Anesthesiology, automation, and artificial intelligence

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ABSTRACT

There have been many attempts to incorporate automation into the practice of anesthesiology, though none have been successful. Fundamentally, these failures are due to the underlying complexity of anesthesia practice and the inability of rule-based feedback loops to fully master it. Recent innovations in artificial intelligence, especially machine learning, may usher in a new era of automation across many industries, including anesthesiology. It would be wise to consider the implications of such potential changes before they have been fully realized.

KEYWORDS Anesthesiology; automation; artificial intelligence; clinical decision support; machine learning

The availability of shorter-acting drugs and improved technology has increased efforts to develop automated anesthesia systems. The earliest efforts date back to 1950 when Bickford described an apparatus to automate maintenance of anesthesia using summated electroencephalography signals to control anesthetic depth.¹ Since then, more technologically complex iterations of anesthesia automation systems have been introduced (e.g., McSleepy), but all current conceptions of autonomous or semiautonomous anesthesia maintenance systems are based on the same underlying concept that began with Bickford's apparatus. Namely, each iteration required rule-based, closed-loop feedback systems to manage one or more of the many domains necessary to successfully maintain general anesthesia, such as hypnosis, analgesia, and muscle relaxation. Designing a closed feedback loop for any one of these domains requires several steps that must be designed in a top-down manner. Initially, a reliably quantifiable target measure must be identified. For instance, the bispectral index is commonly used to assess depth of hypnosis. Then an algorithm consisting of rules and responses must be designed to effect changes in the target variable around a specified range of values, usually via alterations to drug administration rates. In practice, there is constant assessment and adjustment to maintain the target variable around the set point.

Adequate design of even one of these closed-loop domains to a degree that would allow fully autonomous function has proven to be quite complicated, much less coordinating multiple feedback loop systems into a robust, fully autonomous anesthesia machine. Despite these difficulties, though, several metaanalyses have shown that automated systems can be more effective than a human in attaining tight control within a specified range of

target variables and can also result in lower doses of delivered anesthetic with reduced recovery time.^{2–4} Recent studies have shown the feasibility of utilization of such closed feedback loop systems for maintenance of anesthesia not only in simple cases, but also for more complex ones.^{5,6} Of note, these studies showed that such closed-loop systems may be *feasible* to assist in the anesthetic management of complex cases, but they by no means showed that they were ready for fully autonomous control.⁵ The most mature of these attempts at semiautonomous anesthesia system was the Sedasys pharmacologic robot from Johnson & Johnson. It was designed to control the hypnosis and analgesia domains using several closed-loop feedback systems including algorithm-based calculations of standard vital sign data inputs as surrogate measures.⁶ Despite much fanfare upon its approval by the Food and Drug Administration, it was pulled from the market in 2016 due to dismal sales.⁷

Part of the problem with these attempts at automation relates to the systems' reliance on handcrafted algorithms using rigid rules, which has been the Achilles' heel of these early forays into automation in anesthesia. Since the closed-loop feedback systems are ultimately built from a series of rules, then attempts to control more complex systems have required more numerous and complex rules to effectively manage that system. Ultimately, once a sufficient degree of complexity is achieved, then linear, rule-based algorithms fail to supersede, or even match, the ability of a human to perform a task. However, newer innovations have greatly improved the potential for future success. These newer innovations are built on a subtype of artificial intelligence (AI) called machine learning, whereby a computer is programmed in such a way that it gains the ability to learn new information that it was not "explicitly

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programmed” to learn and to make changes to its function based on what it has learned.⁸ Thus, in contrast to the “top-down,” rule-based attempts at automated anesthesia maintenance, AI-based systems would utilize a “bottom-up” design, in which one gives a computer access to the entirety of available medical publications as well as real-world patient data. Then, using the tools of cognitive computing and machine learning, the machine will “learn” the relationships and connections within both the structured and unstructured data. As new data are available, the system will incorporate it, adapt, and respond. This allows for analysis and prediction models to be built “in silico,” converting raw data to actionable information. Or at least that is the goal: The machine teaches itself the skills needed to complete its task.

It is important to realize that AI is not some far-off, futuristic technology; it is already here all around us and has been for quite some time. AI systems have become such a part of our daily lives that we barely even notice their presence anymore—an outcome predicted by John McCarthy, the father of the term “artificial intelligence” in the 1950s, who stated, “As soon as it works, no one calls it AI anymore.”⁹ Conceptually, AI can be divided into two categories: narrow versus general or, alternatively, weak versus strong. We use the term “conceptual” because only narrow, or weak, AI systems currently exist. Narrow is a more apt descriptor than weak, as it implies that the scope of the system is narrow, not that it cannot accomplish its task well within a domain. Like a growing child, though, the abilities of narrow AI systems are expanding in both scope and substance, and many foresee a time where narrow AI will be an integral part of most of our lives. The ultimate goal for AI developers is artificial general intelligence, or strong AI. Such a system would possess intelligence and reasoning capabilities on par with a human across all the domains in which a human could gain mastery. Currently, these systems only exist in science fiction, like HAL from *2001: A Space Odyssey* or Tony Stark’s J.A.R.V.I.S. from the Iron Man comics and movies.

