Intensive Care Med (2025) 51:593–595
https://doi.org/10.1007/s00134-024-07778-w

EDITORIAL

Setting the ventilator with AI support: challenges and perspectives

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Mechanical ventilation (MV) is a cornerstone of intensive care medicine. However, when used inappropriately, it can cause additional harm, including a condition known as ventilator-induced lung injury (VILI) [1]. To mitigate this risk, lung-protective ventilation strategies are of utmost importance. It is, however, essential to note that lung-protective ventilation is also currently evolving from "standard settings" towards a more individualized concept [2]. For example, the optimal ventilation settings for a patient with normal pulmonary compliance may differ significantly from the settings in acute respiratory distress syndrome (ARDS). Even within an individual patient, the optimal setting may need to be adjusted over time in the intensive care unit (ICU) based on changing physiological parameters of the lung. However, not only suboptimal ventilator settings themselves but also conditions, like patient-ventilator-asynchrony, untimely initiation of, or inappropriate weaning from the ventilator, can prolong MV duration and cause undesired consequences [3].

Given the complexity of the numerous static and dynamic parameters involved in setting a ventilator, it is comprehensible that computers are better suited to navigate this multi-dimensional space than humans. For instance, Artificial Intelligence (AI) algorithms are known for their impressive pattern recognition capabilities. Thus, well-trained AI-based models hold promise for optimizing ventilator settings to determine the optimal parameter combination for each patient.

Although several publications exist on expert systems and rule-based approaches for ventilator setting, mainly dating from the 1980s to 2000s, there have been relatively few published applications of AI in a narrower sense [4]. Closed-loop ventilation systems that operate with minimal human input have hardly exploited the great potential of AI to date due to the small number of input features they use [5]. Recent examples of AI applications for MV include the use of reinforcement learning to optimize ventilator settings [6, 7], the detection of the widely underdiagnosed flow starvation [8], or the clinical implementation of a prediction model for mechanical power, a parameter of growing interest including all aspects of MV leading to VILI and well correlated with patient outcome [9]. While the first clinical trials regarding AI-supported weaning from MV showed promising results [10], clinical studies examining AI-based adjustments to ventilator settings are still lacking.

Utilizing the capabilities of AI

In addition to classical ventilation parameters, moreover, a vast array of data collected during ICU treatment – such as laboratory results, blood gas analyses (BGA), vital signs, and patient demographics (age, gender, race, and medical history) – can contribute to the development of AI models for optimizing ventilator settings. Respiratory waveform data, representing e.g. airway pressure or flow curves, contain lots of valuable but mostly underutilized information [11] and data from thoracic imaging (x-ray, CT), and real-time techniques like electrical impedance tomography offer additional input for AI-based models. Furthermore, integrating features such as BGA data could address common issues with parameters used in many automated ventilation systems, which are often unreliable. Peripheral oxygen saturation (SpO2) is prone to artifact due to motion or reduced perfusion of the extremities and end-tidal carbon dioxide ($etCO_2$) may not accurately reflect the actual situation in the arterial blood when gas exchange is severely impaired. Continually

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matching these parameters with the values from an arterial BGA would create a more reliable picture.

Integrating all these diverse data, each representing a different aspect of the patient's condition—like pieces of a mosaic—could lead to a more comprehensive image of the pulmonary situation. Using this holistic data set, AI-based models could assign patients to specific 'phenotypes.' Depending on the respective phenotype, a specifically tailored way of MV, which has been proven beneficial in similar cases, can be recommended to individualize the settings of MV. If such models are extended with in silico models simulating pulmonary behavior under different conditions, this could further enhance predictions of how specific ventilation changes will impact the patient [12].

Lessons learned from closed-loop ventilation

AI techniques are closely related to data collection, processing and exchange. In the medical field, however, missing interfaces, proprietary data formats, and missing or inconsistent data standards are still a daily occurrence. But also the classification of health-related data as particularly sensitive data in the current data protection legislation makes data handling challenging. The usual procedure of asking the patient for consent is hardly possible with ventilated patients.

ICUs usually are considered a technophile environment. All the more it is noteworthy that the spread of closed-loop ventilation systems is still limited. From previous experience with these systems, some lessons can be learned for the implementation of AI in ventilator setting.

The use of closed-loop systems shows only little evidence of an improvement in patient outcome [13]. However, the generation of this evidence is essential before implementing AI in MV therapy. In the first step, AI-based models should be tested on virtual data representing patients in different conditions. Only after exhaustive in silico testing, a model can be brought to the bedside to carry out prospective clinical trials, ideally randomized against a standard-of-care protocol. The evaluation should be carried out gradually from low-risk patients to more heterogeneous and more severely ill ICU patients. Lastly, a transparent presentation and critical discussion of the results is necessary so that AI-based models can build trust. While models used at the bedside must be rigorously tested and certified, this point ignores the fact that patient characteristics, distribution of conditions and diseases—up to complete "de novo" emergence—and treatment strategies in an ICU change over time. This causes a gradual decrease in predictive performance [14]. A model retraining would solve this issue, but it would also generate a "new" model with unknown behaviour. Thus, in some legislations, it would need to undergo the laborious and costly process of certification again.

However, the probably most relevant aspect regarding closed-loop systems was the reluctance of ICU physicians to completely hand over a relevant part of their therapy. This was intensified by reports of critical incidents caused by an undue autonomy of the ventilator [15]. AI-based models, thus, must be designed as decision-support tools and not as autonomous devices. Finally, the ultimate treatment responsibility must remain with the physician.

Focus on the target

Currently, AI's potential can't be utilized to its full extend. However, if the described obstacles can be solved and the great potential of AI in the application of MV is explored further, this could unlock new avenues for clinical research, transform ventilation practices and bring us closer to the goal of individualized therapy, hopefully improving our patients' outcomes.

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Funding

Open Access funding enabled and organized by Projekt DEAL.

Declarations

Conflicts of interest

SJF and MC declare not having competing interests to report.

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Received: 28 October 2024 Accepted: 23 December 2024
Published: 20 January 2025

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