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SPECIAL SUPPLEMENT
Pain Management in the ICU

Innovation

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Innovations in ICU ventilation

The future delivered

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In this article, we aim to summarise the developments in mechanical ventilation that we believe are shaping the present and will shape the future ahead.

Introduction

Many centuries ago, Socrates stated that "the secret of change is to focus all of your energy, not on fighting the old, but on building the new." Nowadays, we may relate his quote with the concept of innovation, which is considered the process of turning an idea into a good or service that adds value. Innovation must satisfy a specific need, involve a deliberate application of information, imagination, and initiative, and ought to include all processes by which new ideas are generated and converted into useful products. As physicians, we tend to assume regular incremental advances in technology and processes, but from time to time disruptive innovations take place.

Even though innovation entails the application of useful novel ideas, these should address our specific challenge: taking care of the patients' needs. New ideas must accept the pathophysiology, at least to a certain level, and aim to prevent further harm. We are bystanders of an exponential increase in knowledge and face complex situations with small response time. Therefore, modern technology comes to play, providing critical care with new tools that meet three major goals: improving management, making better decisions and being more effective in patient care (Pettenuzzo and Fan 2017; Schulman and Richman 2019). In the following paragraphs, some examples of these technological advances are presented.

Advanced monitoring

As healthcare professionals, we face one of our first issues: the visualisation and interpretation of the enormous quantities of patient-specific data in an extensively monitored environment.

Continuous assessment of respiratory status and optimisation of ventilator settings are one of the keystones of advanced monitoring systems, improving our understanding of the disease and the effect of therapeutic strategies (Theerawit et al. 2017; Ergan et al. 2018). Current monitors integrate several parameters at the same time, providing cleared-up information to the user.

In this context, and in order to implement the best possible medicine, clinical decision support systems (CDSS) have been born to stay. CDSS could be defined as health information technology that builds upon the foundation of an electronic health record system, granting specific, filtered and organised information (Josheroff et al. 2012; Korngiebel et al. 2017). In other words, CDSS aid to address the challenges of big data in an era of precision medicine, helping patients and clinicians to make optimal decisions. Some authors have proposed that CDSS address 5 rights: delivering the right evidence-based information, to the right people (healthcare professionals), in the right format, through the right channels and at the right time (Sirajuddin et al. 2009). From our point of view and experience, we also consider that the CDSS must fulfill a set of requirements, grouped in **Figure 1**. CDSS will mean a change in our day-to-day work, as they will be able to predict the emergence of complications and will help select the best possible treatment for each individual patient. However, these outcomes will require joint work of healthcare professionals and machine or Deep Learning systems, especially when a Blockchain Data Encryption System is fully integrated (Mandl and Manrai 2019).

Current examples of applied CDSS are outreach rapid response teams and use of early warning scores (Vincent et al. 2018). An example of the latter takes place at our department, with an ongoing project named **ICU without walls**. It consists in applying computer systems including an algorithm that monitors vital signs of patients admitted to the hospital, in order to allow an early identification of deterioration, decreasing the incidence of organ failure (including respiratory failure and need of ventilatory support), and enabling rapid targeted management (Gordo and Molina 2018). Other examples of applied CDSS are open-loop physiologic model-based decision support systems (Rees 2011; Tams et al. 2017; Karbing et al. 2018; Spadaro et al. 2018); and multimodal CDSS, which incorporate data from bedside, wireless and third-party devices, to upload the information on a platform (**Figure 2**).

In addition to ground-breaking monitoring, lung imaging techniques have experienced overwhelming progress: we currently not only base our knowledge on chest x-ray or computed tomography, but use lung ultrasound, positron emission tomography, electrical impedance tomography or magnetic resonance imaging as decision support tools. As ultrasonography is an evolving part of critical care medicine, it lends itself to innovative applications. Even though its results/images depend on the operator and the patient's characteristics (obese patients, thoracic dressings, subcutaneous emphysema), lung ultrasound may visualise pleural effusion and consolidation (alveolar consolidation, atelectasis), and has demonstrated a potential utility in several clinical conundrums: (a) during the process of recruitment manoeuvres (strong correlation between PEEP-induced lung recruitment and lung ultrasound aeration score), (b) during fluid resuscitation of ARDS patient, avoiding fluid overload (impairment correlated with

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extravascular lung water), and (c) during the process of weaning the patient from mechanical ventilatory support [including diaphragmatic ultrasound] (Mayo et al. 2016; Lui and Banauch 2017).

