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COMMENTARY

Perioperative intelligence: applications of artificial intelligence in perioperative medicine

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Over the past decades, we have made tremendous strides in reducing intraoperative mortality but postoperative morbidity is still high and overall surgical care is costly [1, 2]. Novel technologies like machine learning [3], artificial intelligence [4], and big data [5] may help deliver appropriate and safe perioperative care. But there is lot of hype and it is not clear how. *Perioperative intelligence* provides a framework for collaborative work to deliver safe, timely and affordable perioperative care using artificial intelligence; it focuses on three key domains—*identification of at-risk patients, early detection of complications, and timely and effective treatment.* In other words perioperative intelligence is an application of artificial intelligence in perioperative medicine.

First, we need to understand big data, machine learning and artificial intelligence. Big data is a concept to describe gathering and analyzing data which is high in volume, velocity, variety, variability, and complexity [6]. The healthcare data from electronic health records, genomics, physiologic monitoring, local, and national databases is accumulating to the level of big data. Whereas machine learning is a method of data analysis not relying on specific instructions but learning independently from the data. Machine learning algorithms [7] of varying complexity are used in the analysis of big data. For example, convolutional neural networks are used for deep learning and principal component analysis for dimensionality reduction. Artificial intelligence is more of a goal and is a field of science dedicated to development of systems or machines which can reproduce human intelligence; in other words, artificial intelligence is dedicated to development of technology which can help in clinical decision-making.

The vast majority of current work is focused on *identification of at-risk patients*. Numerous models—for example POSSUM, NSQIP, or Surgical APGAR—are developed to predict postoperative complications, but the broader applicability is lacking. Even the best predictive models, developed by Google, for length of stay and readmission risk are imperfect and lack generalizability [8]. Any predictive/risk score is dependent on the data it is derived from and the technology used to process the data. The POSSUM, NSQIP, Surgical APGAR scores are limited by both the data and technology. Lee et al. used advanced machine learning technology but are limited by the data it is derived from [9]. Even in the best settings, the healthcare data are not complete. Mostly our information is limited to what is documented in electronic health records. We need high quality continuous data from multiple domains to make better predictions. In other words we need to know everything about the patient's present state before the future state is described. Advancements in health data processing, biosensors, genomics, and proteomics all will help provide a complete picture of a patient which will enable perioperative intelligence. The healthcare systems, payers, and technology companies need to collaborate and fund advance technologies.

Early detection of complications is the next logical area where artificial intelligence can help. Currently, in a reactive management system harmful processes are managed once they have already started or the injury is established. We need to move away from this reactive management system,

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and use advanced technologies to build proactive systems to avoid harmful processes altogether. This is where perioperative intelligence can help. Specifically, in early diagnosis, appropriate patient specific treatment, and prevention of a disease state. Amara's law states that "we tend to overestimate the effect of a technology in the short run and underestimate the effect in the long run" [10] which is true in perioperative medicine. For example, much hyped, recently developed algorithms are limited to predicting in-hospital mortality [11], hypotension [12, 13], and bispectral index [14] and, therefore, have narrow impact. To improve outcomes we need to know which patients will benefit from surgery, when the surgery should be performed, what anaesthetic technique should be used, and which perioperative pathway is best for the individual patient. Understanding and sharing dynamic information of patients from disparate data sources like electronic health records, monitoring devices, population health records etc. and combining this knowledge with the best available evidence to provide real-time decision support is needed. (Figure 1) We are not there yet. Gathering and analyzing complete information on a patient from disparate data sources in real-time is still a challenge. Different healthcare specialists, including data scientists, within and outside healthcare organizations need to work together to integrate and analyze data. Thus perioperative intelligence will be realized with collaborative work of healthcare providers, payers, and the industry.

Providing *timely and effective treatment* is central to practice of evidence based medicine. Mostly in medicine we use randomized control trials to evaluate the efficacy of a new intervention. However, the effectiveness of treatment in real world clinical setting requires evaluation of benefit at the patient level. For example, if the appropriate amount and type of fluid is timely given to patient it will help improve patient's outcomes. Similarly, timely and appropriate antibiotic can help to improve a patients' outcomes. Artificial intelligence will help guide appropriate and effective treatment decision for a patient, realizing the goal of precision medicine.

The changes are needed at multiple levels. At the highest-level governmental regulations like Health Insurance Portability and Accountability Act (HIPAA) and European Union's General Data Protection Regulation should be updated to enable needed flow of information while ensuring privacy and rights of individual patients. However, even within hospitals data sharing is a problem. Currently, most clinical data live in silos protected by particular interests. For example, pharmacy, lab, outcome, and cost information is notoriously segregated among different groups and systems who are skeptical of each other motives, rather than patient centric. Furthermore, healthcare organizations are hyper-focused on cost cutting and weary of initial investments to develop the novel infrastructure. Specific intervention and investment from one group may not result in outright success but may benefit patients in long term and should be identified and encouraged. Therefore, current institutional structures need to be changed in favor of organizing and sharing dynamic patient information to achieve shared goals, putting patient's first.

While it all seems an arduous task, we list few applications of perioperative intelligence in developing novel tools. Standardized clinical pathways are a useful tool to reduce variation in care and improve outcomes, however, the evidence supporting a specific intervention is often limited. We used machine learning, topographical data analysis, to automate care path development and monitoring with the collaboration from multiple stakeholder within and outside the organization [15]. The unique unsupervised machine learning approach helped identify interventions associated with good outcomes and was reviewed by clinicians before changing practice. Another example is the use of multimodal machine learning to automated ICD coding in the intensive care unit, possibly reducing coding errors and effort [16]. We used the Medical Information Mart for Intensive Care III (MIMIC -III) dataset to develop and validate separate machine learning models that can handle data from different modalities, including unstructured text, semi-structured text, and structured tabular data. This project highlights the benefit of data sharing and needs external validation and peer review. Ultimately, new tools needs to show improved patient and/or financial outcomes. This is just a beginning.

To summarize, perioperative health data is imperfect and the technical capabilities are currently overstated. Few predictive models are available to identify at-risk patients but technology to guide treatment decision are in infancy and artificial intelligence is a far dream. Using the *perioperative intelligence* framework, we can maximize the benefits of technology and artificial intelligence to deliver safe, timely and affordable healthcare. The key is the integration across all data generating platforms along the journey of a patient and focused collaboration on three key domains—identification of at-risk patients, early detection of complications and offering timely and effective treatment.

Fig. 1 **Perioperative Intelligence** framework highlighting three key area of work. Patient and healthcare providers interact in a **Healthcare system** which includes the primary care clinic, preoperative clinic, surgeon's office, subspecialty clinics, operating rooms, PACU, IMC, ICU, hospital ward, skilled nursing facility and patient's home. **The data** from the electronic health record, population health record, laboratory information systems, radiology, physiologic monitoring devices, wearable sensors, pharmacy, billing, quality reporting systems, education systems, operating room management systems and research programs lives in silos in local institutional databases, research databases and national databases. The goal of Perioperative Intelligence to use this data for identifying at-risk patients, early detection of problems or diagnosis, and offer timely and effective treatment, using artificial intelligence

Compliance with ethical standards

Conflict of interest KM has receiving research Grant from Edwards Lifesciences and is a consultant for Edwards Lifesciences. BS collaborates with Pulsion Medical Systems (Feldkirchen, Germany) as a member of the medical advisory board and received honoraria for giving lectures and refunds of travel expenses from Pulsion Medical

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