Journal of Mechanical Ventilation

Artificial Intelligence supported ventilator management: Current applications, clinical evidence, and future directions

Shun Nakahara, Shunsuke Kondo, Abulhassan Ali, Collin Clarke, Scott Nishioka, Ehab G Daoud

DOI: https://doi.org/10.53097/JMV10159

Cite: Nakahara S, Kondo S, Ali A, Clarke C, Nishioka S, Daoud EG. Artificial Intelligence supported ventilator management: Current applications, clinical evidence, and future directions. J Mech Vent 2026; 7(3):133-145.

Abstract

Background
Mechanical ventilation remains a complex intervention requiring continuous adjustment to balance oxygenation, ventilation, lung protection, patient–ventilator synchrony, and readiness for liberation. Artificial intelligence (AI) may support more individualized ventilator management by integrating multidimensional intensive care unit data.
Methods
We conducted a targeted narrative review of PubMed and Embase for studies evaluating AI, machine learning, deep learning, reinforcement learning, and closed-loop systems in ventilator management.
Findings
AI applications in ventilator management include outcome prediction, patient–ventilator asynchrony detection, ventilator setting optimization, and closed-loop ventilation. Current studies show promising performance in predicting extubation and weaning outcomes, detecting asynchrony from ventilator waveforms, forecasting high risk ventilation patterns, and supporting automated ventilator adjustments. However, most evidence remains retrospective, singlecenter, simulation based, or focused on model performance rather than patient centered outcomes.
Conclusions
AI-supported ventilator management is a rapidly evolving field with potential to enhance individualized respiratory care. Future studies should prioritize external validation, prospective trials, workflow integration, explainability, and safety frameworks to determine whether AI can improve clinically meaningful outcomes in mechanically ventilated patients.

Keywords: artificial intelligence, mechanical ventilation, ventilator management, patient–ventilator asynchrony, closed-loop ventilation

Author:

1. Department of Medicine, John A. Burns School of Medicine, University of Hawaii, Hawaii, USA
2. Associate professor of Medicine, John A Burns School of Medicine, University of Hawai'i, Hawaii, USA

E-mail: shunnaka@hawaii.edu

Conflict of interest/Disclosures: None

Introduction

In current practice, ventilator management relies on standardized protocols, physiologic targets, and intermittent bedside assessment. [1] Although approaches such as lung protective ventilation, positive end-expiratory pressure (PEEP)/fraction of inspired oxygen (FiO_2) tables, spontaneous breathing trial (SBT) protocols, and weaning algorithms have improved consistency of care, they cannot fully capture the heterogeneity and rapidly changing physiology of mechanically ventilated patients. [2,3] Because these decisions often depend on clinician judgment, institutional practice patterns, and the timing of available assessments, substantial variability may occur, particularly in situations where physiologic responses are dynamic or evidence remains uncertain. [4,5]

Artificial intelligence (AI) has emerged as a potential approach to support ventilator management by integrating large volumes of multidimensional intensive care unit (ICU) data including ventilator waveforms, physiologic variables, laboratory results, and clinical context. [6] Machine learning, deep learning, and reinforcement learning have been applied to outcome prediction, detection of patient–ventilator asynchrony, assessment of liberation readiness, ventilator setting optimization, and closed-loop ventilation. [7-10] However, technical performance does not necessarily translate into clinical benefit. Many AI models have been evaluated primarily in retrospective datasets, simulation environments, or single center cohorts, and evidence demonstrating improvements in patient-centered outcomes remains limited. [11]

This narrative review aims to summarize current applications of AI in ventilator management, including outcome prediction, patient-ventilator asynchrony detection, ventilator setting optimization, and closed-loop ventilation systems. We also evaluate the existing clinical evidence, distinguish physiological or process-related improvements from patient centered outcomes, discuss key limitations and implementation barriers, and outline future directions for the safe and effective integration of AI-supported ventilation into critical care practice.

Methods

This narrative review was based on a targeted literature search of PubMed and Embase databases for studies evaluating artificial intelligence, machine learning, deep learning, reinforcement learning, and closed-loop systems in ventilator management. The search was conducted up to June 7th, 2026. Search terms included combinations of "artificial intelligence," "machine learning," "deep learning," "reinforcement learning," "large language model (LLM)," "mechanical ventilation," "ventilator management," "weaning," "extubation," "patient-ventilator asynchrony," and "closed-loop ventilation." We prioritized original studies, randomized trials, systematic reviews, scoping reviews, and clinically relevant validation studies. Particular attention was given to studies addressing outcome prediction, patient–ventilator asynchrony detection, ventilator setting optimization, closed-loop ventilation, and implementation challenges. Additional relevant articles were identified from reference lists of selected publications. The aim was to provide a clinically oriented synthesis of current evidence, limitations, and future directions for AI supported ventilator management.

Overview of AI Techniques in Mechanical Ventilation

AI-supported ventilator management primarily uses machine learning, deep learning, and reinforcement learning. [12] Machine learning is commonly applied to structured clinical data for prediction and risk stratification, whereas deep learning can analyze more complex time-series and waveform data. [13,14] Reinforcement learning is designed for sequential decision-making and may therefore be useful for recommending ventilator adjustments over time. [15]

Among conventional machine learning methods, tree based ensemble methods, such as Random Forest, XGBoost, LightGBM, and CatBoost, are frequently used with structured electronic health record (EHR) data to predict extubation failure, weaning readiness, and reintubation risk. [16] These models integrate routinely collected clinical variables, making them well suited to critical care research. [17] In ventilator management, these approaches have mainly been used for outcome prediction and risk stratification rather than direct treatment recommendation. [18]

Deep learning can analyze complex signals that are difficult to capture with conventional structured variables. [14] Convolutional neural networks (CNNs) have been applied to ventilator waveforms to detect patient–ventilator asynchrony and predict weaning failure during SBT. [19,20] Recurrent neural networks and long short-term memory (LSTM) networks can model temporal changes in ICU data, including vital signs, ventilator parameters, laboratory results, and respiratory mechanics. [21,22] These approaches may identify dynamic changes that are missed by intermittent bedside assessment.
Reinforcement learning is particularly relevant to ventilator management because it is designed for repeated decision-making over time. [23] In this framework, the patient's condition represents the "state," ventilator adjustments the "actions," and clinical goals the "reward." [6] By learning from prior

treatment trajectories, reinforcement learning may support individualized ventilator settings. [24] However, most studies remain retrospective or simulation-based, with limited prospective bedside validation. [15]

The clinical relevance of these AI techniques depends on how they are applied at the bedside. [7] The following section therefore reviews AI applications in ventilator management according to their clinical role, including outcome prediction, patient–ventilator asynchrony detection, ventilator setting optimization, sedation–ventilation interaction, and closed-loop ventilation systems.

