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Research article

Application of a cloud platform that identifies patient-ventilator asynchrony and enables continuous monitoring of mechanical ventilation in intensive care unit

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A R T I C L E I N F O

Keywords:
Intensive care medicine
Mechanical ventilation
Patient-ventilator asynchrony
Monitoring platform
Respiratory mechanics

A B S T R A C T

Background: Patient-ventilator asynchrony (PVA) frequently occurs in mechanically ventilated patients within the ICU and has the potential for harm. Depending solely on the health care team cannot accurately and promptly identify PVA. To address this issue, our team has developed a cloud-based platform for monitoring mechanical ventilation (MV), comprising the PVA-RemoteMonitor system and the 24-h MV analysis report. We conducted a survey to evaluate physicians' satisfaction and acceptance of the platform in 14 ICUs.
Methods: Data from medical records, clinical information systems, and ventilators were uploaded to the cloud platform and underwent data processing. The data were analyzed to monitor PVA and displayed in the front-end. The 24-h analysis report for MV was generated for clinical reference. Critical care physicians in 14 hospitals' ICUs that involved in the platform participated

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in a questionnaire survey, among whom 10 physicians were interviewed to investigate physicians' acceptance and opinions of this system.
Results: The PVA-RemoteMonitor system exhibited a high level of specificity in detecting flow insufficiency, premature cycle, delayed cycle, reverse trigger, auto trigger, and overshoot, with sensitivities of 90.31 %, 98.76 %, 99.75 %, 99.97 %, 100 %, and 99.69 %, respectively. The 24-h analysis report supplied essential data about PVA and respiratory mechanics. 86.2 % (75/87) of physicians supported the application of this platform.
Conclusions: The PVA-RemoteMonitor system accurately identified PVA, and the MV analysis report provided guidance in controlling PVA. Our platform can effectively assist ICU physicians in the management of ventilated patients.

1. Introduction

Mechanical ventilation (MV) is a vital life-support measure in the intensive care unit (ICU), playing a critical role in the treatment of critically ill patients [1,2]. It sustains oxygenation, alleviates respiratory muscle fatigue and mitigates respiratory distress, providing stable respiratory support [3]. As the use of MV continues to rise, so do concerns about its potential risks and the pressing need for personalized care. Patient-ventilator asynchrony (PVA), a mismatch between the patient's respiratory demands and ventilator support, is common among ICU patients [4,5]. PVA poses significant risks, including increased tidal volume, volumetric and pneumatic injuries, and potential ventilator-induced lung injury (VILI) [6,7]. Despite studies indicating the association between PVA and poor prognosis, such as prolonged ICU stays and increased mortality, standardized evaluation criteria are lacking [8–11]. Moreover, the incidence of PVA is often underestimated due to inadequate monitoring or the relative inexperience of physicians [12]. Accurate and timely identification of PVA requires improved monitoring techniques and enhanced expertise among healthcare teams [13].

Various monitoring modalities have been proposed for mechanical ventilation [13]. Compared to other complex and invasive methods such as esophageal balloon, ventilator graphics are crucial for monitoring PVA due to their non-invasive, user-friendly, and practical nature. The healthcare team primarily relies on manual identification of ventilator waveforms. Despite practical methods for interpreting these graphs [14], the proficiency of ICU physicians in identifying and analyzing PVA is generally low, with accuracy heavily reliant on the physician's expertise [15]. Clinicians usually analyze waveforms offline, resulting in significant delays. These challenges underscore the need for real-time PVA monitoring tool. So far, studies have proposed recognition algorithms and monitoring platforms based on ventilator waveforms, demonstrating good capabilities in identifying asynchrony [16–19]. However, the reported algorithms have the limitation of recognizing only a few types of asynchronies, and the monitoring platforms have not yet been widely accepted in clinical practice. There is still a long way to go before automatic monitoring of PVA in the clinic can be realized.

To foster the monitoring of MV in critically ill patients, we develop a patient-ventilator asynchrony remote network platform to continuously monitor MV in patients. The platform incorporates the PVA-RemoteMonitor system, a real-time MV monitoring module, and a 24-h MV analysis report. Meanwhile, we conducted a survey to investigate the acceptance and satisfaction of physicians with the platform. The research was conducted in the ICUs of 14 hospitals that used the platform, and the questionnaire was distributed to all physicians within these ICUs. Ten critical care physicians of different professional ranks were interviewed as well.

