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Clinical Decision Support Systems: Future or Present in ICU?

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Clinical decision support systems (CDSS) are today, a reality. More complex, useful systems will be developed in the near future, forging CDSS an essential part of ICU monitoring. However, we need to understand the algorithms embedded in CDSS and to assess them correctly. They will need to first prove their worthiness before becoming indispensable.

Healthcare professionals working in the ICU environment are exposed to a large amount of data, both because of the intrinsic complexity of the patients, as well as patients' close monitoring. There is also an exponential increase in medical knowledge, and thus an exponential difficulty in treating patients accordingly. Even interventions clearly established in the medical literature as beneficial are not universally applied. For example, when the LUNG-SAFE study (Bellani et al. 2016) was conducted, three interventions had proven to improve survival in Acute Respiratory Distress Syndrome (ARDS): low tidal volume <6 ml/kg, prolonged sessions of prone positioning and neuromuscular blocking for 48 hours; provided data showed mean tidal volume of 7.6 ml/kg, use of prone position in 16% of the cases and NMBA in 37.8%. One-thousand eight hundred to 250,000 deaths per year have been estimated to be due to medical errors regarding adverse effects (Makary and Daniel 2016; Sunshine et al. 2019). Derived costs from medical errors reached 19.5 billion in 2008 (Andel et al. 2012).

CDSS have to be efficient, able to integrate with the workflow, avoiding overload

Use of computer systems during clinical practice started during the 1960s (Ledley & Lusted 1959). Clinical Decision Support Systems (CDSS) are defined as "a process for enhancing health-related decisions and actions with organised clinical knowledge, to improve health care delivery." In other words, CDSS are health information technology that builds upon the foundation of an electronic health record (EHR) to provide professionals with specific, filtered and organised information.

Recently, several elements make possible the deployment of this concept into significant and practical applications:

- Digitalisation and increased connection of medical devices with EHR.
- Possibility of incorporating CDSS both in the EHR and in the medical devices themselves, from monitors to ventilators.
- Improvement in data processing: new analytical techniques, based on the analysis of big data, and different forms of machine learning (Núñez Reiz et al. 2019; Sanchez-Pinto et al. 2018).
- Change from an old working model focused on ICU mortality to a new model focused on the patient's continued care (including ICU and hospital ward) (Vincent

and Creteur 2015).

CDSS Classification

There are different types of CDSS depending on the work-chain link they support. CDSS can be more specific by supporting a single specific task, such as anticoagulant weekly dosing, or more complex by integrating different aids, such as guiding the management of a septic patient along the hospital stay (from initial screening to the ICU admission). CDSS can improve:

- **Data entry:** Automating this step minimises errors and decreases workload. When automation is not possible CDSS may ease data entry using smart forms. CDSS may also detect errors during data entry and present immediate alerts if necessary, and transform unstructured inputs to analytically processable data. For example, there are systems that are capable of data-mining diagnostics (structured data) from free text inputs (unstructured data).
- **Data review:** CDSS may provide summary of relevant data through predictive and retrospective analysis. This process may allow screening of deteriorating patients.
- **Management:** CDSS may present relevant references and resources like guidelines and protocols, and advise during prescription adjustment of medication or techniques. Computerised physician order entry (CPOE) refers to computer-based systems that facilitate the medication ordering process, including clinical assistance systems. It is a field where CDSS have great impact, although once established it can go unnoticed. It eliminates transcription errors in which medication administration errors occurred due to errors in the eligibility of prescriptions, and it facilitates pharmacology departments' follow-up, which entails significant savings (Calloway et al. 2013). Prescription help systems generate automatic alerts of allergies, interactions and dose adjustment depending on creatinine clearance.
- **Alerts:** Alerts and tasks not initiated by the user, by patient data or by time. For example, systems predicting ICU admission of patients staying at the hospital ward, systems detecting worsening in ICU patients and systems predicting need of prolonged mechanical ventilation.

Features and Limitations

We must acknowledge the characteristics CDSS should include and the problems they may face in their application.

CDSS should give advice on relevant issues, including staff and patient needs. This advice must be intuitive and easy to use; required training to obtain results should not be needed. The way in which CDSS advises the user must be respectful, and its implementation explained so that the staff accepts it (Ginestra et al. 2019).