AI Applications in Ventilator Management

The current evidence for major AI applications in ventilator management is summarized in Table 1

1. Outcome prediction models

Artificial intelligence has been most commonly applied to outcome prediction in ventilator management, particularly for extubation success and failure, weaning readiness, and reintubation risk. These models aim to support one of the most difficult decisions in mechanical ventilation: whether the patient can be safely liberated from invasive support without exposing them to either premature extubation or unnecessary prolongation of ventilation. [18,25]

1.1. Early Prediction Models Using Structured ICU Data
A review by Igarashi et al. summarized seven studies that used machine learning to predict extubation success in mechanically ventilated patients. Across these studies, models used 8-78 variables, including demographic data, vital signs, laboratory results, ventilator parameters, clinical interventions, and clinical scores. Reported performance varied substantially, with sensitivity ranging from 0.64 to 0.96, precision from 0.91 to 0.97, specificity from 0.73 to 0.85, and area under the receiver operating characteristic curve (AUROC) from 0.70 to 0.98. This wide range reflects heterogeneity in study design, feature selection, outcome definitions, algorithms, and validation methods. [18]

Several earlier studies used structured ICU data to predict extubation success or failure. Otaguro et al. [26] retrospectively analyzed 117 mechanically ventilated ICU patients, of whom 13 required reintubation within 72 hours. The investigators extracted 57 features, including demographics, vital signs, laboratory data, and ventilator data, and compared Random Forest, XGBoost, and LightGBM models. LightGBM achieved the best performance, with an AUROC of 0.950, accuracy of 0.927, precision of 0.915, and recall of 0.960. The most important feature was duration of mechanical ventilation, followed by FiO_2, PEEP, maximum and mean airway pressures, and Glasgow Coma Scale score. These findings suggest that machine learning models largely rely on clinically plausible markers of respiratory load, ventilator requirement, and neurological reserve.

Fabregat et al. [27] developed a machine learning decision support tool for programmed extubation using heterogeneous ICU data, including monitor signals, patient admission data, medical records, and respiratory event logs. Among the tested classifiers, the support vector machine model predicted extubation outcome with an accuracy of 94.6%. A relevant feature of this study is that the model did not depend solely on spontaneous breathing trial results but instead used routinely available monitoring and clinical data. This approach illustrates a potential role for AI as a pre-extubation decision support tool that complements bedside assessment rather than replacing it.

1.2. Large Scale Database Models and External Validation
Larger database studies have addressed some limitations of early single center models. Zhao et al. [28] developed a CatBoost model using 16,189 patients from MIMIC-IV who underwent extubation; 2,756 patients, or 17.0%, met the definition of extubation failure, defined as need for noninvasive ventilation, reintubation, or death within 48 hours after extubation. After recursive feature elimination, the final model used 19 features, including age, body mass index, stroke, heart rate, respiratory rate, mean arterial pressure, SpO_2, arterial pH, tidal volume, PEEP, mean airway pressure, pressure support level, duration of mechanical ventilation, SBT success times, urine output, crystalloid amount, and antibiotic types. The compact CatBoost model achieved an AUROC of 0.835 in internal validation and 0.803 in prospective validation at a cardiac surgical ICU. Shapley additive explanations analysis identified mechanical ventilation duration and pressure support level as the most important predictors.

These findings highlight a key methodological point: high apparent accuracy in small single center datasets may not translate into generalizable clinical performance. Igarashi et al. noted that only one of the early extubation prediction studies included external validation, and that single-center models may learn institution specific extubation practices rather than generalizable physiological signals. Zhao et al. [28] partially addressed this issue through prospective validation, although the validation cohort was limited to one cardiac surgical ICU, which may not represent general medical ICU patients or difficult-to-wean populations.

1.3. Prediction of extubation readiness before clinical decision making

More recent work has shifted from predicting extubation outcome at the moment of extubation to predicting extubation readiness before the decision is made. Fenske et al. [25] developed machine learning models to predict next day extubation using 37 EHR-derived clinical features aggregated from midnight to 8 AM. The study included 448 patients and 3,095 ICU days in the internal cohort and 333 patients and 2,835 ICU days in an external community hospital cohort. The best model, an LSTM model, achieved an AUROC of 0.870 in both the internal test cohort and the external test cohort. Important features included plateau pressure and Richmond Agitation Sedation Scale score, linking respiratory mechanics and sedation/neurological status to readiness for extubation. The model also predicted many patients as potentially ready before actual extubation; 63.8% of predicted extubation events occurred within 3 days of true extubation.

This shift is clinically important. A model that predicts extubation failure only after a patient has already been selected for extubation may mainly function as a confirmatory tool. In contrast, a next day readiness model could be used during morning rounds to prompt SBT consideration, standardize screening, and reduce missed opportunities for liberation. However, Fenske et al. emphasized that such tools should be tested against protocol-based care in prospective randomized trials before being used to change practice. [25]

1.4. High resolution ventilator data and weaning timing prediction

Another line of research has focused on prediction during spontaneous breathing trials using high resolution ventilator data. Park et al. [29] developed a CNN based model using only continuous ventilator derived parameters collected during SBTs. The study included 138 patients, of whom 35, or 25.4%, experienced weaning failure. The model used three waveform variables and 25 numerical ventilator parameters and achieved an AUROC of 0.912 and an AUPRC of 0.767. Compared with rapid shallow breathing index, the CNN model performed better, with AUROC 0.912 versus 0.558 and AUPRC 0.767 versus 0.522. The authors also used Grad-CAM to visualize waveform regions contributing to the model's prediction, which may help clinicians judge whether a prediction reflects a physiologically meaningful signal or artifact.

