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REVIEW

Advances in Machine Learning for Mechanically Ventilated Patients

Yue Xu[1,*], Jingjing Xue[1,*], Yunfeng Deng[1,*], Lili Tu[1], Yu Ding[2], Yibing Zhang[1], Xinrui Yuan[1], Kexin Xu[1], Liangmei Guo[3], Na Gao[1]

[1]Department of Cardiology, The Second Medical Center & National Clinical Research Center for Geriatric Diseases, Chinese People's Liberation Army (PLA) General Hospital, Beijing, 100853, People's Republic of China; [2]Department of Gastroenterology, The Second Medical Center & National Clinical Research Center for Geriatric Diseases, Chinese People's Liberation Army (PLA) General Hospital, Beijing, 100853, People's Republic of China; [3]Health Sciences, The Second Medical Center & National Clinical Research Center for Geriatric Diseases, Chinese People's Liberation Army (PLA) General Hospital, Beijing, 100853, People's Republic of China

*These authors contributed equally to this work

Correspondence: Na Gao, Department of Cardiology, The Second Medical Center & National Clinical Research Center for Geriatric Diseases, Chinese People's Liberation Army (PLA) General Hospital, Beijing, 100853, People's Republic of China, Tel +86 18515165409, Email gaona301s@163.com; Liangmei Guo, Email amy_kuo@163.com

Background: Mechanical ventilation, a key ICU life-support tech, carries risks. ML can optimize patient management, improving clinical decisions, patient outcomes, and resource use.

Objective: This review aims to summarize the current applications, challenges, and future directions of machine learning in managing mechanically ventilated patients, focusing on prediction models for extubation readiness, oxygenation management, ventilator parameter optimization, clinical prognosis, and pulmonary function assessment.

Methods: Multiple databases, including PubMed, Web of Science, CNKI and Wanfang Data were systematically searched for studies on machine learning in mechanical ventilation management. Keywords included mechanical ventilation, machine learning, weaning, etc. We reviewed recent studies on using machine learning to predict successful extubation, optimize oxygenation targets, personalize ventilator settings, forecast mechanical ventilation duration and clinical outcomes. The review also examined challenges of integrating machine learning into clinical practice, such as data integration, model interpretability, and real - time performance requirements.

Results: Machine learning models have demonstrated significant potential in predicting successful extubation, optimizing oxygenation strategies through non-invasive blood gas prediction, and dynamically adjusting ventilator parameters using reinforcement learning. These models have also shown promise in predicting mechanical ventilation duration, clinical prognosis and pulmonary function parameters. However, challenges remain, including data heterogeneity, model generalizability, workflow integration, and the need for multicenter validation.

Conclusion: Machine learning shows great potential for improving intensive care quality and efficiency in mechanically ventilated patients. However, challenges like model interpretability, real-time performance, clinical and validation remain. Future research needs to focus on these limitations via large-scale, multicenter trials, better data standardization, and improved physician training to safely and effectively integrate ML into clinical practice. Collaboration among medical, engineering, and ethical experts is also essential for advancing this promising field.

Keywords: machine learning, mechanical ventilation, weaning, prognostication models

Mechanical ventilation is one of the most common therapeutic interventions in intensive care, playing a pivotal role in the treatment of conditions such as acute respiratory failure and chronic respiratory dysfunction.[1] While it can temporarily replace or assist spontaneous breathing, maintaining oxygenation and carbon dioxide elimination, mechanical ventilation is not without risks. Complications such as ventilator-associated lung injury, respiratory infections, and hemodynamic disturbances can severely impact patient outcomes.[2] Current clinical practice guidelines, primarily informed by empirical evidence, have significantly improved ventilation management by establishing population-level

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average treatment effects through standardized protocols. However, these evidence-based approaches inherently overlook individual patient heterogeneity in treatment responses, creating a gap between population-based evidence and personalized medicine. Traditional management of mechanical ventilation relies heavily on the experience of healthcare professionals and intuitive judgment, combined with population-level evidence. While this approach has been effective, it has limitations in addressing individual variability, particularly in dynamic clinical settings. Furthermore, high-quality empirical evidence in some areas of mechanical ventilation science remains limited, leaving significant uncertainty in clinical decision-making.