> other CDSS screening examples are systems that detect specific syndromes, such as sepsis

Black boxes are not desirable; clinicians should understand the advice before accepting it. The only exception would be that there was no other option, or its usefulness was clearly demonstrated (e.g. in a randomised clinical trial, where the result is relevant without question).

CDSS have to be efficient, able to integrate with the workflow, avoiding overload. They should keep advice only for relevant information, reducing alert fatigue, should avoid the need for manual data collection, and should ease the needed tasks when different computer systems and medical devices that hinder the extraction work together. Anonymised data is mandatory, notably if databases are exported for collaborative research networks.

Assess CDSS

Like any medical intervention, CDSS must have a scientific basis and provide evidence about its usefulness. There is a specific regulation on closed loop systems where a software or a set of software and hardware intervenes directly in a patient, but, to our knowledge, there is no paperwork on systems that guide the healthcare staff interventions.

Sometimes it is difficult to define what a correct decision is. We should focus on obtained CDSS outcomes compared to other clinicians or experts rather than on a specific decision within a specific case. Moreover, CDSS must include systems that correct predictable and unpredictable errors, monitoring their performance.

Examples in Critical Care

It is out of scope to review all existing CDSS. We will however present some current examples with which we are familiar.

Early detection of patients with clinical worsening (Vincent et al. 2018) is a well-studied field. Computer systems have the ability to monitor all generated data within the hospital, providing itself feedback for continuous improvement (Cardoso et al. 2011). Vital signs collection systems at emergency departments and wards are automated to reduce errors, avoiding increase of the burden of nursing. It is crucial for the healthcare staff to be aware of its usefulness (if some of the data collection depends on their participation, this has to be performed correctly).

Processing data has gone a long way. Scoring systems, like Early Warning Scores (EWS), allocate points based on several physiological variables, yielding a total

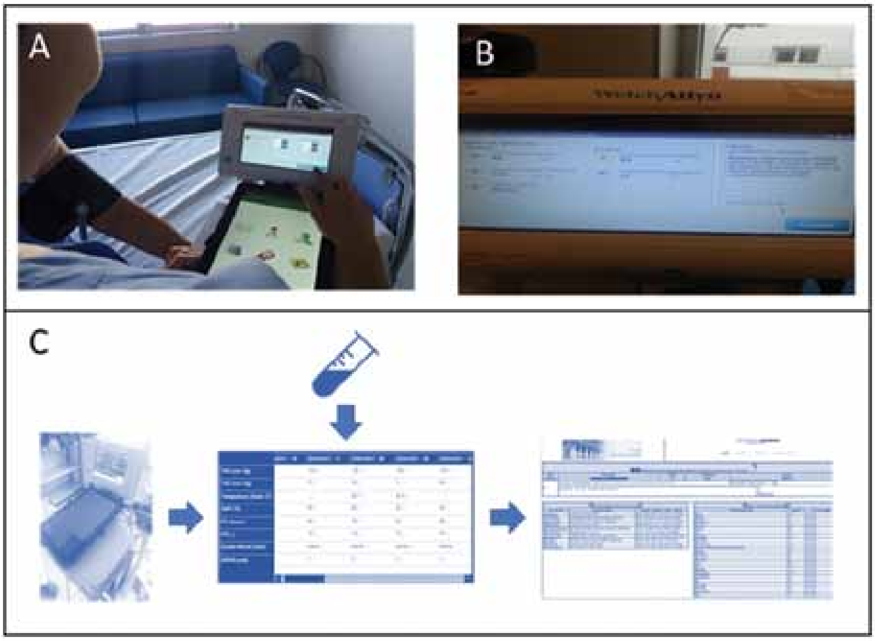

Figure 1. Early Warning Score Application. A) Example of an intelligent vital signs monitoring system with a customised early warning system integrated. B) On the left of the monitor the sum of the score. On the right the given advice to the nurse (e.g. alert the ICU team). C) Data of vital signs are connected automatically with the EHR. These data and lab test results generate warnings of patients at risk to the ICU team.