Conversely, electrical impedance tomography (EIT) has been a remarkable technological advance in the field of lung monitoring, and mechanical ventilation adjustments EIT may assist in (a) defining mechanical ventilation settings, (b) assess distribution of tidal volume and of end-expiratory lung volume, (c) contribute to titrate PEEP/tidal volume combinations and (d) quantify gains (recruitment) and losses (overdistention or de-recruitment), granting a more realistic evaluation of different ventilator

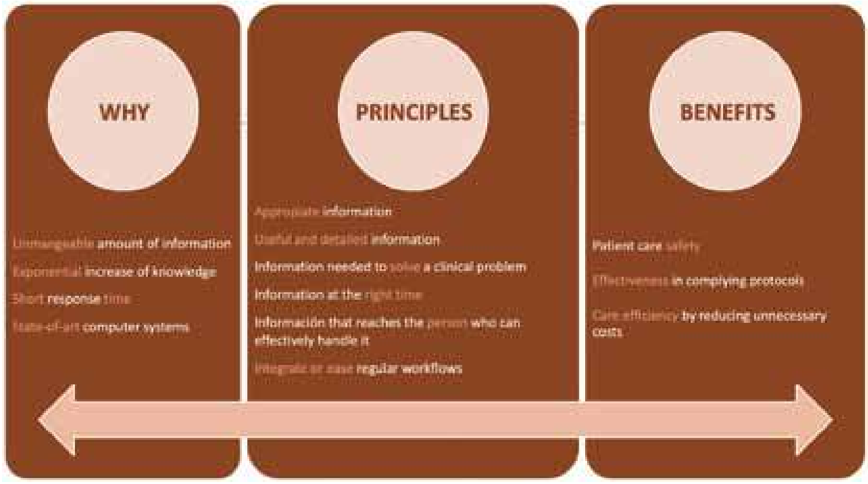

Figure 1. CDSS requirements.

Figure 2. Example of CDSS interface. Beacon Caresystem® (Mermaid Care A/S, Nørresundby, Denmark) providing real-time information and recommendations regarding ventilator settings.

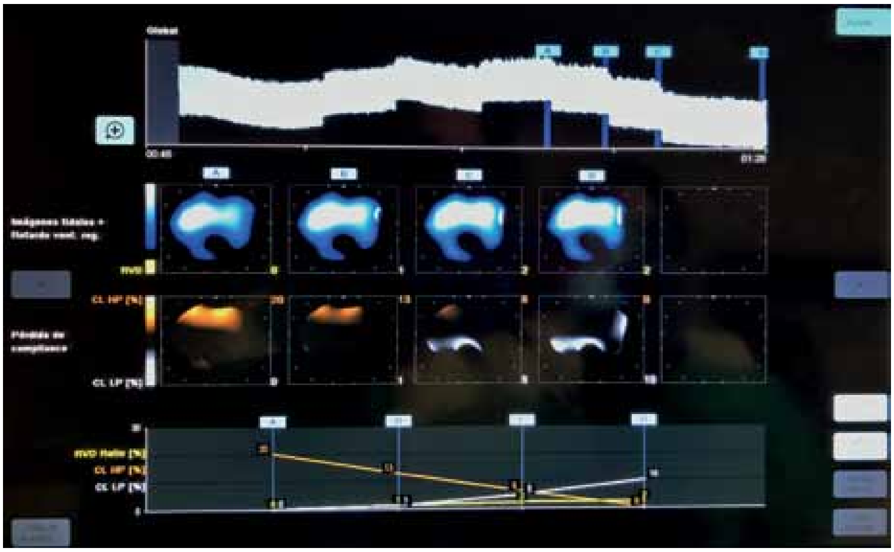

Figure 3. Pulmovista® 500 (Dräger Medical GmbH, Lündbeck, Germany). After recruitment we can observe overdistension (orange colour) and collapse (grey colour), being able to infer an optimal PEEP value.

modes or recruitment manoeuvres (Lobo et al. 2018) (**Figure 3**). EIT also contributes to the management of life-threatening lung diseases such as pneumothorax, and aids in guiding fluid management in the critical care setting. Indications for the use of EIT at the bedside are especially promising in the light of the first results, although its use on a daily basis will be the result of the clinicians' acquired experience over the years.

Ventilation strategies

Potential optimisation of ventilation bundles starts by re-evaluating the crucial components of respiratory mechanics (Bos et al. 2018). After more than half a century of modern positive-pressure ventilation, it seems that mechanical ventilation has a fairly narrow therapeutic index between the effective and damaging dose. Targets have changed from aiming normal oxygen, pH or carbon dioxide levels, to tolerating atelectasis and accepting low arterial oxygen levels and/or hypercapnia. Moreover, and as part of what could be called muscle protective ventilation strategies, a big effort has been put into preventing or shortening the use of mechanical ventilation as much as possible, besides using ventilator settings that are considered to be "lung protective."

The complexity of mechanical ventilation and of ventilators causes more than one headache to healthcare professionals. In the face of this conundrum, automation of ventilation settings could yield a solution (Rose et al. 2015; Branson 2018). Closed-loop systems have been classified into simple, physiological signal-based and explicit computerised protocols or ECP (Wysocki et al. 2014). ECP systems use multiple inputs to control one or several ventilator outputs. Some examples of automation of mechanical ventilation are: Adaptive Support Ventilation (ASV; which titrates ventilator output on a breath-to-breath basis providing a preset level of minute

> ❝ we must deepen our understanding of the principles of respiratory physiology and respiratory system mechanics ❞

ventilation while minimising work of breathing), Intellivent ASV (an extension of ASV, including automated selection of FiO2 and PEEP) (Bialais et al. 2016), and SmartCarePS (control of pressure support level based on the patient's respiratory characteristics) (Rose et al. 2008). Other examples available on the market (although not totally automated) are proportional assisted ventilation plus (PAV+) and NAVA.