In recent years, the accumulation of medical big data and the rapid development of artificial intelligence technologies, such as machine learning, have opened new avenues for optimizing the management of mechanically ventilated patients. Machine learning has the potential to extract valuable patterns and rules from extensive clinical data, establish predictive and decision support models, and provide more scientific and precise management recommendations.[3] Notably, a study demonstrated the potential of Bayesian frameworks in addressing challenges associated with limited data in medical image classification, using Bayesian Convolutional Neural Networks to develop a probabilistic classification system.[4] This innovation highlights the feasibility of applying machine learning to individualized treatment effect assessment, bridging the gap between population-based evidence and personalized medicine. Machine learning has shown broad application prospects across various aspects of mechanical ventilation management. In weaning management, machine learning models can predict the likelihood of successful extubation, providing a basis for determining optimal timing and strategies.[5] In oxygenation management, these techniques enable real-time monitoring of patient oxygenation status, early detection of abnormalities, and optimization of ventilation strategies, thereby reducing the incidence of ventilation-associated complications.[6] In monitoring and early warning, machine learning models can predict the risk of complications, offering timely alerts and targeted intervention measures.[7] In addition, machine learning can assist in formulating personalized treatment plans, including pulmonary rehabilitation guidance, to improve therapeutic outcomes.[8]

Despite its promising potential, the application of machine learning in mechanical ventilation management faces significant challenges. Patient heterogeneity and dynamic clinical conditions complicate management, while traditional guidelines often overlook individual differences. While machine learning offers a promising approach to addressing these challenges by extracting patterns from complex clinical data, its translation into clinical practice is hindered by data limitations, model interpretability, and regulatory challenges. This review critically analyzes the current state of machine learning in mechanical ventilation management, identifies research gaps, and suggests future research directions to advance the field toward more personalized and effective care.

Prediction of Weaning and Extubation

Successful extubation is a critical step in the process of discontinuing mechanical ventilation. In recent years, machine learning technology has made significant advances in predicting patients' readiness for extubation and weaning, providing robust support for clinical decision-making.

Prediction of Successful Extubation

Current research indicates that machine learning models can utilize various clinical parameters, such as respiratory rate, tidal volume, and blood gas analysis results, to effectively assess patients' readiness, thereby reducing the risk of reintubation.[9–11] Hsieh et al[9] developed a model using artificial neural networks to predict successful extubation, achieving an accuracy rate of 83.6% in the validation set, surpassing the traditional rapid shallow breathing index. Suresh et al[10] created a real-time prediction model based on long short-term memory networks, capable of continuously monitoring patients' physiological status and dynamically updating the probability of successful weaning. Another study[11] found that a support vector machine classifier accurately predicted extubation outcomes with a 94.6% accuracy rate. Additionally, the CatBoost model[12] demonstrated superior performance in predicting extubation failure in the Intensive Care Unit (ICU) compared to other algorithms. Research on premature infants[13] also confirmed the effectiveness of machine learning methods such as artificial neural networks, logistic regression, and Bayesian classifiers in predicting extubation outcomes. These results highlight the potential and prospects of machine learning models in predicting successful extubation. However, although numerous studies have demonstrated the predictive potential of machine learning, many rely on single-center homogenized patient data, limiting external validity. Models developed in high-resource ICUs may perform poorly in resource-limited settings due to differences in equipment, staffing, or patient demographics.

In addition to predicting the success or failure of extubation, machine learning technology can also forecast the optimal timing for extubation, which is equally important for minimizing unnecessary mechanical ventilation duration and reducing the risk of reintubation. Parreco et al[14] developed a model using the random forest algorithm that predicts the likelihood of prolonged mechanical ventilation and tracheostomy, assisting in the timely identification of high-risk patients and the formulation of appropriate weaning strategies. A study[15] developed a decision support model based on convolutional neural networks to predict the timing of extubation. Another study[16] utilized time series ventilator-derived parameters to predict successful extubation in real-time for mechanically ventilated patients using machine learning models such as logistic regression, random forest, and support vector machines, with the random forest model showing good performance in predicting successful extubation at various time points.

