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Published in:
British Journal of Anaesthesia

DOI:
10.1016/j.bja.2021.03.011

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British Journal of Anaesthesia, 127 (2): 184–187 (2021)
doi: 10.1016/j.bja.2021.03.011
Advance Access Publication Date: 20 April 2021

VitalDB: fostering collaboration in anaesthesia research

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This editorial accompanies: Deep learning models for the prediction of intraoperative hypotension by Lee et al., *Br J Anaesth* 2021:126: 808–817, doi: 10.1016/j.bja.2020.12.035

Keywords: big data; clinical databases; data mining; data science; open data; perioperative medicine; predictive analysis

In the April issue of *British Journal of Anaesthesia*, Lee and colleagues[1] reported the development and validation of deep learning models for the prediction of intraoperative hypotension. The authors developed an algorithm that, unlike marketed algorithms,[2–5] make use of multimodal biosignal waveforms, acquired using routine invasive and noninvasive patient monitoring to predict future hypotensive events. Using data from 3301 patients from their database, they trained and validated their model. Although some aspects of the methodology may still be improved, such as (acausal) extraction of events,[6] their model demonstrates strong predictive performance for hypotension up to 15 min before its actual occurrence, particularly when model inputs included combined rather than single signals. What really sets the study apart from others of its kind, however, is that the authors have released both the code and data that underpin their findings.[7]

Although practices are changing, there are still too few motivations for researchers to share their well-curated data and self-developed software. The effort taken by the authors to create, document, and release this unprecedented perioperative dataset, the *VitalDB database*, along with their analysis code should serve as a lesson for the community. The creation of easily accessible physiologic databases within anaesthesia and intensive care has created outstanding education and research opportunities over the past two decades.[8–10] These databases have offered fundamental insights into clinical care and created a platform for interdisciplinary educational programmes and projects. Here, we highlight the accomplishments of the authors and consider this relatively new VitalDB database in the context of other currently available datasets in the field of anaesthesia and intensive care (Table 1).

DOI of original article: 10.1016/j.bja.2020.12.035.

Table 1 Overview of large, openly available databases in anaesthesia and intensive care. DUA, digital user agreement; MIMIC, Medical Information Mart for Intensive Care; PIC, Paediatric Intensive Care; eICU, The eICU Collaborative Research Database; HiRID, High time Resolution ICU Dataset; AmsterdamUMCdb, Amsterdam University Medical Centre database; VitalDB, Vital database.

Name *n* time span	Approximate resolution of vital signs (HR, MAP, etc.)	Access requirements			General remarks
		DUA	Training/ course	Submission of a summary of planned research	
MIMIC-IV 60 000+ patients 2001–16	Every 1 h, matched waveforms offer possibility of higher resolution	Required	Required	Not required	Widely used in critical care research, comprising data from a tertiary academic medical centre in Boston, MA, USA. The latest version of MIMIC, MIMIC-IV, includes a broad range of data modalities, including chest radiograms, electrocardiogram and other haemodynamic waveforms, structured clinical observations, and unstructured notes.
PIC 12 000+ patients 2010–8	Varying because of manual entries (during surgery every 5 min)	Required	Required	Not required	Comprises paediatric ICU admission data from a children's hospital in China. The database includes vital sign measurements, medications, laboratory measurements, fluid balance recordings, diagnostic codes, demographic information, and more
eICU 200 000+ patients 2014–5	Every 5 min	Required	Required	Not required	Comprises of data from more than 200 critical care units across the continental USA collected as part of a critical care telehealth programme. Includes demographics and time series observations including vital signs, medications, laboratory tests.
HiRID 33 000+ patients 2008–16	Every 2 min	Required	Required	Required	HiRID has a higher time resolution than other published datasets, most importantly for bedside monitoring with most variables recorded every 2 min. This creates unique opportunities for reliably characterising the haemodynamic status of patients during their ICU stay.
AmsterdamUMCdb 23 000+ patients 2003–16	Up to one value every min	Required	Required	Not required	The dataset includes demographics, vital signs, laboratory tests, and medications from ICU admissions.
VitalDB 6000+ patients 2016–7	Every 1–7 s and waveforms also available	Required	Not required	Not required	The first perioperative high-resolution waveform database (holding ECG, arterial blood pressure, plethysmography, etc.). It also holds surgery-related and clinical information such as patient demographics, surgical procedure, comorbidities, outcomes (mortality), preoperative and intraoperative laboratory values, treatments and other information (e.g. estimated blood loss)