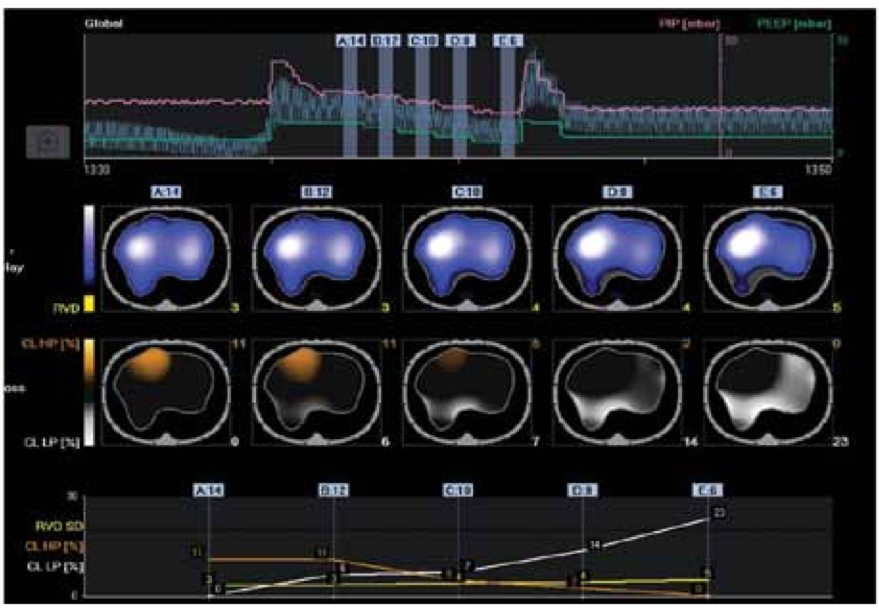

Figure 2. Electrical Impedance Tomography monitoring an optimal PEEP manoeuvre. The software automatically interprets different levels of PEEP during the last minutes of monitoring. The user supervises the choice of the stages before being compared. The software also represents the areas of overdistension and atelectasis so that the user can choose the optimal PEEP.

score after summing up the different points (Royal College of Physicians 2012; Subbe et al. 2001). EWS are used in real workflows; in our particular case, we have been working with an "ICU without walls model" for the past decade, improving patient monitoring admitted in the hospital wards (Abella Álvarez et al. 2013). This system, based on technological support and multi-professional collaboration, uses wirelessly connected with EHR monitors (Welch Allyn®), and customised with our own EWS system (Henares EWS). The CDSS integrates clinical data, vital signs and lab data of patients, improving the alert system and allowing rapid intervention **(Figure 1)**. Other models using deep learning are in development and validation phase on retrospective databases (Desautels et al. 2016).

Other CDSS screening examples are systems that detect specific syndromes, such as sepsis. In this case, machine learning based systems detect patients hours before the onset of sepsis (Desautels et al. 2016; Giannini et al. 2019; Nemati et al. 2018; Shashikumar et al. 2017). They show good clinical application, including shorter ICU and hospital length of stay and lower hospital mortality (Shimabukuro et al. 2017).

Another good example of CDSS use within the ICU imply the management of mechanical ventilation (MV). There are basic computerised protocols that standardise and guide medical decisions using inputs generated by the ventilator or the other monitoring systems (Sorenson et al. 2008). More complex systems integrate data generated by the patient into physiological models. There are currently closed loop systems from different MV manufacturers: they do not require clinician intervention, and are currently being used in the transition to assisted modes and in automatic weaning (Rose et al. 2015). A compelling number of ongoing trials will assess its significant usefulness.

Moreover, new CDSS regarding management of MV can be integrated in a monitor. This software allows an electrical impedance monitor to semi-automatically recognise an optimal PEEP manoeuvre and present the overdistention and atelectasis information so that the clinician decides on the optimal PEEP level **(Figure 2)**. New machine learning applications manage to recognise asynchronies (Gholami et al. 2018; Sottile et al. 2018) and predict prolonged mechanical ventilation (including need for tracheostomy).

Conclusion

Clinical decision support systems are today a reality. More complex, useful systems will be developed in the near future, forging CDSS an essential part of ICU monitoring. However, we need to understand the algorithms embedded in CDSS and to assess them correctly. They will need to first prove their worthiness before becoming indispensable.

Conflict of Interest

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

Key Points

- Clinical Decision Support Systems are defined as a process for enhancing health-related decisions and actions with organised clinical knowledge, to improve health care delivery.
- CDSS can be more specific by supporting a single specific task, such as anticoagulant weekly dosing, or more complex by integrating different aids.
- CDSS can improve data entry, data review, management and alerts.
- CDSS are a reality. More complex, useful systems will be developed in the near future, forging CDSS an essential part of ICU monitoring.

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