Furthermore, reinforcement learning, a specialized machine learning approach that learns optimal strategies through interaction with the environment, has shown potential in developing adaptive weaning strategies for mechanical ventilation. In the context of mechanical ventilation weaning, Prasad et al[17] proposed a reinforcement learning-based method to optimize weaning strategies in the ICU, adjusting ventilation parameters in real-time according to patients' conditions for a more personalized and efficient weaning process. A study[18] used reinforcement learning to deduce the parameters considered by clinical staff when deciding to discontinue mechanical ventilation in the ICU, finding that clinicians focused more on patients' physiological stability (eg, heart rate and respiratory rate) rather than the oxygenation criteria (Fraction of Inspired Oxygen, FiO2, Positive End-Expiratory Pressure, PEEP, and Peripheral Capillary Oxygen Saturation, SpO2) supported by previous reinforcement learning methods. Reinforcement learning aims to mimic clinicians' decision-making, bringing consistency to decisions. However, it's limited by the clinicians' actions in the training set. So, while RL models can decide when to extubate patients like the clinicians in the training data, they might not find the optimal extubation strategy and still need further research.

Prediction of Successful Spontaneous Breathing Trials

Predicting the success of Spontaneous Breathing Trials (SBTs) is a focal area in the weaning of mechanically ventilated patients. Enhancing the accuracy of SBT success prediction can reduce unnecessary SBT attempts and potential complications, such as respiratory muscle fatigue, worsening oxygenation, hemodynamic fluctuations, psychological stress, and patient discomfort. Unnecessary attempts can still lead to patient discomfort and risks. Therefore, enhancing predictive accuracy helps more precisely identify patients suitable for extubation, reducing these unnecessary burdens. Current research shows that machine learning models have made significant strides in predicting SBT success. A study[19] developed a machine learning model using only continuous monitoring parameters obtained from the ventilator during SBT to predict weaning outcomes. The study employed Gradient-Weighted Class Activation Mapping to provide a visual explanation of the model's predictions, highlighting influential features. The proposed predictive model aids clinicians in making real-time ventilator weaning decisions, potentially improving patient outcomes. Another study[20] utilized data mining and artificial intelligence to explore predictive factors for successful mechanical ventilation weaning, including body mass index at admission, occlusion pressure at 0.1 seconds, and heart rate analysis parameters measured before SBT, as well as heart rate during SBT (overall performance 62%; specificity 83%). Moreover, Graph Neural Network methods have been applied to predict the success of SBTs in mechanically ventilated patients, designing graph structures considering feature correlations, and developing a novel deep learning model—the Feature-Marker Graph Attention Network.[21] These studies demonstrate the advantages of machine learning techniques in capturing complex physiological patterns and dynamic changes, enhancing model interpretability.

Addressing the common issue of imbalanced datasets in biomedical data mining, a study[22] proposed a feature selection optimization that balances sensitivity and specificity, applied to the classification problem of weaning patients from mechanical ventilation using Support Vector Machine, achieving an accuracy rate of 80%, a balance index of 18.64%, a sensitivity of 74.36%, and a specificity of 82.42%. This underscores the importance of data preprocessing in machine learning applications. Additionally, researchers have begun to explore multi-modal data fusion methods, combining various types of data to enhance the accuracy of weaning predictions. This approach fully leverages the complementary advantages of different data types, which is significant for practical applications. Thille et al[23] reviewed predictive factors in mechanical ventilation weaning, emphasizing the importance of integrating multiple clinical parameters. Although this article did not directly employ machine learning methods, it provided an essential theoretical foundation for subsequent machine learning research. Future research should further refine predictive models to enhance their robustness and applicability in complex clinical scenarios and strengthen their integration with clinical practice, promoting the widespread application of machine learning technology in critical care.