VitalDB and VitalRecorder: a collaborative approach to anaesthesia research

The authors make use of their own database, VitalDB, which was recently released and is, to our knowledge, the first open and large database containing high-resolution waveform data from the intraoperative setting (www.vitaldb.net).[7] The high-resolution waveforms from more than 6000 patients were captured from the vital signs monitors (ECG, arterial blood pressure, plethysmography, etc.), ventilator (airway pressure and capnography waveforms captured at a rate of 62.5 Hz), and depth-of-anaesthesia monitor (EEG waveforms from the bispectral index [BIS] monitor, sampling rate of 180 Hz). Furthermore, data from infusion pumps (drug, infusion rate and volume) and cardiopulmonary trending variables (e.g. heart rate and respiratory rate; available every 1–7 s) were captured, and essentially include the numbers displayed on the monitors used in the operating room during the given procedure, from which data were recorded. In addition, more than 60 surgery-related clinical information variables are provided in the database to help interpret the signals. On top of this, extensive descriptive information is available such as patient demographics, surgical procedure, comorbidities, outcomes (mortality), preoperative and intraoperative laboratory values, treatments, and other information (e.g. estimated blood loss). With this plethora of data, one can think of many potentially interesting observational studies to conduct.

In addition to data, the authors have released, free of cost, the software used for its creation, the *VitalRecorder*. This application allows other institutions to set up a similar database, but can also be used for simple bedside data capture in prospective studies.[11–13] For instance, in haemodynamic research, we often want to obtain haemodynamic waveforms at the bedside of a specific patient. Data export solutions, whether from device manufacturers or third parties, have been costly and often limited by supporting only one specific monitoring modality. Today, at least two freely available software solutions exist: the *VitalRecorder*[7] and *VSCapture*.[14] Both support data export from different, partly overlapping, sets of devices. VitalRecorder provides a real-time graphical feedback of the waveforms, visually confirming the captured data, whereas VSCapture seems underway with development of such visualisations of the captured data in real-time. VSCapture is open source, allowing project-specific modifications to the software.

VitalRecorder is able to capture data from an impressive array of monitoring devices. The team maintains an accessible, illustrated guide to connecting to these devices. Although the software is free to use, it is not yet open source. There are valid reasons to keep such software closed, but it impedes some aspects of usability such as collaborative development for integration with new devices. Many research projects will require data to be collected from devices not yet supported by VitalRecorder. Developing support for new devices is a slow and cumbersome process, and often requires direct access to the device. Allowing the research community to contribute with support of new devices could greatly increase the applicability of this already remarkable research tool. Making research software development a shared effort could also support the research community and prompt international collaborations.

