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Editorial

Big data are here to stay!

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Big data – the huge amounts of information that are now being collected from widespread digitalisation in almost every walk of life – are having a growing impact in the healthcare sector, including the intensive care unit (ICU), facilitated by the widespread introduction of electronic medical records and data collection from modern bedside monitoring systems. The analysis of these large volumes of rapidly generated, highly varied digital data is being made possible by remarkable developments in technology and data science. Too large for traditional analytic techniques, data mining, using machine learning techniques and artificial intelligence, is used to process and learn from big data. This whole field of data science has resulted in the introduction of multiple new terms, including "supervised" and "unsupervised" learning, "structured" and "unstructured" data, "latent class analysis", "digitisation" and "digitalisation", "overfitting" and many more [1]. The considerable and exciting potential for application of these techniques at the bedside in the intensive care environment is well-described in the insightful review by Pirracchio and colleagues [2].

The ICU is an almost ideal place for big data, as patients have complex, often rapidly evolving disease processes, and many patients have several different conditions simultaneously. This complexity renders identification of single diagnoses particularly challenging, so that intensivists often choose to speak about syndromes, like sepsis and acute respiratory distress syndrome (ARDS), easily forgetting that these are not diseases in themselves, but manifestations of disease, and grouping patients into such syndromic categories does not solve the problem of underlying heterogeneity. The negative results of so many randomised controlled trials targeting mortality in relatively non-specific critically ill patient populations has been very disappointing [3]. It has not only consumed considerable amounts of energy and resources, but has fostered the impression that the only treatment that will work in our patients is to reduce iatrogenicity.

Much of the data we collect from our patients is wasted, yet the potential applications for big data in intensive care medicine are vast if the methods to store and analyse the data appropriately can be harnessed. The diagnostic implications of big data are relatively straightforward, for example to facilitate the rapid distinction between several differential diagnoses using more or less complex algorithms [4]. However, obtaining a diagnosis, but not being able to provide treatment, is of limited value. Much more attractive in the field of intensive care medicine is the use of big data to optimise therapeutic interventions. Here we will briefly mention a few simple examples of how the analysis of big data will impact on clinical practice in the near future. Firstly, researchers have begun to use data mining techniques, including latent class analysis, combined with modern omics technologies, to identify subgroups of ICU patients with different characteristics, different outcomes and different responses to therapeutic interventions [5–8]. Identification of a patient's phenotype may therefore help select the most appropriate therapeutic intervention for that patient. For example, Calfee et al. [8] identified two subphenotypes of ARDS, with distinct clinical and biological characteristics. Patients with a hyper-inflammatory subphenotype had higher 28-day mortality than those with the hypo-inflammatory subphenotype, and were less likely to have a favourable response to treatment with a statin. Similarly, Famous et al. [7] identified subgroups of ARDS patients with different responses to fluid administration, and a similar approach identified patients with septic shock who benefitted from corticosteroids more than others [9,10]. Indeed, it is difficult to believe that in 2019 we still decide whether or not to give corticosteroids to patients with septic shock based just on an impression that they "look very sick"!

Secondly, machine learning using big data derived from haemodynamic monitors and electronic medical records can be used to help predict events, for example for early identification of sepsis or haemodynamic deterioration [11,12], enabling appropriate therapies to be started more rapidly. Thirdly, big data could be used to develop strategies to aid clinical decision-making. For example, Komorowski et al. [13] recently used reinforcement learning to develop a program that dynamically suggested the optimal fluid and vasopressor management for patients with sepsis. Their results suggested that treatments provided by their "artificial intelligence clinician" might have been better than those given by the practicing intensivist. This approach is more likely to be of practical use and benefit to the patient than a randomised controlled trial conducted in a heterogeneous patient population, such as the recent Restrictive IV Fluid Trial in Severe Sepsis and Septic Shock (RIFTS) study. Patients were randomised to a strategy

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of standard fluid management or restrictive fluids, but the study did not even include a description of the monitoring systems used to make fluid administration decisions, thus limiting interpretation of the results [14]. Similarly, big data could be used to determine which patients are most likely to benefit from a blood transfusion. Randomised controlled trials have compared two groups of patients based on pre-set haemoglobin thresholds, although we know that multiple other factors, including coronary artery disease, respiratory problems, need for rehabilitation, can also influence response to red cell transfusion and should be taken into account when deciding whether or not to transfuse. A more personalised approach to transfusion decisions is needed [15]. Large observational studies have already suggested that blood transfusions may be beneficial in certain groups of critically ill patients [16]. Big data analysis will certainly provide further important input in this field and could ultimately provide the clinician with real-time predictive information to help determine if and when a transfusion may be of value.

We are at the beginning of an exciting new era in the history of intensive care medicine as data collection and analysis continue to expand, and the derived information is gradually integrated into routine clinical practice at the bedside. Detractors of this new approach highlight the challenges of ensuring that the large quantities of data are of good quality, that data science methodology is appropriate and accurate, and that human decisions and clinical notes are also included [1]. Concerns about data privacy and security have also been raised. But big data are here to stay and we must address these challenges and collaborate with experts in data mining techniques to ensure that we exploit the possibilities of this new technology. Used correctly, big data can help identify how best to use many therapeutic interventions in individual patients, drawing us closer to true personalised medicine. Importantly, clinicians should not feel threatened by this approach; the practice of medicine is increasingly complex and the human mind simply cannot simultaneously handle as much data as a machine [17], especially when we are tired or distracted; moreover personal biases can also influence our decision-making. We must embrace and engage with this new technology to improve our ability to offer real personalised medicine for the benefit of our patients.

Disclosure of interest

The authors declare that they have no competing interest.

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