AI models have also been developed to predict the timing of weaning rather than binary extubation success. Liu et al. [30] proposed a two stage AI system for ventilator liberation: one stage predicted readiness to transition from controlled to support mode, and the second predicted readiness for complete weaning from mechanical ventilation. The first stage model included 5,873 cases and achieved AUCs of 0.843–0.953 across prediction time points, whereas the second stage model included 4,172 cases and achieved AUCs of 0.889–0.944. The model was implemented as a digital dashboard that refreshed automatically, and a preliminary impact analysis suggested that AI-assisted decision making shortened intubation time by 21 hours. Although this was not a randomized trial, it represents a more implementation oriented approach than most retrospective prediction studies.

Individual acute respiratory distress syndrome (ARDS) prediction studies show similar issues. Jiang et al. [31] developed a machine learning model to predict sepsis associated ARDS using early clinical data. After comparing eight algorithms, Gaussian naïve Bayes showed the best performance; the final model achieved AUCs of 0.777 in training, 0.770 in validation, and 0.781 in the test set, with accuracy of 78.6% and sensitivity of 82.4%. The most important variables included PaO_2/PAO_2, A-a DO_2, oxygen tension variables, CRP, RDW, and electrolytes. This model is clinically plausible because oxygenation and inflammatory markers are strongly linked to ARDS development, but its performance remains moderate and requires external validation before clinical use.

1.5. Clinical interpretation and remaining evidence gaps

Overall, outcome prediction is currently the most developed AI application in ventilator management. Across studies, the strongest predictors are not surprising: duration of mechanical ventilation, oxygenation indices, ventilator pressures, respiratory rate, neurological status, sedation level, and general markers of organ dysfunction repeatedly appear as important features. This pattern supports biological plausibility but also indicates that many models may be learning refined combinations of variables already considered by clinicians. [18,26]

The major limitation is that prediction performance has not yet been consistently linked to improved clinical outcomes. High AUROC or accuracy does not prove that AI-guided extubation decisions reduce reintubation, ventilator duration, tracheostomy, ICU length of stay, or mortality. In addition, outcome definitions differ across studies; for example, extubation failure may be defined as reintubation within 48 hours, reintubation within 72 hours, need for noninvasive ventilation, or death. These differences affect model training, performance estimates, and clinical interpretation. [32] Therefore, AI-based outcome prediction should currently be framed as decision support rather than decision replacement. The most defensible clinical role is to provide an additional risk estimate during structured ventilator liberation workflows, such as daily screening and SBT based assessment. Future studies should prioritize prospective validation, comparison against protocolized weaning, calibration assessment, subgroup performance, and patient-centered outcomes. [25]

2. Patient–Ventilator Asynchrony Detection

Patient-ventilator asynchrony (PVA) refers to a mismatch between the patient's neuro respiratory drive and the mechanical breath delivered by the ventilator with respect to timing, effort, flow, volume, or pressure. [33] Various subtypes include missed trigger, double triggering, early/reverse triggering, flow starvation (work shifting), and cycling abnormalities, with some degree of PVA reported in up to 80% of mechanically ventilated patients. [33,34] Two meta-analyses of predominantly observational studies have examined the association between PVA and clinical outcomes. Kyo et al. [35] reported that an asynchrony index of 10% or greater was associated with prolonged mechanical ventilation (mean difference 5.16 days; 95% CI 2.38 to 7.94), increased ICU mortality (OR 2.73; 95% CI 1.76 to 4.24), and increased hospital mortality. De Bie et al., [36] in a subsequent systematic review of 19 studies (n= 2,672), corroborated the association with prolonged ventilation (mean difference 3.29 days) and ICU length of stay (mean difference 3.65 days) but found no significant association between PVA and mortality. These analyses are limited by heterogeneity in asynchrony definitions and detection methods, and whether PVA independently mediates harm or serves as a marker of illness severity remains an open question.

2.1 Detection methods

The conventional method for identifying PVA is visual inspection of airway pressure, flow, and volume waveforms at the bedside, where each asynchrony subtype produces recognizable signal distortions. [33] In practice, this is difficult to sustain. Inter-rater agreement is often variable even among experienced clinicians, and a mechanically ventilated patient may generate up to 25,000 breaths per day, sometimes in clusters, making continuous manual review difficult. [37,38] These constraints led to the development of automated detection systems. The earliest approaches used rule-based algorithms that applied fixed thresholds to pressure and flow waveforms. In a prospective observational study of 50 ICU patients, Blanch et al. used software to analyze over 8.7 million breaths, and asynchronies were present in all patients, across all ventilator modes, and a statistically significant association with ICU mortality was observed. [39] While the study was not designed to establish causality, it demonstrated that continuous automated monitoring captures the burdens of asynchrony that intermittent bedside assessment may not, along with the need for further investigations and clinical studies to establish a causal relationship between asynchrony and clinical outcomes.

Rule-based algorithms, which predated modern machine learning approaches, depend on manually selected thresholds and pre-defined waveform features based on expert consensus. This limits their performance when applied across different patient populations or ventilator platforms.40 Machine learning and deep learning methods allow for more complex analysis of data, and mimicry of biologic neural networks, and have since been applied to attempt to address these limitations. A systematic review of 19 studies reported pooled sensitivity of 0.80, specificity of 0.93, and accuracy of 0.92 across the included algorithms, though only 58% of studies used a physiologic reference standard for patient effort such as esophageal manometry or electrical activity of the diaphragm, raising concerns about the accuracy of asynchrony labeling in the datasets used to train these algorithms.40 Sottile et al. trained an algorithm on 4.26 million breaths from 62 patients with or at risk for ARDS and reported an AUROC exceeding 0.89 for the detection of double-triggered, flow-limited, and ineffective-triggered breaths. [38] Subsequent work has extended automated detection to subtypes that were previously difficult to identify, including flow starvation during volume-controlled ventilation and reverse triggering in ARDS.41,42 A scoping review of 26 studies reported that hybrid deep learning architectures achieved classification accuracy between 87% and 99% for selected asynchrony subtypes. [43] Despite these results, the majority of published algorithms remain in the development or internal validation phase, and external validation across institutions and ventilator models is limited.