Management of Optimal Oxygenation

Oxygenation management is a crucial component of mechanical ventilation treatment, affecting the adequacy of oxygen delivery to patients and the rationality of mechanical ventilation parameter settings. Determining optimal oxygenation targets for this patient population remains an open question. Traditional oxygenation assessment methods depend on clinical experience and basic physiological monitoring indicators, yet they are often affected by subjectivity and timeliness issues. Due to differences in experience, knowledge, and personal habits, different doctors may interpret the same data or symptoms differently. For instance, cyanosis assessment can vary among doctors, impacting the evaluation of oxygenation. Moreover, these traditional methods cannot dynamically reflect the patient's oxygenation status in a timely and accurate manner. The introduction of machine learning methods offers new possibilities for oxygenation assessment.

Accurate assessment of a patient's oxygenation status is essential for guiding treatment. Oxygen therapy is central to the management of mechanically ventilated patients, but excessive oxygenation can lead to oxygen toxicity, while insufficient oxygenation can impact tissue oxygen supply. The impact of oxygenation targets on clinical outcomes for critically ill patients remains debated. A systematic review and meta-analysis[24] showed that for ICU patients aged ≥18 years, there were no differences in mortality, need for RRT, ventilator - free days by day 28, or ICU length of stay between lower and higher oxygenation targets. However, due to significant heterogeneity in specific oxygenation targets across individual studies, no definitive conclusions could be drawn about the effect of oxygenation targets on ICU outcomes. Another systematic review and meta-analysis[25] identified possible increased mortality with liberal oxygen targeting strategies and no difference in morbidity between high or low oxygen targets in mechanically ventilated adults. Findings were limited by substantial heterogeneity in study methodology and further research is urgently required to define optimal oxygen therapy targets. A study[26] has found that among children admitted to the Paediatric Intensive Care Unit (PICU) as an emergency, receiving invasive ventilation and supplemental oxygen, a conservative oxygenation target resulted in a small but significant increase in the probability of a better outcome in terms of duration of organ support at 30 days or mortality rate when compared to a liberal oxygenation target. Widespread adoption of a conservative oxygenation saturation target (with SpO_2 of 88% to 92%) could help improve health outcomes and reduce costs for critically ill children admitted to PICUs. However, other studies have indicated that a low oxygenation strategy did not reduce the 28-day mortality rate in ICU patients expected to have prolonged mechanical ventilation.[27] Thus, establishing the appropriate oxygenation targets remains an unresolved challenge.

A study discovered that personalized oxygenation targets could decrease the mortality rate in critically ill adults on mechanical ventilation. A research team from the University of Chicago developed a machine learning model to predict the impact of various SpO2 target treatments on individual patient mortality, validating it using machine learning from randomized trials.[28] This provides a feasible plan for individualized oxygenation management. Accurate interpretation of blood gas analysis results is crucial for correctly identifying the status of oxygen therapy. Traditional blood gas analysis requires arterial puncture to obtain blood samples, which not only causes patient discomfort but also carries risks such as infection. Machine learning technology also offers new possibilities for predicting non-invasive blood gas analysis parameters. A study[29] developed a machine learning model based on pulse oximeter data to predict arterial blood gas values, using the random forest algorithm. By analyzing pulse oximetry, heart rate, and other physiological parameters, it successfully predicted arterial oxygen partial pressure, carbon dioxide partial pressure, and pH, laying the foundation for continuous blood gas monitoring. However, the predictive accuracy of such models still needs to be improved. In the future, more non-invasive physiological parameters could be integrated, and more advanced algorithms such as deep learning could be explored to enhance performance.

For mechanically-ventilated patients, patient positioning is key to improving oxygenation. A study in COVID-19 mechanically ventilated patients[30] using machine learning to predict prone positioning showed that despite the application of various machine learning techniques such as logistic regression and random forest, there are limitations to the prediction success rate, indicating that predicting the success of prone positioning with existing parameters remains challenging. Proper positioning, eg, prone ventilation, can enhance oxygenation and cut mortality. Still, ML cannot offer personalized position-management plans per patients' disease severity, physical status, or comorbidities. Position-management involves complex multi-factor interactions, and data collection is tough. Individual differences also exist, making it hard to get enough high-quality data for model training, which hinders ML's application here. Future research should seek to offer patients personalized position choices.

