laryngospasm persisted, resulting in complications despite the use of jaw thrust, CPAP, and oxygen 100%.[8–10] Of note, succinylcholine was not used as a therapeutic option in these cases.

Fibreoptic bronchoscopy-proven sugammadex-induced laryngospasm in unintubated patients has also been discussed by McGuire and Dalton[4] who noted that patients receiving propofol rather than inhalational anaesthesia developed less airway obstruction, whereas those receiving neostigmine or no reversal exhibited no obstruction. According to case reports in which sugammadex use after a failure to ventilate further complicated airway management,[11,12] McGuire and Dalton[4] opine that sugammadex-induced laryngospasm may be a contributing factor for the increased difficulty encountered in 'cannot intubate, cannot oxygenate' scenarios.[4] Although this work met criticism on ethical grounds,[13] it clearly merits attention, as the phenomenon described is both credible and important, especially when reviewed in the context of the referenced case reports. These cases highlight the importance of maintaining availability of succinylcholine for treatment of refractory laryngospasm.

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Perioperative automation: Time to become artificial intelligence literate? Response to *Br J Anaesth* 2020; 125: 843–6

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Keywords: artificial intelligence; curriculum; machine learning; medical safety; postgraduate education; safety; technology

Editor—Artificial intelligence (AI) and machine learning (ML) research, publications, and applications in medicine are accelerating,[1] and anaesthesia is not exempt from this trend.[2] The more AI-based algorithms become part of our perioperative work environment, the more we need to ensure that we have an appropriate understanding of the risks. We provide a timely assessment of some of the limitations of this emerging technology in response to the recent article by O'Reilly-Shah and colleagues.[3]

The example of pulse pressure variation that the authors mention initially is a good reminder of why an expert-in-the-loop who is aware of technological limitations is much needed. There are many different platforms that display stroke or pulse pressure variation data to assist clinicians in determining optimal haemodynamic management.[4] But even these relatively simple algorithms and platforms require a sound understanding of their inclusion criteria to safely translate data into practice. In particular, when it comes to pulse pressure or stroke volume variation (PPV/SVV), there are several key limiting factors.[5] If one were to take PPV/SVV data at face value without considering the significant effects of spontaneous ventilation and arrythmias, fluid responsiveness would certainly be misjudged. Similarly, one would not begin treatment of a sudden, severely elevated blood pressure value from an arterial pressure transducer before confirming that the transducer is at the appropriate height, is zeroed, and is still performing correctly in terms of damping considerations.[6] These are just a few examples that underscore the importance of a thorough 'device literacy' that we must maintain to deliver optimal care when using state-of-the-art technology.

Anaesthesia often tries to emulate the strong safety culture of the aviation industry. The unfortunate events with Boeing's 737 Maneuvering Characteristics Augmentation System (MCAS) should serve as a stark warning of why we in anaesthesia need to pursue algorithmic awareness, training, and competence, in short 'AI literacy'. Boeing's MCAS was designed to assist pilots by automatically pointing the airplane's nose downward in certain circumstances when sensors registered dangerous climb angles. This unfortunately led to a series of near-crashes and crashes when a sensor delivered inaccurate information forcing the plane down even when it was not indicated.[7] Reporting suggests that some pilots knew how the system functioned or found out in time how to override it, whereas others, unfortunately, were not trained adequately in this new algorithmic system resulting in tragic loss of life.[7]