2.2 Real time implementation

Most published algorithms have only been tested on previously recorded waveform data, and whether they can perform reliably in real time at the bedside remains largely unknown. [40,43] Early work suggests this may be feasible. Some investigators have developed systems that read waveforms directly from ventilator screens without requiring proprietary data connections, and others have shown that asynchrony events can be identified within the first 500 milliseconds of a breath, with sensitivity and specificity above 99% in a single-center study. [40,43] However, algorithms that perform well at one institution frequently perform worse when tested on data from different hospitals or different ventilator manufacturers. Multicenter validation will be necessary before any of these tools can be recommended for routine clinical use.

2.3 Clinical Implications

The clinical relevance of automated PVA detection rests primarily on two areas: sedation practice, and lung protection. Regarding sedation, current practice frequently defaults to deepening sedation when patient-ventilator interaction appears suboptimal. Sottile et al. [38] reported that deep sedation reduced the frequency of dyssynchronous breaths but did not eliminate them. In addition, potentially injurious tidal volumes persisted even in deeply sedated patients, and that over-sedation may paradoxically increase ineffective triggering.

Continuous quantitative monitoring of PVA type and frequency could, in principle, allow clinicians to pursue targeted ventilator adjustments before resorting to pharmacologic suppression of respiratory drive, though this strategy has not been tested in randomized trials.

In terms of lung protection, specific asynchrony subtypes have a plausible mechanistic link to ventilator-induced lung injury. Double-triggered breaths produce breath stacking in which the cumulative volume of consecutive breaths may substantially exceed the set tidal volume, undermining lung-protective ventilation strategies. Sottile et al. reported that 40% of double-triggered breaths delivered tidal volumes exceeding 10 mL/kg predicted body weight, compared with 0.2% of synchronous breaths ($p < 0.001$). [38] Reverse triggering has been associated with significant transpulmonary pressure swings, though its direct contribution to clinical lung injury has not been established in prospective studies. [42] The EPISYNC cohort study reported that clustering of double triggering was independently associated with worse outcomes, suggesting that the temporal distribution of asynchrony events, not only their frequency, may carry prognostic significance. [44] These data provide physiologic rationale for the hypothesis that automated detection and correction of injurious asynchrony patterns could reduce lung injury, but this hypothesis remains untested in clinical trials.

3. Ventilator Setting Optimization

3.1. Physiologic basis for ventilator optimization

Lung-protective ventilation (LPV), which generally aims to minimize the risk of ventilator-induced lung injury (VILI), remains the predominant approach to management of mechanical ventilation. [45,46] Initially developed in the context of ARDS management, further evidence has also supported its widespread use even in patients without ARDS. [47] Despite these consistently demonstrated benefits, however, implementation of this approach in clinical practice is complex and requires carefully balancing patient oxygenation and ventilation against the risk of VILI. This is only further complicated by patient-level variations in respiratory mechanics, illness severity, and hemodynamics.

Classically, VILI is described as a multifactorial process resulting from six key pathophysiologic mechanisms: repetitive alveolar opening and collapse (atelectrauma), high energy delivered by the ventilator (ergotrauma), high positive pressures and high stress (barotrauma), overdistension and high strain (volutrauma), high patient efforts resulting in Patient-Self Induced Lung Injury (P-SILI), and consequent inflammatory response (biotrauma). [45] Extensive research has been dedicated to identifying key parameters associated with VILI particularly tidal volume, driving pressure, and plateau pressure. However, these parameters are often assessed intermittently and may not fully capture the cumulative dynamic burden imposed by mechanical ventilation over time.

More recent developments in this field include the concept of Mechanical Power (MP), which describes the overall energy burden delivered from the ventilator to the respiratory system. [48] Initially described by Gattinoni et al. [49] in 2016, MP is calculated by integrating elastic and resistive processes throughout respiration i.e. tidal volume, driving pressure, respiratory rate, inspiratory flow, and PEEP. A systematic review has reported strong associations between increasing MP and worse clinical outcomes. [50] This highlights the potential benefits in utilizing MP to guide ventilator management.

3.2. AI based prediction of VILI risk and mechanical power

Current ventilator management ultimately relies on frequent clinical assessment and judgment. However, the recent expansion of AI based decision support has raised the possibility of improving personalization of ventilator care and reducing clinician workload. The large amounts of data generated in modern ICUs including real-time hemodynamic monitoring, continuous ventilator waveforms, frequent lab draws, and regular imaging make mechanical ventilation an appropriate setting for training, validating, and applying newer artificial intelligence models to clinical practice. Potential applications of AI could therefore include early prediction of high VILI risk, forecasting outcomes, personalizing ventilatory settings based on patient physiology, and even providing specific recommendations to optimize LPV. [7,51]

Preliminary studies provide some evidence that AI may help to identify patients at risk for VILI, based on their ventilator requirements. [52] In a 2020 study, Hagan et al. [53] developed a machine learning model to predict increases in tidal volume beyond standard LPV thresholds 1 hour in advance. Similarly, using data from a retrospective observational cohort of 1,967 patients, Ruiz-Botella et al. [54] developed a mixed neural network model to forecast MP 15 minutes in advance. They demonstrated a high accuracy (94%) in predicting MP exceeding a threshold of 18 J/minute, which has previously been linked with high VILI risk. By identifying and alerting clinicians to high-risk ventilation, this may increase timely, proactive changes to ventilator settings that ultimately promote LPV.

3.3. AI based recommendation of ventilator settings

Beyond predicting VILI risk, certain studies have developed AI based algorithms that also formulate treatment recommendations to optimize and personalize ventilator settings. Liu et al. [24] developed a reinforcement learning model to recommend optimal PEEP, FiO_2, and tidal volume based on patient comorbidities, physiologic data, and illness severity. In simulations against a retrospective validation cohort of over 26,000 patient ICU visits, AI-based recommendations reportedly decreased mortality compared to the observed outcomes. Peine et al. [6] similarly utilized a reinforcement learning model, which was validated against an independent secondary dataset of over 200,000 ICU stays. Of note, in addition to better performance, they found that their model consistently recommended more frequent changes than the physicians included in cohort. Therefore, preliminary offline evidence suggests that AI based ventilator recommendations may support more timely adjustment of ventilator settings, although their impact on clinical outcomes remains unproven. Closed-loop ventilation systems represent a distinct but related approach, in which selected ventilator adjustments are automated rather than merely recommended to clinicians.