Where does that leave anesthesiology as a specialty? Anesthesiologists enjoy a good mix of cognitive and dexterity-based labor, and given that AI will primarily result in the automation of cognitive work, it may be that our hands prevent full automation of the specialty. The general dexterity that humans possess allows for a wide range of functional interaction with our environment, such as routine activities like tracheal intubation, venous cannulation, or neural blockade, and these same capabilities are simply not present in robotics at this time. AI systems utilizing machine learning tools may be extremely effective in one regard, though. Clinical decision support (CDS) tools have been shown in anesthesiology to be helpful for minor tasks, such as reminders for antibiotic administration or clinical documentation,¹⁰ but have been criticized for ignoring the needs of the individual patient due to their rigid structure. In the future, adding machine learning capabilities to CDS tools could improve the descriptive and predictive analytic capacities and greatly improve the sophistication and

capabilities of CDS tools. It is feasible that these advances may be able to produce clinical pathways that are truly evidence based, in that they are built on the evaluation of the entirety of available data, as well as individualized based on the demographics and comorbidities specific to each patient and procedure. Such systems would also be able to respond more rapidly to newly published evidence and will likely be able to generate new knowledge themselves based on analysis of pooled patient data from electronic medical records. Such advances could give individual providers the cognitive “boost” needed to deal with the massive quantity of available medical data, yet also provide better clinical pathways to more effectively improve patient outcomes. Another potential outcome is that as AI-based automation systems gain further capability, they may be able to perform semiautonomous anesthesia maintenance, where the AI-enabled machine takes over specified domains of anesthesia maintenance.

At some point in the future, if a fully autonomous anesthesia maintenance system could be created and validated, then it could certainly result in profound effects on the workflow patterns and needs of anesthesia providers. While some consider AI-enabled automation to be a harbinger of widespread unemployment due to an invasion of super-intelligent machines,¹¹ others see a completely different outcome. In this latter scenario, it is theorized that massive increases in productivity will come about as AI systems work alongside humans in a more symbiotic relationship, automating and offloading some of the cognitive workload and allowing humans to pursue higher-order activities. In health care, these higher-order activities could be a renewed emphasis on the doctor-patient relationship as we can once again address the wants, needs, hopes, and fears of our patients without compromising productivity and quality. In the specific case of anesthesiology, these innovations may allow anesthesiology the freedom to reinvent itself from an intraoperative specialty to one of true perioperative medicine. Such changes are already underway with the emphasis on non-operating room subspecialties like pain medicine and critical care. Furthermore, larger strategic efforts within the specialty, such as the American Society of Anesthesiologists perioperative surgical home,^{12,13} would be greatly aided by the development of a narrow AI autonomous anesthesia maintenance machine.

Despite such high potential, substantial hurdles remain in the successful implementation of any such machine that approaches clinical relevance. Though beyond the scope of this article, one of the greatest impediments remains the task of bringing together experts in data analytics, computer science, and medicine to create and curate the database from which a narrow AI system would “learn” to deliver anesthesia. One of clinicians’ greatest challenges will be validating the safety and efficacy of these systems. In the same way we observe a junior resident, we will have to closely observe the machine’s clinical decisions in order to ensure proper care is provided, but we must also work closely with the architects of such systems to be able to diagnose and correct any flaws in the machine’s decision-making process. Thus, these systems cannot be a “black

box”; we must have full transparency into how clinical decisions are made.

This brings up yet another challenge: security. While we must have transparency around the decision-making progress, we must also insist on robust security measures to prevent breaches of personal data, yet also prevent malicious actors from gaining control of or influencing the system. Much of this aspect of development will fall under the purview of our computer science and data analytic colleagues, but poor security leading to a high risk of hacking of medical devices has become a topic of great concern given the rapid development and dissemination of Internet-connected medical devices.^{14–16}

For the time being, though, both the hopeful and dystopian futures are possible, and there is no way to reliably predict which outcome is more likely. As a specialty, anesthesiologists have tended to be early adopters of technology, and we tend to be comfortable incorporating technological solutions to improve patient care. We should continue this trend and not only stay abreast of advances in AI, but make concerted efforts to integrate them into our practice now so that we can be the authors of our own future: improving provider productivity and each patient’s outcome by building and working in concert with narrow AI learning systems that create truly individualized, evidence-based clinical guidelines built in real time based on analysis of the entirety of medical literature and pooled patient data from electronic medical records.

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