Optimising and Personalising Ventilator Settings

Ventilator settings are crucial for maintaining the stability of mechanically ventilated patients. Improper ventilator settings may lead to a series of complications, such as lung injury and hemodynamic instability. Therefore, optimizing ventilator parameters to achieve personalized ventilation strategies is essential for improving patient outcomes. Traditionally, the adjustment of ventilator parameters mainly depends on the experience of medical staff and the physiological parameters of patients. However, this method has a certain degree of subjectivity and does not fully consider the individual differences and dynamic changes of patients. In recent years, machine learning technology has shown tremendous potential in optimizing ventilator settings for mechanically ventilated patients. By analyzing a large amount of patient data, researchers have developed various algorithms aimed at improving the efficiency and accuracy of ventilator parameter optimization. A study[31] developed a suggestive multilayer perceptron neural network model to predict the level of inhaled oxygen delivered by the mechanical ventilator, as well as changes in mode and PEEP. The model identifies some real-time data of patients, including regular arterial blood gas analysis, continuous pulse oximetry readings, and mechanical ventilator settings analyzed by statistical paired analysis using R programming, to reduce the workload of healthcare professionals. A study[32] explored the feasibility of using machine learning methods to predict successful ventilator mode transitions in adult ICU patients. The study established two models to predict successful transitions from full support to partial support ventilation (WPMV model) or from partial support to spontaneous breathing trial (sSBT model). The AUROC for the WPMV model and sSBT model were 0.76 and 0.79, respectively. Additionally, a study[33] successfully developed a reinforcement learning-based algorithm capable of dynamically adjusting mechanical ventilation parameters (eg, positive end-expiratory pressure [PEEP], tidal volume). In both simulated environments and retrospective clinical data validation, the algorithm significantly optimized the effectiveness of mechanical ventilation, demonstrating improvement in patient oxygenation levels (eg, PaO_2/FiO_2 ratio) and reducing the risk of ventilator-induced lung injury (VILI).

Ventilation-perfusion mismatch is an important cause of oxygenation disorders. Chiew et al[34] proposed a model-based PEEP optimization method that automatically adjusts PEEP levels to improve ventilation-perfusion matching by analyzing pressure-volume curves. It is also necessary to consider incorporating patient position changes, hemodynamic status, and other factors into the model for real-time assessment of ventilation-perfusion distribution to further enhance optimization effects. High-frequency oscillatory ventilation (HFOV) is a special mechanical ventilation mode with complex parameter settings. In preterm infants, nasal HFOV reduces reintubation rates, particularly in those with a gestational age of ≤32 weeks and those diagnosed with ARDS.[35] It also lowers Pco_2 levels and improves oxygenation without significantly affecting short-term neurobehavioral development. In infants with ARDS after congenital heart surgery, HFOV combined with prone positioning significantly improves oxygenation and pulmonary ventilation without serious complications.[36] Additionally, HFOV with volume guarantee reduces systemic inflammatory responses, decreases the incidence of hypercapnia and hypocapnia, and shortens postoperative mechanical ventilation time in these infants. However, the use of HFOV in adult ARDS patients is more controversial. While it may improve oxygenation, it does not necessarily reduce mortality. A study[37] found that patients in the HFOV group received higher doses of sedatives, more neuromuscular blocking agents, and vasopressors, and used vasopressors for a longer time than the control group, suggesting that HFOV may be associated with more pharmacological interventions and potential lung injury risks. Extracorporeal Membrane Oxygenation (ECMO) technology provides additional oxygenation support for critically ill patients, but its management is complex. Schmidt et al[38] developed the SAVE scoring system to predict the survival rate of patients on VA-ECMO. The next step could be to explore the use of machine learning algorithms to optimize ECMO parameter settings, such as blood flow and oxygen flow, to achieve personalized oxygenation management. At the same time, developing predictive models to assess when ECMO support can be safely withdrawn is also important. Machine learning technology is used to predict patients' responses to different ventilator settings, automatically adjust ventilator parameters, formulate personalized ventilation strategies, and optimize multiple parameters. These technologies are expected to help medical staff adjust ventilator settings more accurately, improve the safety and efficiency of mechanical ventilation, and thus improve patient outcomes.