4. Closed-loop Ventilation Systems

4.1. Concept and commercially available systems

Closed-loop ventilation systems represent the closest approximation to automated ventilator management in current clinical practice. [55] Unlike decision-support models that provide recommendations for clinicians to interpret and implement, closed-loop systems directly adjust ventilator settings in response to continuously monitored physiological parameters. [56] These systems may modify variables such as tidal volume, respiratory rate, FiO_2, and PEEP with the goal of maintaining predefined targets for oxygenation, ventilation, and lung protection. However, it is important to distinguish closed-loop ventilation from modern machine learning-based AI.

Most currently available closed-loop systems rely primarily on predefined rule-based or physiology-based control algorithms, often combined with adaptive control mechanisms, rather than fully autonomous machine learning or reinforcement learning approaches. [57,58]

Several commercially available systems have been developed, including SmartCare and INTELLiVENT-ASV. SmartCare is primarily designed to automate aspects of ventilator weaning, whereas INTELLiVENT-ASV integrates automated control of ventilation and oxygenation targets. These systems are intended to optimize ventilatory support across multiple domains, including oxygenation, ventilation, and weaning, while reducing clinician workload. Clinical studies have demonstrated that such systems can maintain ventilation within target ranges and decrease the frequency of manual ventilator adjustments. [59–61]

4.2. Clinical Evidence from Randomized Trials and Systematic Reviews

One of the most extensively studied systems is INTELLiVENT-ASV, which has been shown to reduce clinician workload by decreasing the frequency of manual ventilator adjustments while maintaining safety and efficacy comparable to conventional ventilation strategies. [62] Interest in closed-loop ventilation has increased as investigators seek to determine whether automation can improve not only workflow efficiency and process measures, but also patient-centered outcomes. To date, the largest and most rigorous randomized trial evaluating this technology is the ACTiVE trial conducted by Sinnige et al. [56] This multicenter study enrolled 1,201 critically ill adults across seven ICUs in the Netherlands and Switzerland. Patients were randomized within one hour of intubation to receive either INTELLiVENT-ASV or protocolized conventional ventilation, with standardized sedation and weaning protocols applied in both groups. The primary endpoint of ventilator-free days at day 28 did not differ significantly between groups, and there were likewise no significant differences in 28 day mortality, ICU length of stay, hospital length of stay, or 90-day mortality. Importantly, the trial demonstrated that large-scale implementation of automated ventilation strategies is feasible and safe within heterogeneous ICU populations.

Broader evidence syntheses have provided a more favorable overall assessment of closed-loop ventilation systems. The most recent Cochrane review by Rose et al. [55] concluded with moderate-certainty evidence that automated closed-loop systems probably reduce the duration of mechanical ventilation as well as ICU and hospital length of stay compared with non-automated ventilation approaches. Notably, while closed-loop ventilation appeared to have little or no effect on mortality, it was associated with reductions in several clinically relevant adverse outcomes, including reintubation, prolonged mechanical ventilation, need for post-extubation noninvasive ventilation, and tracheostomy.

These conclusions represent an important advancement over the prior 2014 Cochrane review, which had characterized the evidence base as low certainty. [57]
Similarly, a 2024 systematic review by Goossen et al. [63] evaluating 51 randomized clinical trials found that closed-loop ventilation systems consistently improved the management of ventilator variables associated with lung-protective ventilation across diverse patient populations, while adverse events were infrequently reported.

However, despite these encouraging findings, most individual trials were relatively small and underpowered to detect definitive improvements in mortality or other major patient centered outcomes. [63] Furthermore, although reduction in clinician workload is frequently cited as a major theoretical advantage of closed-loop ventilation, few studies have evaluated this outcome in a rigorous or standardized manner. Collectively, the current literature suggests that automated ventilation systems are generally safe and operationally effective, but additional large-scale prospective studies are needed to clarify their impact on long-term clinical outcomes, ICU resource utilization, and implementation across different care environments.

Limitations and challenges

Several important limitations currently restrict the clinical impact of AI supported ventilation. First, most studies are retrospective, single-center, simulation-based, or focused on model performance rather than clinical effectiveness. [64,65] In particular, it remains uncertain whether AI supported ventilation reduces mortality, ventilator duration, reintubation, ventilator-free days, ICU length of stay, or long-term functional outcomes. [56] Prospective validation and randomized trials are therefore needed to determine whether AI adds meaningful benefit beyond standard care. [64]

Second, integration into existing clinical workflows remains a major barrier. Implementing AI systems in critical care often requires substantial changes to bedside routines, EHR systems, ventilator interfaces, alarm structures, and clinician responsibilities. [66] AI systems must fit into existing EHR and ventilator workflows without creating excessive alerts, additional workload, or disruption to bedside care. [67-69]

Third, the increasing use of LLMs introduces additional challenges specific to generative AI. LLMs introduce additional concerns because they may generate plausible but incorrect outputs, while their reasoning may be difficult for clinicians to verify or interpret. [70-73] Although emerging statistical and probabilistic methods, including approaches based on semantic uncertainty, may help identify unreliable outputs, these methods require further validation in clinical settings. [74]

Finally, data quality, bias, privacy, and potential manipulation of model inputs or training data also require careful attention. [71,75] These concerns highlight the importance of clinician oversight, appropriate governance, and continued monitoring of AI systems after implementation. [76] At present, AI-supported ventilation should augment rather than replace clinical judgment.

Future directions

Future research should shift from model development toward clinically validated, interpretable, and workflow-integrated AI systems. External validation across different ICUs and ventilator platforms, followed by prospective studies and randomized trials, will be important to determine whether these tools improve patient-centered outcomes. [76] AI systems should also fit naturally into clinical workflows without adding unnecessary alerts or workload. [77] Safety and governance will also be essential. Clinician oversight, protection of patient data, and ongoing monitoring after implementation will be necessary as these systems become more widely used. [78]

Foundation models and LLMs may eventually support multimodal ICU data integration, but they should remain investigational until their accuracy, reliability, and safety are rigorously evaluated and proven in clinical settings. [69] Ultimately, the value of AI in ventilator management will depend on whether it improves care, not simply on how well the model performs.

