Journal of Anesthesia (2025) 39:326–329
https://doi.org/10.1007/s00540-024-03412-7

LETTER TO THE EDITOR

Impact of societal change on anesthesia practice in Japan

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Received: 12 September 2024 / Accepted: 15 September 2024 / Published online: 26 September 2024

Keywords Society 5.0 · AI · Virtual reality · Closed-loop anesthesia · Target-controlled infusion

To the Editor:

Societal change to date in Japan has been characterized by four eras. These are the hunting-based (Society 1.0), agricultural-based (Society 2.0), industrial-based (Society 3.0), and information-based societies (Society 4.0). The future defined as "a human-centered society in which economic development and the solution of social issues are compatible with each other through a highly integrated system of cyberspace and physical space." represents the fifth era (Society 5.0) (Fig. 1). Significantly, in this new era, healthcare will change. Artificial intelligence (AI) will analyze real-time measurement data, medical information, and environmental information of individual residents with analysis and results being placed in a virtual space. Using these results, optimal lifestyle support, health promotion and treatment for each resident (AI driven individualized treatment/care) will be provided with the potential to reduce disease burden and costs. Anesthesia practice will need to change to make use of the wider benefits of this new information and AI-based societal changes.

AI and anesthesia machines

Closed-loop anesthesia

Closed-loop anesthesia is a method in which anesthetics and muscle relaxants are automatically administered according to the depth of sedation and muscle relaxation assessed using EEG and neuromuscular blockade monitoring to achieve a stable anesthetic state. The advent of remifentanil and propofol has facilitated closed-loop anesthesia. The closed-loop infusion system can automatically regulate target-controlled infusion (TCI) of propofol and maintain bispectral index (BIS) over an adequate range more effectively than a traditional open-loop system [1].

Inaccuracy of TCI

Why is TCI inaccurate? This is because TCI pumps use pharmacokinetic models to calculate infusion rates based on patient factors such as age and weight. However, as many clinical conditions affect plasma anesthetic concentrations, predicting these is difficult. Hemorrhage would increase plasma propofol concentration when cumulative blood loss exceeded 600 g with a decrease in cardiac output [2]. Thoracic aortic cross-clamping significantly increases plasma propofol concentration with a decrease in BIS [3]. Propofol measured concentrations would be much higher than its predictive concentrations in the TCI pump in patients with severe hepatic impairment [4]. As TCI pumps cannot account for these real-world events, they are inaccurate.

Monitoring of exhaled intravenous anesthetic concentrations

Systems for monitoring exhaled anesthetic concentrations are being developed [5–11]. Changes in exhaled propofol concentrations are similar to changes in blood propofol

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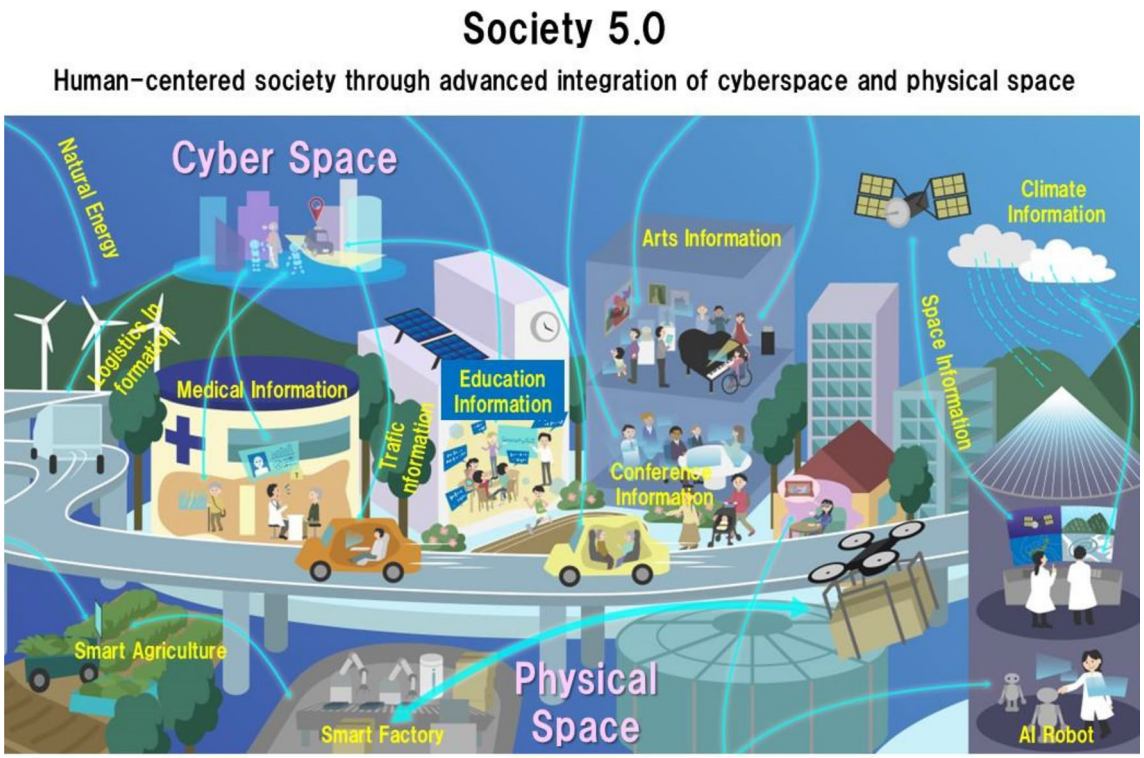

Fig. 1 Society 5.0: Human-centred society through advanced integration of cyberspace and physical space

concentrations [9]. Although the TCI pump is inaccurate, the expiratory anesthetic monitor may be able to compensate for the problems of TCI. Therefore, expiratory anesthetic monitor-guided TCI closed-loop anesthesia systems offer advantages over traditional TCI closed-loop anesthesia system. We recommend that expiratory anesthetic monitoring should be included in AI-based anesthesia machine development. The closed-loop anesthesia system of the future has the potential to produce a step change in anesthesia delivery/monitoring.