Prognostication Models

Mechanical ventilation is a commonly used life support technology in intensive care, but it also comes with many potential complications and risks. Early identification of potential risks is crucial. In recent years, machine learning technology has shown a broad application prospect in this field.

Mechanical Ventilation Duration Prediction

Accurately predicting the duration of mechanical ventilation required is an important but challenging issue. Previous studies have found that even with machine learning methods such as multilayer perceptrons, it is difficult to predict the duration of mechanical ventilation for patients with moderate to severe ARDS early.[39] However, another study[40] using data from the MIMIC-IV, eICU-CRD, and AmsterdamUMCdb databases found that models based on the XGBoost algorithm performed more stably and accurately in predicting the duration of mechanical ventilation for ICU patients with ARDS. Although this study shows that the XGBoost model performed consistently across the three datasets, such research remains limited and prospective multicenter validation is urgently needed. In addition, some scholars[41] have developed predictive models based on artificial intelligence and machine learning for predicting the duration of mechanical ventilation. Parreco et al[14] developed an artificial intelligence model for studying the duration of mechanical ventilation, successfully predicting the required duration of mechanical ventilation by analyzing clinical data at admission. These study results demonstrate the potential of machine learning technology in predicting the duration of mechanical ventilation, but further exploration is needed to integrate multidimensional information such as physiological parameters, disease progression, and treatment response into the predictive model to achieve more accurate duration prediction.

Clinical Prognosis Prediction

Machine learning technology is also widely used in predicting the clinical prognosis of mechanically ventilated patients. A study[42] using the MIMIC-III database established predictive models for the prognosis of mechanically ventilated patients through various machine learning methods, including k-nearest neighbors, logistic regression, Bagging, decision trees, random forests, XGBoost, and neural networks, showing that the XGBoost model performed best in predicting the mortality of ventilated patients. Another study[43] systematically reviewed the effectiveness of frailty risk prediction models for mechanically ventilated patients, finding that all included studies used Logistic regression to build models with overall good predictive performance, but further optimization is needed in terms of data sources, construction design, and statistical analysis. Future research should conduct external validation of existing models or develop high-quality predictive models with excellent performance. Some scholars[44] also explored the good predictive performance of machine learning-based logistic regression for in-hospital mortality in mechanically ventilated patients after moderate to severe traumatic brain injury, which is helpful for integrating machine learning methods into trauma case systems in the future to provide immediate clinical decision support. In addition, machine learning models have been applied to the early warning of ventilator-associated pneumonia,[7] facilitating early intervention for patients and reducing the occurrence of complications, showing higher performance than traditional clinical pulmonary infection scoring (CPIS) models. Pirracchio et al[45] established a machine learning model to predict the risk of discharge or transfer of patients from the intensive care unit, helping to identify high-risk patients in a timely manner, take targeted intervention measures, and reduce the occurrence of adverse outcomes.