Table1: Summary of Current Evidence for AI Applications in Ventilator Management

AI application domain	Representative tasks	Evidence base / validation	Key findings	Key limitations	Key references
Outcome prediction	Prediction of extubation success/failure, weaning readiness, reintubation risk	Mostly retrospective development studies, with several internal, external, or prospective validation cohorts	Models generally show moderate-to-high discrimination. In a review of 7 studies, AUROC ranged from 0.70–0.98. Larger models have shown performance around AUROC 0.80–0.87 in prospective or external validation.	Heterogeneous outcome definitions and limited prospective impact studies. Improved predictive performance has not been shown to improve patient outcomes.	18,25–32
Patient–ventilator asynchrony detection	Detection of ineffective triggering, double triggering, reverse triggering, and flow starvation	Primarily retrospective waveform studies and internal validation; systematic and scoping reviews available	A systematic review reported pooled sensitivity of 0.80, specificity of 0.93, and accuracy of 0.92. Some deep-learning studies report high accuracy for selected asynchrony types.	External validation across ICUs and ventilator platforms is limited. Only 58% of studies in one review used a physiologic reference standard, and clinical benefit from automated detection remains unproven.	33–44
Ventilator setting optimization	Prediction of VILI risk or mechanical power; recommendation of PEEP, FiO_2, and tidal volume	Early evidence from retrospective cohorts, simulation, and offline reinforcement-learning studies	AI models can forecast potentially injurious ventilation; one model predicted mechanical power >18 J/min with 94% accuracy. Reinforcement-learning models have generated individualized ventilator recommendations in large retrospective datasets.	Recommendations remain largely offline or simulation-based and have not been shown to improve outcomes in prospective trials.	45–54
Closed-loop ventilation systems	Automated adjustment of ventilation, oxygenation, and weaning	Most mature evidence base, including randomized trials and systematic reviews	Closed-loop systems improve time within ventilation targets and reduce manual adjustments. The 2025 Cochrane review found moderate-certainty evidence for shorter ventilation duration and ICU/hospital stay. The ACTiVE trial (n = 1201) found no improvement in ventilator-free days or mortality.	Mortality benefit has not been demonstrated, and evidence for other major patient-centered outcomes remains limited.	55–63

Conclusion

AI-supported ventilator management has shown promising results in optimizing ventilator settings, predicting readiness for weaning and extubation, and detecting patient–ventilator asynchrony. However, evidence of improved patient-centered outcomes remains limited. Future studies should focus on prospective validation, clinical implementation, and identifying patients most likely to benefit.

Reference

1. Rackley CR. Monitoring during mechanical ventilation. Respir Care 2020; 65(6):832-846.

2. Park KJ. Lung-protective ventilation strategy in acute respiratory distress syndrome: a critical reappraisal of current practice. Crit Care 2025 ;29(1):444.

3. Major VJ, Chiew YS, Shaw GM, et al. Biomedical engineer's guide to the clinical aspects of intensive care mechanical ventilation. Biomed Eng Online 2018; 17(1):169.

4. Qadir N, Bartz RR, Cooter ML, et al. Variation in early management practices in moderate-to-severe ARDS in the United States: The severe ARDS: Generating evidence study. Chest 2021; 160(4):1304-1315.

5. Goligher EC, Ferguson ND, Brochard LJ. Clinical challenges in mechanical ventilation. Lancet 2016; 387(10030):1856-1866.

6. Peine A, Hallawa A, Bickenbach J, et al. Development and validation of a reinforcement learning algorithm to dynamically optimize mechanical ventilation in critical care. NPJ Digit Med. 2021;4(1):32.

7. Viderman D, Ayazbay A, Kalzhan B, et al. Artificial intelligence in the management of patients with respiratory failure requiring mechanical ventilation: A scoping review. J Clin Med 2024; 13(24):7535.

8. Rubulotta F, Blanch Torra L, Naidoo KD, et al. Mechanical ventilation, past, present, and future. Anesth Analg 2024; 138(2):308-325.

9. Merola R, Battaglini D, Schultz MJ, et al. Physiology-guided personalized mechanical ventilation to prevent ventilator-induced lung injury. Front Med (Lausanne) 2026; 13(1764151):1764151.

10. Moralez GM, Amado F, Liu VX, et al. Data-driven quality of care in the ICU: A concise review. Crit Care Med 2025; 53(12):e2720-e2728.

11. Berkhout WEM, van Wijngaarden JJ, Workum JD, et al. Operationalization of artificial intelligence applications in the Intensive Care unit: A systematic review: A systematic review. JAMA Netw Open 2025; 8(7):e2522866.

12. Greco M, Caruso PF, Cecconi M. Artificial intelligence in the intensive care unit. Semin Respir Crit Care Med 2021; 42(1):2-9.

13. Sun K, Roy A, Tobin JM. Artificial intelligence and machine learning: Definition of terms and current concepts in critical care research. J Crit Care 2024; 82(154792):154792.

14. Tungushpayev M, Suleimenova D, Sarria-Santamerra A, et al. The value of machine and deep learning in management of critically ill patients: An umbrella review. Int J Med Inform 2025; 204(106081):106081.

15. Otten M, Jagesar AR, Dam TA, et al. Does reinforcement learning improve outcomes for critically ill patients? A systematic review and level-of-readiness assessment. Crit Care Med 2024; 52(2):e79-e88.

16. Pai KC, Su SA, Chan MC, et al. Explainable machine learning approach to predict extubation in critically ill ventilated patients: a retrospective study in central Taiwan. BMC Anesthesiol 2022; 22(1):351.

17. Zhu Y, Zhang J, Wang G, et al. Machine learning prediction models for mechanically ventilated patients: Analyses of the MIMIC-III database. Front Med (Lausanne) 2021; 8:662340.

18. Igarashi Y, Ogawa K, Nishimura K, et al. Machine learning for predicting successful extubation in patients receiving mechanical ventilation. Front Med (Lausanne). 2022; 9:961252.