Likewise, patient-ventilator interaction still represents a challenge for most healthcare professionals (Pham et al. 2018; Subira et al. 2018). Asynchronies cause discomfort, increase dyspnoea, may induce lung injury and prolong ventilator use. Current knowledge on asynchronies mainly comes from small physiologic or observational studies, and precise information, such as epidemiology, assessment, and management, is lacking (Gutierrez et al. 2011; Longhini et al. 2017). We must therefore, deepen our understanding of the principles of respiratory physiology and respiratory system mechanics and, as a scientific community, join forces against asynchronies. New technologies may help us in their management (predicting and preventing them), but there's still a long way to go.

The future: big data and artificial intelligence

Alongside big data techniques, new approaches such as deep machine learning and artificial neural ICU data integration are starting to become effective tools for data analysis (Lovejoy et al. 2019; Nunez Reiz 2019). Big data analysis is employed in other fields, such as marketing, banking, and logistics. But in healthcare, it depends, at least partially, on data entered by the professionals. Which information is more relevant? Have we been trained to know how to prioritise correctly?

In this new era, artificial intelligence (AI) is beginning to receive interest. In AI, data is fed into the computers, which detect and implement the rules, and continuously assess the information to re-calibrate if needed. AI could reduce the inter-clinician variability and offer other benefits, as search of complex relationships in the vast quantity of data, analyse variables to predict outcomes of interest and develop additional models that could aid healthcare professionals in extracting useful information for clinical decision making.

Ongoing examples of research in AI:

A) Neural networks for breathing-pattern recognition: machine learning algorithms that have the ability to learn input and output relationships from sets of data; being able to detect asynchronies and wean patients (Kuo et al. 2015).

B) Decision tree classification, such as the AEGLE project, for predicting risk of certain events using logistic regression models that recognise patterns of data, which are then used as inputs for a machine learning based patient-specific algorithm to evaluate the risk that a specific event or outcome (Olive and Owens 2018).

C) Development of smart alerts via machine-learning methods to avoid ever-growing evidence of alarm fatigue (Kane-Gill et al. 2017, Winters et al. 2018).

Conclusion

We are looking at a progressive shift in the intensive care standards of care. Modern ICU environment is data-rich, providing fertile soil for the development of new and more accurate technologies, where clinical decision-making is being assisted by computers that integrate and analyse recollected data. Accurate predictive models to anticipate events, better decision support tools, and greater personalisation of care are becoming a quality standard.

However, we would like to point out two concerns. Firstly, ICU data integration is the main challenge in developing effective tools for data analysis. We need big databases, such as MIMIC (Multiparameter Intelligent Monitoring in Intensive Care), that can supply our computers all possible variables (e.g. physiologic, haemodynamic and demographic variables needed to develop a CDSS for the prediction of in-hospital mortality), highlighting the importance of clinical expertise in the development of data-driven analytic models. Secondly, the introduction of new accurate tools must be prudent (Gonzalez de Molina Ortiz et al. 2018; Urner et al. 2018; Clarissa et al. 2019). Technological development must respond to the real needs of patients and clinicians. As healthcare professionals, our primary goal is the meticulous care of our patients and their families. In the face of booming technologies, we need to promote further the humanisation of intensive care. We are compelled to strive, first and foremost, proper sedation management, promote restful sleep, encourage early mobilisation, and encourage family involvement in patient care. Within ventilatory management, we ought to tackle the intrinsic problems that result in the non-application of lung protective strategies [such as low tidal volume, monitor of driving pressure, etc.] (Bellani et al. 2016). We should, therefore, focus on solving problems and seek appropriate strategies for interprofessional collaboration that bring this technological development closer. ■

Conflict of interest

Federico Gordo has performed consultancy work and formation for Medtronic and formation for Medtronic and MSD. The other authors have no competing interests.

Abbreviations

AI	Artificial Intelligence
ASV	Adaptive Support Ventilation
CDSS	Clinical Decision Support Systems
ECP	Explicit Computerised Protocols
EIT	Electrical Impedance Tomography
FiO2	Fraction Of Inspired Oxygen
ICU	Intensive Care Unit
NAVA	Neurally Adjusted Ventilatory Assist
PAV+	Proportional Assisted Ventilation Plus
PEEP	Positive End-Expiratory Pressure

Key points

- Modern technology can provide critical care with new tools that meet three major goals: improving management, making better decisions and being more effective in patient care
- Clinical decision support systems (CDSS) address 5 rights: delivering the right evidence-based information, to the right people in the right format, through the right channels and at the right time
- In addition to ground-breaking monitoring, lung imaging techniques have also experienced overwhelming progress
- Artificial Intelligence (AI) is beginning to receive interest and could reduce inter-clinician variability and offer other benefits

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