Anesthesia practice using virtual reality (VR)

VR prehabilitation for prevention of postoperative delirium (POD) [12]

The following have been identified as significant risk factors for POD: advanced age, vascular disease, diabetes, anemia, psycho-neurological disease, chronic pain and alcohol abuse, pre-existing cognitive impairment and severe illness. A prehabilitation program including exercise, nutritional support, psychological support, and behavioral modification has been reported to reduce the onset of POD by improving patients' baseline health. However, elderly patients often have diseases that impair their ability to engage in exercise and, hence, the effectiveness of prehabilitation. These include stroke, Parkinson's disease and cognitive impairment, impaired cardiac and/or pulmonary function, lumbago, coxalgia, and gonalgia. Several articles suggest VR prehabilitation is of benefit. We recommend that VR training programs should be routinely offered as prehabilitation in patients with limited exercise tolerance.

VR in palliative care and pain management

Palliative care: cancer patients are more likely to develop depression [13]. Chirico et al. [14] investigated the efficacy of virtual reality and music therapy in improving anxiety and mood states in breast cancer patients undergoing chemotherapy. They found that the VR program was most effective not only for tension, anger, and fatigue, but also for depression, although music therapy was also effective for all mental states except depression. Niki et al. [15] investigated the effects of a VR travel program on physical symptoms and emotions in terminally ill cancer patients. The results showed that the VR travel program significantly improved many physical symptoms, especially those regarding depression and happiness. Emotional responses such as enjoyment and pleasure were also increased.

Acute pain: Norouzkhani, et al. [16] conducted a systematic review and meta-analysis to examine the effects of VR

interventions on pain during wound care in burn patients. They found that VR significantly reduced pain compared to the control group. Specifically, an immersive VR intervention with goggles had a significant analgesic effect, whereas the non-immersive intervention without goggles did not. Pandrangi and colleagues [17] reported that immersive VR gaming significantly reduced pain scores and opioid use when comparing an immersive VR game with a VR headset to a smartphone-based game for postoperative pain management in head and neck surgery patients.

Chronic pain: Bair and colleagues [18] performed a literature review and found that patients with depressive illness often have pain symptoms and that pain negatively affects their treatment. In addition, moderate to severe chronic pain is associated with more depressive symptoms and can exacerbate depression. Basic science data indicate an association between chronic pain and depression. Indeed, several studies have found that both pain- and depression-induced neuroplasticity and neurobiological mechanism overlap [19]. Faraj and colleagues [20] reported that pain, opioid craving, anxiety, and depression decreased with a reduction in salivary cortisol levels.

Based on these observations, VR is likely to be useful for palliative care and pain management.

Prediction of perioperative outcomes using AI

Fritz and colleagues [21] compared AI models such as deep learning (a multipath convolutional neural network [MPCNN] model and a deep neural network [DNN]), machine learning (a random forest [RF] and a support vector machine [SVM]), and logistic regression (LR) for predicting 30-day postoperative mortality using preoperative patient's characteristics data and intraoperative data for 60 min prior to a randomly selected time point. In this study, 941 (1%) of 95,907 patients died within 30 days. MPCNN predicted 30-day postoperative mortality with an area under the receiver operating characteristic curve of 0.867 (95% confidence interval [CI] 0.835–0.899), which was higher than that of DNN (0.825; 95% CI 0.790–0.860), RF (0.848; 95% CI 0.815–0.882), SVM (0.836; 95% CI 0.802–870), and LR (0.837; 95% CI 0.803–0.871). MPCNN has the highest predictive accuracy. Lee and colleagues (22) performed a comparative analysis to determine which AI learning model could better predict hypotension after tracheal intubation using data from 4 min to 1 min before tracheal intubation in patients undergoing laparoscopic cholecystectomy. They compared machine learning models (RF, extreme gradient boosting [Xgboost] and deep learning (the convolutional neural network [CNN)] model and DNN). In this study, 151 of the 282 patients developed post-induction hypotension. Experiments on raw data showed that CNN had the best predictive accuracy of 72.63%, followed by RF (70.32%) and Xgboost (64.6%).

AI is being considered for the prediction of perioperative complications. AI models may have higher predictive accuracy than conventional logistic regression models. And we recommend their further evaluation in anesthetic practice.

Conclusion

Preoperative care "is the practice of patients-centered, multidisciplinary, and integrated medical care of patients from the moment of contemplation of surgery until full recovery [https://cpoc.org.uk/about-cpoc/what-perioperative-care]". The complex interplay between the medical professional, patients, and the wider society lends itself to interrogation by AI. This extends to the pain clinic, intensive care, and beyond. We recommend that anesthesia and anesthesiologists prepare for these changes.

Acknowledgements We thank Professor David G Lambert (University Department of Cardiovascular Sciences, Anaesthesia, Critical Care and Pain Management, University of Leicester, Leicester, UK) for his valuable comments.

Declarations

Conflict of interest The authors declare that they have no conflicts of interest.

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