19. Jiang G, Ma J, Xu H, et al. Application progress of machine learning in patient-ventilator asynchrony during mechanical ventilation: a systematic review. Crit Care 2025; 29(1):295.

20. Jia Y, Kaul C, Lawton T, et al. Prediction of weaning from mechanical ventilation using Convolutional Neural Networks. Artif Intell Med 2021; 117(102087):102087.

21. Mamandipoor B, Frutos-Vivar F, Peñuelas O, et al. Machine learning predicts mortality based on analysis of ventilation parameters of critically ill patients: multi-centre validation. BMC Med Inform Decis Mak 2021; 21(1):152.

22. Wang Y, Bai Y, Jin G. Explainable deep-learning models to predict diaphragmatic dysfunction and cognitive stress in ICU patients under mechanical ventilation. Front Physiol 2026; 17(1765898):1765898.

23. Liu S, See KC, Ngiam KY, et al. Reinforcement learning for clinical decision support in critical care: Comprehensive review. J Med Internet Res 2020; 22(7):e18477.

24. Liu S, Xu Q, Xu Z, et al. Reinforcement learning to optimize ventilator settings for patients on invasive mechanical ventilation: Retrospective study. J Med Internet Res 2024; 26:e44494.

25. Fenske SW, Peltekian A, Kang M, et al. Developing and validating machine learning models to predict next-day extubation. Sci Rep 2025; 15(1):27552.

26. Otaguro T, Tanaka H, Igarashi Y, et al. Machine learning for prediction of successful extubation of mechanical ventilated patients in an intensive care unit: A retrospective observational study. J Nippon Med Sch 2021; 88(5):408-417.

27. Fabregat A, Magret M, Ferré JA, et al. A machine learning decision-making tool for extubation in Intensive Care Unit patients. Comput Methods Programs Biomed 2021; 200(105869):105869.

28.Zhao QY, Wang H, Luo JC, et al. Development and validation of a machine-learning model for prediction of extubation failure in Intensive Care units. Front Med (Lausanne) 2021; 8:676343.

29. Park JE, Kim DY, Park JW, et al. Development of a machine learning model for predicting weaning outcomes based solely on continuous ventilator parameters during spontaneous breathing trials. Bioengineering (Basel) 2023; 10(10):1163.

30. Liu CF, Hung CM, Ko SC, et al. An artificial intelligence system to predict the optimal timing for mechanical ventilation weaning for intensive care unit patients: A two-stage prediction approach. Front Med (Lausanne) 2022; 9:935366.

31. Jiang Z, Liu L, Du L, et al. Machine learning for the early prediction of acute respiratory distress syndrome (ARDS) in patients with sepsis in the ICU based on clinical data. Heliyon 2024; 10(6):e28143.

32. Zhang Z, Liu J, Xi J, et al. Derivation and validation of an ensemble model for the prediction of agitation in mechanically ventilated patients maintained under light sedation. Crit Care Med. 2021; 49(3):e279-e290.

33. Epstein SK. How often does patient-ventilator asynchrony occur and what are the consequences? Respir Care 2011; 56(1):25-38.

34. Thille AW, Rodriguez P, Cabello B, et al. Patient-ventilator asynchrony during assisted mechanical ventilation. Intensive Care Med 2006; 32(10):1515-1522.

35. Kyo M, Shimatani T, Hosokawa K, et al. Patient-ventilator asynchrony, impact on clinical outcomes and effectiveness of interventions: a systematic review and meta-analysis. J Intensive Care 2021; 9(1):50.

36. de Bie MJ, Rietveld PJ, van der Velde-Quist F, et al. The association between patient-ventilator asynchrony and clinical outcomes in mechanically ventilated patients: A systematic review. Crit Care Med 2025; 53(11):e2261-e2270.

37. Ramírez II, Gutiérrez-Arias R, Damiani LF, et al. Specific training improves the detection and management of patient-ventilator asynchrony. Respir Care 2024; 69(2):166-175.

38. Sottile PD, Albers D, Higgins C, et al. The association between ventilator dyssynchrony, delivered tidal volume, and sedation using a novel automated ventilator dyssynchrony detection algorithm. Crit Care Med 2018; 46(2):e151-e157.

39. Blanch L, Villagra A, Sales B, et al. Asynchronies during mechanical ventilation are associated with mortality. Intensive Care Med 2015; 41(4):633-641.

40. Rietveld TP, van der Ster BJP, Schoe A, et al. Let's get in sync: current standing and future of AI-based detection of patient-ventilator asynchrony. Intensive Care Med Exp 2025; 13(1):39.

41. de Haro C, Santos-Pulpón V, Telías I, et al. Flow starvation during square-flow assisted ventilation detected by supervised deep learning techniques. Crit Care 2024; 28(1):75.

42. Baedorf-Kassis EN, Glowala J, Póka KB, et al. Reverse triggering neural network and rules-based automated detection in acute respiratory distress syndrome. J Crit Care 2023; 75(154256):154256.

43. Muñoz J, Ruíz-Cacho R, Fernández-Araujo NJet al. Artificial intelligence in the management of patient-ventilator asynchronies: A scoping review. Heart Lung 2025; 73:139-152.

44. Sousa MLEA, Magrans R, Hayashi FK, et al. Clusters of double triggering impact clinical outcomes: Insights from the EPIdemiology of patient-ventilator aSYNChrony (EPISYNC) cohort study: Insights from the EPIdemiology of patient-ventilator aSYNChrony (EPISYNC) cohort study. Crit Care Med 2021; 49(9):1460-1469.

45. Slutsky AS, Ranieri VM. Ventilator-induced lung injury. N Engl J Med 2013; 369(22):2126-2136.

46. van den Berg MJW, Heunks L, Doorduin J. Advances in achieving lung and diaphragm-protective ventilation. Curr Opin Crit Care 2025; 31(1):38-46.

47. Serpa Neto A, Cardoso SO, Manetta JA, et al. Association between use of lung-protective ventilation with lower tidal volumes and clinical outcomes among patients without acute respiratory distress syndrome: a meta-analysis: A meta-analysis. JAMA 2012; 308(16):1651-1659.

