Digital future in perioperative medicine: Are we there yet?

Digital transformation has revolutionized our everyday life including medical sciences; referring to the current innovative trends as the "age of automation" is perhaps not too much of an overstatement. Alan Turing and Warren McCulloch laid the foundations for artificial intelligence (AI) about eight decades ago.[1,2] Since John McCarthy coined the term "artificial intelligence" in 1950, the discipline has advanced significantly in various domains. We are at a critical stage in the history of medicine where AI has taken a significant role breaking all human barriers of language and communication.[3] AI can be divided into two broad categories: narrow and general. Currently, several "narrow AI systems" in domains such as games, images, speech, and cars are nearly fully developed and will soon be an integral part of most of our lives. The ultimate goal for AI developers is "general AI systems" that would have the intelligence and reasoning capabilities on par with a human brain. There is ever-growing data in healthcare; health data science has become a fully developed field on its own. Medical researchers are now increasingly applying machine learning to develop predictive models. There are several challenges for clinicians, patients, and healthcare systems to overcome. The Topol Review,[4] a report on preparing the healthcare workforce of NHS England to deliver the digital future, details how technological and other developments such as genomics, AI, digital medicine, and robotics are likely to change roles and responsibilities of clinical staff over the next two decades to ensure safer, more productive, and more effective and personal care for patients.

The current healthcare systems are overwhelmed with ever-expanding advances in the treatment modalities to provide safe and cost-effective patient care. For new digital healthcare technologies to reach their full potential without the need to increase resources, the whole health and care system will need to anticipate and plan for the future. One of the challenges for these integrated digital health systems is supporting perioperative clinical decision-making. A few studies were found to address these challenges with the use of AI Simulation Framework. They were also found to be beneficial in ensuring optimal decision-making including the most complex situations.[5]

Anesthesiologists have always been early adopters of technology to improve patient care and outcomes. In anaesthesiology, AI can be used to develop Clinical Decision Supportive Tools (CDS). Machine learning, a subset of AI that focuses on enabling algorithms to learn from the data provided, gathers insights and makes predictions on previously unanalyzed data using the information gathered. The three basic models of machine learning are supervised, unsupervised, and reinforcement learning. In perioperative practice, the current focus is on using machine learning to develop CDS tools and clinical pathways which have both descriptive and predictive capabilities. Machine learning has certain limitations. The information generated by the machine learning algorithms can be overwhelming. It can be difficult to make meaningful clinical interpretations and to ensure that the data are validated. Nonetheless, despite such limitations, machine learning algorithms seem to lead the future in perioperative medicine.[6]

Since the introduction of closed-loop systems in anesthesia and intensive care, developments have focused on improvement of automated system control and the stability of controlled variables. Closed-loop systems can reduce the task load in perioperative practice and may free up the clinician's time to manage other aspects of patient care without compromising patient safety. The main limitations to automation in anesthesia are complexity of agile tasks and also that the rule-based feedback loops may not fully accomplish the task. Automated closed-loop systems have been tried for anesthetic drug delivery, vasopressor administration, insulin administration, ventilation strategy, and weaning from ventilation. Brogi *et al*. undertook a meta-analysis to explore the accuracy and safety of closed-loop systems compared with manual control. They concluded that automated systems increased the length of time that a given variable was maintained in the desired range compared with manual control.[7,8]

Hypotension in the perioperative period is associated with significant risks. A forewarning of imminent hypotension episode facilitates clinicians to manage the patient safely. Large data of high-fidelity arterial waveforms have been used to train a machine learning model and predictive algorithms have been developed to indicate real-time perioperative hypotension at least 15 minutes prior to the hypotensive episode.[9]

Sepsis continues to be one of the common causes for morbidity and mortality. Optimizing fluid and vasopressor strategies in these patients could be challenging. Reinforcement Learning, a modality of machine learning, has been used to optimize treatment strategies for patients with sepsis in intensive care units.[10] This tool was found to be more reliable than human decisions with good patient outcomes.

While it is prudent to have a monitoring tool with a specific defined application, monitoring depth of anesthesia continues to be a challenge. Bispectral index (BIS) is one of several technologies used to monitor depth of anesthesia. There is a potential for variability in the predictability of the measured BIS and effect site concentration using target-controlled infusion with propofol and remifentanil during total intravenous anesthesia. Lee *et al.* found their deep learning algorithm–based prediction of BIS index to be more accurate. However, among the limitations of this study was inability of the algorithm to predict whether either propofol or remifentanil dose is doubled as this was not included in the data while training the system.[11] Perhaps in future, better machine learning systems can be devised to improve awareness prediction under anesthesia.

Optimal use of resources and avoiding waste is pivotal to healthcare systems. AI has emerged significantly in optimizing medication usage and reducing medication-related errors, and enhancing clinician's ability to diagnose accurately.[12] AI algorithms are found useful in predicting readmission rates of patients to hospitals and reducing incidence of medication-related errors and nosocomial infections. AI tools are being developed to study the real-time anatomy of the airway and facilitate prediction of difficult intubation. Machine vision, using data from various sensors, is a tool that can be used to help monitor critically ill patients, check appropriate handwashing, and alert staff of patients who are at risk of falling.

AI-assisted technologies will be useful in administrative jobs such as prioritizing clinic appointments, staffing, planning operating theater lists, coding of the procedures, and billing. AI algorithms can assist patients taking care of their own health. Smart watch–based algorithms have been developed which enable the watch to monitor and detect abnormalities in heart rate, rhythm, and even predict high potassium levels from electrocardiogram. Patient compliance to medical treatment can also be monitored.

Big data is providing newer biomedical research and discoveries. More and more predictive models in clinical practice are being developed. It is vital that the data used should be relevant for patient safety and outcomes. The machine learning models and algorithms should not only be consistent but should allow meaningful interpretation and free from random coincidence. Luo *et al.* suggested guidelines to ensure appropriate use of data and thereby applying machine learning models.[13]

As a speciality, anesthesia and intensive care should continue to create and refine real-time evidence-based individualized, CDS Tools and guidelines. One of the future clinician's greatest challenges will be validating the safety and efficacy of these systems. The revolution in AI is so much so that there may be a risk of technological collusions such as cloud and edge computing to even surpass human intelligence in the years to come. The challenge for health care professional in particular is the willingness to accept technology and the transformation that is inevitable. Effective clinical governance to ensure patient safety is vital for digital health.

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