Pulmonary Function Prediction

During mechanical ventilation, accurate assessment of pulmonary physiological parameters is key to improving treatment outcomes. In mechanical ventilation, patient response assessment traditionally depends on respiratory-system compliance and airway resistance. These parameters show high variability in clinical evidence, making them hard to predict before starting ventilation therapy. A study[46] used high-fidelity and low-fidelity finite element models and trained and validated various machine learning architectures (including Gaussian process regression and artificial neural networks) to successfully predict the mechanical response of the lungs. The high-fidelity Gaussian process regression model is more accurate than the low-fidelity Gaussian process and neural network models in estimating respiratory-system compliance and airway resistance, and it is extremely computationally efficient. Regarding lung function, specific structural parameters exhibit a nearly matched nonlinear behavior with chest wall stiffness. Tissue permeability is also found to strongly modulate airway resistance. In research on mechanical ventilation in COVID-19 patients, deep learning algorithms were used to analyze high-granularity ventilator waveform data to obtain information about patient-ventilator asynchrony, finding that the use of high plateau pressure and neuromuscular blocking agents was related to the reduction of the asynchrony index risk.[47] There is also research that created a whole-lung finite element model to simulate the 3D response of the lungs during mechanical ventilation and recover physiological parameters with high clinical relevance, such as respiratory system compliance and resistance.[48] This modeling-based approach may become a new path for assessing lung function.

In addition to the assessment of pulmonary physiological parameters, machine learning technology has also shown advantages in monitoring patient-ventilator synchrony. Patient-ventilator asynchrony can lead to discomfort and reduced ventilation effectiveness. Gholami et al[49] developed a machine learning method for the automatic detection of patient-ventilator cycle asynchrony, successfully replicating the judgment of human experts and achieving real-time monitoring of asynchrony. Another study[50] developed four different machine learning algorithms to identify ventilator asynchrony phenomena, which could help improve clinical adjustments of ventilator settings to better meet patient needs. A researcher[51] attempted to control the pressure and volume of the mechanical ventilator through machine learning algorithms to reduce patient-ventilator asynchrony. The study validated the accuracy and effectiveness of the iterative learning proportional integral derivative (PID) controller, with the proposed narrow neural network achieving an accuracy rate of 92.4% and 89.29% for pressure and volume, respectively. Diaphragmatic contraction asynchrony during mechanical ventilation could impair diaphragmatic function. A study found that machine learning algorithms could analyze the synchrony between the ventilator and the patient, identifying asynchrony in inspiratory afterload that could lead to diaphragmatic injury.[52]

The management of mechanical ventilation involves complex clinical decision-making. In recent years, the application of machine learning technology in assisting clinical decisions for mechanically ventilated patients has become increasingly widespread, with researchers developing various models to assist in lung rehabilitation guidance. These models integrate a large amount of clinical data and the latest research evidence to provide personalized treatment recommendations for the clinic, which is expected to improve the accuracy and consistency of decision-making. A study[53] explored a lung rehabilitation mechanical ventilation strategy based on human-computer interaction. The study established a pneumatic model of the mechanical ventilation system and proposed a new fuzzy control method for the ventilator support pressure, which is of great significance for improving patients' spontaneous breathing ability and avoiding lung function damage such as respiratory muscle weakness. A study[54] proposed a lung function index prediction model based on machine learning algorithms, accurately predicting the GOLD classification of COPD patients, while developing intelligent rehabilitation training action recognition and assessment methods to improve the scientific and personalized nature of training. A review study[55] discussed the diverse applications of artificial intelligence and machine learning in cardiopulmonary rehabilitation, including using deep learning to analyze rehabilitation effects and provide dietary and exercise suggestions, as well as the application and effectiveness of explainable artificial intelligence in this field.

Although ML shows great potential in mechanical ventilation clinical decision support systems, its application is still in the development and improvement phase with certain limitations, where further research is needed. ML has not been reported in nutritional management of mechanical ventilation patients. Adequate nutrition is crucial for patients' immune function, muscle strength, and prognosis. Yet, ML cannot predict individual nutritional needs, formulate precise nutrition plans, or monitor nutrition - treatment effects in real-time. This is likely due to the complexity, multi-source nature, and dynamic changes of nutritional management data, which ML models struggle to integrate and process effectively. Future work should focus on more research, better data collection and integration, and model optimization to advance mechanical ventilation clinical decision-support systems, offering more precise and comprehensive medical services to patients.