Public databases and sharing of analysis code

In recent years, there has been wider use of electronic health record systems and increasing recognition of the importance of data sharing.[15] Several detailed patient-level datasets have become publicly available to researchers over the past decade, with communities often working together to share and reuse analytical code. VitalDB is one such resource and the only large perioperative database that includes waveforms, although other databases exist in the area of anaesthesia and intensive care (Table 1). One of the most widely known of these databases is the Medical Information Mart for Intensive Care (MIMIC), a publicly available dataset that comprises de-identified health data associated with >60 000 patients admitted to an ICU of a tertiary hospital in the USA.[8,16] The dataset is widely used by investigators and engineers around the world, helping to drive research in clinical informatics, epidemiology, and machine learning. Following in the footsteps of MIMIC is the Paediatric Intensive Care (PIC) database, a paediatric-specific intensive care database populated with data acquired during routine hospital care in the Children's Hospital of Zhejiang University School of Medicine in Zhejiang, China. The PIC database encompasses 13 499 distinct hospital admissions from 12 881 distinct paediatric patients (aged 0–18 yr). Another notable publicly accessible dataset is the eICU Collaborative Research Database, a multicentre critical care dataset comprising more than 200 000 hospital admissions to >200 hospitals in the USA, collected as part of the Philips eICU Research Institute.[9] As yet, however, none of the aforementioned databases includes *intraoperative* data, so VitalDB fills an unmet need.

European datasets have also recently emerged. The Swiss, single-centre, *HiRID* database[10] comprises nearly 34 000 ICU patients' admission data and resembles the MIMIC dataset in many ways. Another recent European dataset is the Dutch ICU database, *AmsterdamUMCdb*,[15] which contains de-identified health data from more than 23 000 ICU admissions. Although other medical databases have been available for some time within the EU, such as the UK Biobank,[17] this is the first freely accessible intensive care database from within the EU. HiRID and AmsterdamUMCdb both require credentialed access, similar to MIMIC, but a remarkable aspect of the two European ICU databases is that they both comply with the EU General Data Protection Regulation (GDPR). Many European researchers advocating data sharing struggle with the national interpretation of GDPR and have substantial difficulties in figuring out how sharing of de-identified (or pseudonymised) data is possible. For example in the early days and first interpretations of GDPR legislation, it was debated in Denmark how (and even if at all) the well-established national registries could be used under the new legislation. The GDPR legislation remains difficult to fully grasp for most researchers and the Dutch database leaders have been very progressive in this aspect. In Table 1, all the mentioned databases are described in more detail including their content, approximate resolution, and how to obtain access. Most datasets are available after credentialing, which includes completion of a training course and signing off a data use agreement mandating responsible handling of the data and adherence to the principle of collaborative research. The training course required for most databases is not extensive and can typically be completed within 1–2 h.

More data, more research

The emergence of open and freely available datasets along with advances in data transfer speed and computation have led to a rapid increase in the reuse of routinely collected clinical data for research. The descriptive paper for MIMIC-III, published in 2016, was cited more than 1100 times according to Scopus, 465 times in 2020 alone, illustrating the massive use and research impact of releasing the dataset.

Making datasets readily available undoubtedly facilitates interdisciplinary, computational research too. This is exemplified by the statements of the creators of the AmsterdamUMCdb database[15]: 'Our main goal is to connect healthcare with data science'. By opening up data, data scientists, engineers and clinicians can connect and *work* with the data together, and in turn learn the hard, frustrating discipline of getting acquainted with the complexities of clinical data. This creates the melting pot necessary for new ideas and insights to emerge and generates a focal point for collaboration. Therefore, the VitalDB is a most welcome dataset for being the first, large, and open dataset to hold detailed intraoperative monitoring data.

Authors' contributions

Organising and writing the first draft of the editorial. Proofreading and final approval of the manuscript: STV.
Organising and contributing to the first draft of the editorial. Proofreading and final approval of the manuscript: TJP.
Organising and contributing to the first draft of the editorial. Proofreading and final approval of the manuscript: JNE.
Organising the first draft of the editorial. Proofreading and final approval of the manuscript: TWLS.

Declarations of interest

TJP received funding from the US National Institute of Biomedical Imaging and Bioengineering (Bethesda, MD, USA) grant number R01EB030362, and from Philips Healthcare. TWLS received research grants and honoraria from Edwards Lifesciences (Irvine, CA, USA) and Masimo Inc. (Irvine, CA, USA) for consulting and lecturing and from Pulsion Medical Systems SE (Feldkirchen, Germany) for lecturing. All other authors declare that they have no conflicts of interest.

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