48. Kondo S, Corpuz A, Clarke C, et al. Mechanical power in mechanical ventilation: Physiologic basis, evidence, and clinical implications. J Mech Vent 2026; 7(1):1-15.

49. Gattinoni L, Tonetti T, Cressoni M, et al. Ventilator-related causes of lung injury: the mechanical power. Intensive Care Med 2016; 42(10):1567-1575.

50. Sato R, Kondo S, Ali A, et al. The association between mechanical power and mortality in critically ill patients receiving invasive mechanical ventilation: A systematic review and meta-analysis. Crit Care Med 2026; 54(7):1742-1754.

51. Misseri G, Piattoli M, Cuttone G, et al. Artificial intelligence for mechanical ventilation: A transformative shift in critical care. Ther Adv Pulm Crit Care Med 2024; 19:29768675241298918.

52. Ossai CI, Wickramasinghe N. Intelligent decision support with machine learning for efficient management of mechanical ventilation in the intensive care unit - A critical overview. Int J Med Inform 2021; 150(104469):104469.

53. Hagan R, Gillan CJ, Spence I, et al. Comparing regression and neural network techniques for personalized predictive analytics to promote lung protective ventilation in Intensive Care Units. Comput Biol Med 2020; 126(104030):104030.

54. Ruiz-Botella M, Manrique S, Gomez J, et al. Advancing ICU patient care with a Real-Time predictive model for mechanical Power to mitigate VILI. Int J Med Inform 2024; 189(105511):105511.

55. Rose L, Schultz MJ, Cardwell CR, et al. Automated versus non-automated weaning for reducing the duration of mechanical ventilation for critically ill adults and children. Cochrane Database Syst Rev 2025; 7(7):CD009235.

56. Sinnige JS, Buiteman-Kruizinga LA, Horn J, et al. Effect of automated closed-loop ventilation vs protocolized conventional ventilation on ventilator-free days in critically ill adults: A randomized clinical trial: A randomized clinical trial. JAMA 2026;335(10):874-884.

57. Burns KEA, Lellouche F, Nisenbaum R, et al. Automated weaning and SBT systems versus non-automated weaning strategies for weaning time in invasively ventilated critically ill adults. Cochrane Database Syst Rev 2014; 2018(9):CD008638.

58. Platen P von, Pomprapa A, Lachmann B, et al. The dawn of physiological closed-loop ventilation-a review. Crit Care 2020; 24(1):121.

59. Arnal JM, Katayama S, Howard C. Closed-loop ventilation. Curr Opin Crit Care 2023; 29(1):19-25.

60. Botta M, Wenstedt EFE, Tsonas AM, et al. Effectiveness, safety and efficacy of INTELLiVENT adaptive support ventilation, a closed-loop ventilation mode for use in ICU patients - a systematic review. Expert Rev Respir Med 2021; 15(11):1403-1413.

61. Arnal JM, Daoud EG. Guidelines on setting the target minute ventilation in Adaptive Support Ventilation. Journal of Mechanical Ventilation. J Mech Vent 2021; 2(3):80-85.

62. Bialais E, Wittebole X, Vignaux L, et al. Closed-loop ventilation mode (IntelliVent®-ASV) in intensive care unit: a randomized trial. Minerva Anestesiol 2016; 82(6):657-668.

63. Goossen RL, Schultz MJ, Tschernko E, et al. Effects of closed loop ventilation on ventilator settings, patient outcomes and ICU staff workloads - A systematic review. Eur J Anaesthesiol 2024; 41(6):438-446.

64. Gallifant J, Zhang J, Del Pilar Arias Lopez M, et al. Artificial intelligence for mechanical ventilation: systematic review of design, reporting standards, and bias. Br J Anaesth 2022; 128(2):343-351.

65. Muñoz J, Fernández-Araujo NJ, Ruíz-Cacho R, et al. Artificial intelligence and computerized decision support in adult intensive care: A systematic review of randomized controlled trials. J Crit Care 2026; 94(155600):155600.

66. Pinsky MR, Bedoya A, Bihorac A, et al. Use of artificial intelligence in critical care: opportunities and obstacles. Crit Care 2024; 28(1):113.

67. Murali M, Ni M, Karbing DS, et al. Clinical practice, decision-making, and use of clinical decision support systems in invasive mechanical ventilation: a narrative review. Br J Anaesth 2024; 133(1):164-177.

68. Böhm-Hustede AK, Lubasch JS, Hoogestraat AT, et al. Barriers and facilitators to the implementation and adoption of computerised clinical decision support systems: an overview of reviews. Syst Rev. 2025;14(1):2.

69. Agard G, Hraiech S, Gauss T. From promise to practice: A roadmap for artificial intelligence in critical care. J Crit Care 2026; 91(155263):155263.

70. Idan D, Einav S. Primer on large language models: an educational overview for intensivists. Crit Care 2025; 29(1):238.

71. Huo B, Boyle A, Marfo N, et al. Large language models for chatbot health advice studies: A systematic review. JAMA Netw Open 2025; 8(2):e2457879.

72. Chow M, Li AY, Quek DYJ, et al. The cognitive ecology of medicine: generative AI, clinical reasoning, and the preservation of adaptive expertise. Postgrad Med J 2026;qgag068.

73. Armitage RC. Implications of large language models for clinical practice: Ethical analysis through the principlism framework. J Eval Clin Pract 2025; 31(1):e14250.

74. Farquhar S, Kossen J, Kuhn L, et al. Detecting hallucinations in large language models using semantic entropy. Nature 2024; 630(8017):625-630.

75. Ferryman K, Mackintosh M, Ghassemi M. Considering biased data as informative artifacts in AI-assisted health care. N Engl J Med 2023; 389(9):833-838.

76. Workum JD, Meyfroidt G, Bakker J, et al. AI in critical care: A roadmap to the future. J Crit Care 2026; 91(155262):155262.

77. Abgrall G, Holder AL, Chelly Dagdia Z, et al. Should AI models be explainable to clinicians? Crit Care 2024; 28(1):301.

78. Palmieri S, Robertson CT, Cohen IG. New guidance on responsible use of AI. JAMA 2026; 335(3):207-208.