Limitations and Challenges

Challenges of Machine Learning in Clinical Practice

Although machine learning (ML) models have demonstrated promising predictive performance in many studies, their integration into clinical practice faces significant challenges, including integration with ICU workflows, comparison with standard care practices, and validation through clinical trial results. Future research should verify clinical effectiveness through multicenter randomized controlled trials (RCTs) and explore strategies to seamlessly integrate ML tools into existing clinical workflows. Models developed in high-resource ICUs may perform poorly in resource-limited settings due to differences in equipment, patient demographics, or data quality. Many studies rely on single-center data with small sample sizes, missing data, or training data biases, which may undermine model reliability and generalizability. Future research should enhance model adaptability and generalizability through multicenter collaboration and data standardization.

Limitations of Data Integration and System Compatibility

ICU data originate from heterogeneous platforms such as ventilators, patient monitors, and laboratory systems, which often use different protocols and formats, complicating data integration. Complex preprocessing and standardization pipelines are required to ensure consistency for ML applications. Additionally, incompatible electronic health record (EHR) systems across hospitals further exacerbate operational challenges. Models trained on data from one EHR system may fail to generalize to others due to differences in data structure, coding standards, or missing variables. Future efforts should prioritize the development of standardized data-sharing frameworks and universal interfaces to harmonize multi-source ICU data and enable seamless model deployment across diverse clinical environments. AI applications in ICUs also face regulatory hurdles, including ethical concerns, data privacy protection, and stringent approval processes. Future research should collaborate with regulatory agencies to establish clear approval pathways, ensuring AI system safety and reliability while balancing innovation with patient safety. Given the complexity of the ICU environment, strategies are urgently needed to integrate ML with ICU workflows, handle multi-source data, and ensure compatibility across EHR systems.

Real-Time Performance Requirements in Time-Sensitive Environments

The timeliness of ICU decision-making imposes strict requirements on ML models, including low-latency processing and frequent model updates. Current research often overlooks the computational demands of real-time inference, such as data collection delays or the time required for model retraining. While reinforcement learning (RL) algorithms theoretically support dynamic parameter adjustments, their reliance on high-frequency data streams and computational resources may hinder practical implementation. Future research should explore edge computing solutions and lightweight model architectures to optimize processing speed without sacrificing accuracy. Furthermore, integrating ML predictions into clinical workflows must align with ICU time constraints, such as automatically alerting for impending complications or adjusting ventilator parameters during acute patient deterioration.

Enhancing Physician Acceptance and Trust

Skepticism toward “black-box” ML systems remains a major barrier to adoption. To address this, models should prioritize interpretability, such as using techniques like SHAP (SHapley Additive Explanations) or gradient-weighted class activation mapping to highlight key features in predictions. Transparency can be improved by reporting model performance across diverse patient subgroups and conducting rigorous external validation in multicenter trials. Additionally, user-centered design principles should guide the development of interfaces that align with physicians’ workflow habits, such as decision dashboards embedded within EHR systems. Physician familiarity with ML tools can be enhanced through training programs and simulation workshops, building trust through hands-on experience. A collaborative framework involving physicians, data scientists, and ethicists is essential to ensure that ML systems meet clinical needs and adhere to ethical standards.

Conclusion

The application of machine learning in managing mechanically ventilated patients has broad prospects. It is expected to enhance the quality and efficiency of intensive care and improve patient prognosis by reducing adverse events, optimizing workflows, and supporting clinical decision-making. Despite progress, challenges remain in applying this technology to clinical practice, including model interpretability, real-time performance, clinical validation, ethical and legal issues, workflow integration, and data quality and standardization. To further strengthen this field, future research should focus on addressing current challenges and exploring how to better combine machine learning with clinical expertise. Limitations of current studies, such as dataset heterogeneity and lack of standardization affecting model generalizability, must be acknowledged and tackled. Moreover, more large-scale, multicenter randomized controlled trials are needed to verify the effectiveness and safety of these technologies in real clinical settings. How to train medical staff to use these new technologies effectively and how to evaluate the long-term impact of these systems are also crucial issues requiring attention. Future research necessitates close cooperation among experts from medicine, engineering, ethics, and other fields to ensure comprehensive and balanced development in this promising area.

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Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, analysis and interpretation; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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