Taking into consideration the Boeing MCAS events and recent AI publications has affirmed our belief that there are two interconnected concerns that have to be addressed to ensure optimal safety. First, we should treat AI as another medical device that needs appropriate safety regulation and oversight, similar to the aviation industry's strict regulation of airplanes. In this context, it is fitting that the US Food and Drug Administration recently proposed regulatory framework modifications for AI/ML-based Software as Medical Device (SaMD).[8] As SaMD is aimed towards guaranteeing appropriate technological standards and safety requirements of medical AI systems, it should address the first concern. Sadly, the Boeing events demonstrate that 'Swiss cheese holes' can still align and unanticipated errors can still occur despite rigorous regulatory scrutiny. This leads to the crucial second component of AI safety: AI awareness and literacy. As mentioned, it appears that some pilots were tragically 'out-of-the-loop' and could not make a life-saving difference in time despite their expertise in flying the aircraft. The lesson should be clear: not only do we need experts who can fly the airplane or provide safe anaesthesia, but with AI systems in (partial) control, we need experts who are truly 'in-the-loop' and AI device literate. We should therefore invest in training the next generations to become 'anaesthesiologists-in-the-loop' (AITL) who understand applied AI, its limitations, and are proficient in recognising AI bias and inappropriate actions, so they can intervene in time. Consequently, we advocate incorporation of AI training into anaesthesia curricula to ensure that we produce AITLs who are capable of preventing harm from (semi-) automatic, algorithmic systems that are malfunctioning because of factors such as faulty sensor data or AI bias as exemplified by O'Reilly-Shah and colleagues.[3]

In the absence of current international and national educational standards, but encouraged by recent publications in the field,[9] we decided to start in our own academic environment and developed a 'Fundamentals of AI' course to provide the next generation of consultants with AI expertise that they can build upon. For our inaugural class, we selected suitable virtual lectures from recognised AI experts that are available on online platforms so they can be completed in addition to a demanding clinical anaesthesia training curriculum. Topics not only cover AI and ML fundamentals, but also bias, ethics, and safeguarding, in addition to expert-in-the-loop, explainable AI, and big data in healthcare concepts. We made sure to include a module on how to critically evaluate AI/ML research literature as this requires additional knowledge.[10] This year-long course concludes with an introduction to AI/ML platforms and autoML concepts that allow physicians who are not experts in coding to design their own AI projects and contribute to AI advances in our specialty.

The significant increase in AI publications in the perioperative field and the rise of still mostly experimental AI-enabled anaesthetic titration devices[11] has us convinced that becoming an anaesthesiologist-in-the-loop may soon be a prerequisite for sound decision making and life-saving interventions. As AI has arrived in anaesthesia, now is the time to begin our path towards 'AI literacy'.

Declarations of interest

The authors declare that they have no conflicts of interest.

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Variability in experimental pain studies: nuisance or opportunity?

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Editor—Pain is a variable experience, even in studies that use controlled nociceptive stimuli in healthy humans.[1] This variability is unsurprising considering that nociception (the neural process of encoding noxious stimuli) and pain (a conscious experience) do not share an isomorphic relationship.[2] Pain is influenced by a broad range of biological, cognitive, contextual, and mood-related factors that may vary from moment to moment.[3] Even a well-controlled experimental laboratory environment presents limited scope to control all these factors, and it is rare for pain to be elicited with high consistency.

The intraindividual variability in pain reporting may reflect important personal features that are relevant to our understanding of pain and the impact of analgesic strategies. With this in mind, several clinical studies have used high frequency pain assessment in longitudinal designs to examine the possibility that intraindividual variability may be relevant to clinical outcomes. They report that intraindividual variability in pain ratings may be related to depression,[4,5] self-efficacy,[4] emotional and physical functioning,[6] and may predict benefits from sham medication or active treatments.[7–9]

Nevertheless, experimental pain research in humans has largely neglected to acknowledge explicitly the importance of intraindividual variability in pain reporting. To our knowledge, only a handful of studies have attended to intraindividual variability.[1,10–14] Instead, the common practice is to analyse averages gained from repeated measurements and thus smooth out variability. Raw data are seldom presented. Thus, intraindividual variability is considered a nuisance, rather than a feature worthy of attention.

Obscuring variability has practical disadvantages. Many experimental studies rely on calibrating stimulus intensities to each individual participant and then assuming that subsequent stimuli are experienced at an intensity that reflects the data from that initial calibration. Intraindividual variability in trial-by-trial pain reports undermines this assumption, and points to contemporary experimental designs that allow for drift in stimulus-response relationships and detect shifts over time in, for example, the effect of one stimulus-response on a subsequent stimulus-response. Accounting for variability in research design or statistical analyses will allow greater confidence in interpreting the effect of analgesic interventions on stimulus-response relationships.

Obscuring variability has external validity disadvantages. The common approach to experimental pain studies is sequential averaging, where the averaged intraindividual