage the medication delivery rate based on the population models of pharmacokinetics [3]. These robots operate as open loop systems, meaning they receive no input from the patient, making their performance reliant on the accuracy of the underlying models. Newer pharmacologic robots are designed as closed loop systems which process the input from the patient and utilize it to modulate drug administration. In the recent decades these devices have demonstrated the capacity to outperform manual controls and TCIs at maintaining the target anesthesia depth with isoflurane and propofol respectively [5].

Early pharmacologic robots were designed as single input single output (SISO) systems, capable of monitoring a single variable of interest and administering one type of medication. Newer designs have emerged in the last decade, possessing the capabilities to monitor multiple patient parameters and deliver multiple medications - multiple input multiple output (MIMO) systems [5]. These devices were shown to outperform manual controls at maintaining the anesthesia depth within the target range [6]. Current MIMOs function on semi-autonomous basis, meaning they are intended to assist the clinician in managing anesthesia, rather than providing complete automation [1]. Development of fully autonomous systems would require establishment of cross-communication between different feedback loops so that patients' vitals signs, hemodynamic parameters, and EEG-derived data are all integrated into a complete clinical picture.

The closed-loop design of pharmacologic robots makes them well suited for delivery of the medical therapy however, they do not have capabilities to determine the optimal treatment targets. In contrast, clinical decision support (CDS) systems are designed to assist clinicians in optimizing patient management by providing reminders, clinical assessments, and guideline-based recommendations [5]. CDSs have made their way into a wide variety of clinical settings, from reminder systems for perioperative medication administration to assistance with ultrasound-guided procedures [4].

Predictive therapy represents a particularly exciting area of CDS applications. Recent years have been marked by the development of programs aimed at detecting prodromal features of hemodynamic instability. Hatib and colleagues have created an algorithm capable of analyzing arterial pressure waveforms to forecast hypotensive episodes up to 15 minutes in advance, with 88% sensitivity and 87% specificity [7]. Other teams have utilized AI to predict the hypnotic4 and hemodynamic [8] impacts of anesthetic induction with greater accuracy compared to trained practitioners. These preliminary findings point to the immense promise of CDSs in enhancing the practice of risk assessment and minimizing complications across all perioperative stages.

Combining the cognitive support capabilities of CDS tools with precise control of therapy delivery of closed loop systems represents the ultimate step towards the development of autonomous anesthetic robots. As we continue to enhance our capacity to understand the relevant clinical targets and convey them to AI systems, we are moving closer to the establishment of devices that are capable of both - determining and providing the optimal medical therapy [5]. While unlikely to emerge in the near future, these fully autonomous systems represent an exciting frontier, capable of revolutionizing the practice of anesthesia.

In addition to offering a multitude of potential benefits, the ever-increasing computerization of the field of anesthesia poses several challenges that require careful consideration. Clinically, the key areas of concern outlined in the literature include disruption of workflow, clinician skill atrophy, and direct patient harm [5,9]. From an ethical standpoint, a major issue is the loss of patient confidentiality in the face of the need for clinical data for machine learning along with the inherent delay between emerging technology and the corresponding regulations [7,9]. This concern is not just theoretical - a 2014 FDA issued health IT report stated that the organization only aims to establish close oversight in a select few areas of CDS application, leaving many domains unsupervised [10]. With many questions unanswered, the process of ensuring optimal integration of AI into our healthcare system requires thorough planning and continuous reassessment.

At the present day, we remain long ways away from fully automating even the most routine anesthetic procedures. Majority of anesthetic robots and machine learning models have not been utilized outside of the research setting. It is not uncommon for devices to receive approval for commercial use but ultimately fail to achieve meaningful integration into clinical practice. Such was the case for Sedasys robot - a semiautonomous sedation system which promised to optimize propofol delivery during endoscopic procedures but was removed from the market due to poor sales in 2016 [1].

Nonetheless, AI-assisted anesthesia is not a matter of fiction or a distant future possibility. The ever-evolving capabilities of machine learning are paving new ways for the computerization of clinical practice. As anesthetic robots continue to evolve, many routine procedures would require less time and effort on behalf of the provider. This may enable anesthesiologists to attend to additional duties and further expand their scope of practice. Non-operating room services such as pain medicine, pre-operative clinics, and intensive care are ripe for further anesthesiology engagement.

Ultimately, the current state of AI does not allow for complete automation of the clinical duties in the foreseeable future, with technological developments being instead aimed at assisting anesthesiologists in their work. This points to several exciting possibilities where innovations broaden clinicians' scope of practice rather than limiting it. For such desirable scenario to become a reality, physicians should take on an active role in guiding the development and integration of the emerging technologies into the clinical practice. By remaining mindful of the implications of the ongoing technological evolution and establishing a clear vision of the desired future of the profession, the community of anesthesiologists can utilize AI to shape the practice in a way that enhances physician capabilities, promotes evidence-based medicine, and most importantly - improves patient outcomes [11-14].

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