2. Methods

2.1. Design framework

This study proposes a PVA remote monitoring (PVA-RemoteMonitor) system to achieve the remote monitoring of mechanical ventilation and real-time recognition of PVA in ICU. The PVA-RemoteMonitor system mainly includes four parts—Data Source, Data Platform, Algorithm Module, and View Module, which correspondingly acquire, process, apply, and display data, as shown in Fig. 1. The design was based on our previous study [20]. The tracings of pressure, flow, and volume were recorded by the ventilator itself, and no extra gear was added to detect data. The real-time data generated by the ventilator were transmitted to the Remote-VentilateView

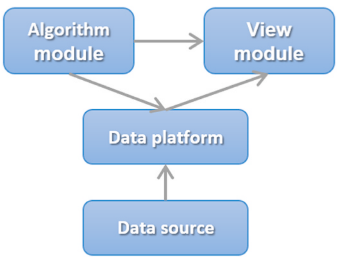


Fig. 1. Structure of the PVA-RemoteMonitor system.

platform server through the ventilator, Data Transfer Unit (DTU, Jinan Usr IOT Technology Limited), switch, desensitization encryption server, and Virtual Private Network (VPN).

Data Source collects raw data, including previous electronic medical records (EMR), Clinical Information System (CIS), and respiratory waveform. The Data Platform includes two parts, data processing, and data storage, in which data processing includes traditional data processing and data annotation. Algorithm Module mainly includes alarms generated by algorithms and data analysis reports. View Module is a visualization of mathematical exhibition and data analysis reports, which is the part directly exhibited to physicians. Through the View Module, physicians can observe data, check abnormalities, proofread alarms of the Algorithm Module, data annotation, and data analysis reports. PVA-RemoteMonitor system greatly facilitates physicians' remote monitoring of ventilation conditions of patients, expands the influencing scope of intensive care medicine, and provides feasible solutions for patients of remote areas to receive high-quality healthcare services.

2.2. Software and hardware

Ventilators involved in this system include Myeri, Vaillant, Covidien, and Mykovi, which are commonly used in ICU. The sampling frequency of ventilators is 50Hz. Three waveforms are collected: paw-time waveform, flow-time waveform, and volume-time waveform. Waveforms are stored as the raw data in the database, which are processed into the form required for the algorithmic model.

The configuration of the front-end machine involved in this study—CPU is 4 cores and 8 threads, RAM is 16G, and hard disk is 256G. The operating system involved in this study is CentOs-7.5 and Ubuntu-18.04. The development languages involved in this study are Java-1.8, Python3.8, and TypeScript-3.9.

The Data Transfer Unit (DTU) involved is USR IOT-G771/G781, and the data transfer method used is 4G wireless transmission communication with RS232 communication. This study's cloud computing service provider is Alibaba/China Mobile Cloud.

2.3. Data processing

EMR and CIS data serve as auxiliary information for physicians to determine a patient's condition, greatly assisting them in diagnosing diseases, diagnosing and recommending treatments, and proofreading algorithmic results. This study mainly performs data processing on EMR and CIS data but not respiratory waveform data. This is because the respiratory waveform data has strong characteristics such as periodicity, volatility, temporal sequence, and data limitations, which make it unsuitable for these data processing operations. Data processing includes traditional parts and data annotation. Traditional data processing includes data deduplication, data merging, data classification, data type conversion, data missing handling, and data outlier processing.

Data deduplication and data merging requires first deduplication and merging of data in this database, then deduplication and merging data from different data sources. Data deduplication consists of complete and incomplete deduplication. First, the data from different sources are completely deduplicated, in which the corresponding fields of two data records are the same. Then, these data are incompletely deduplicated, where there are partially the same data in the corresponding fields of two data records, the duplicate field value of one record is retained, and the duplicate field value of another is set to null to prepare for data merging. Data merging is merging data from different sources pointing to the same patient. It includes mutually exclusive merging and cross-merging. Mutually

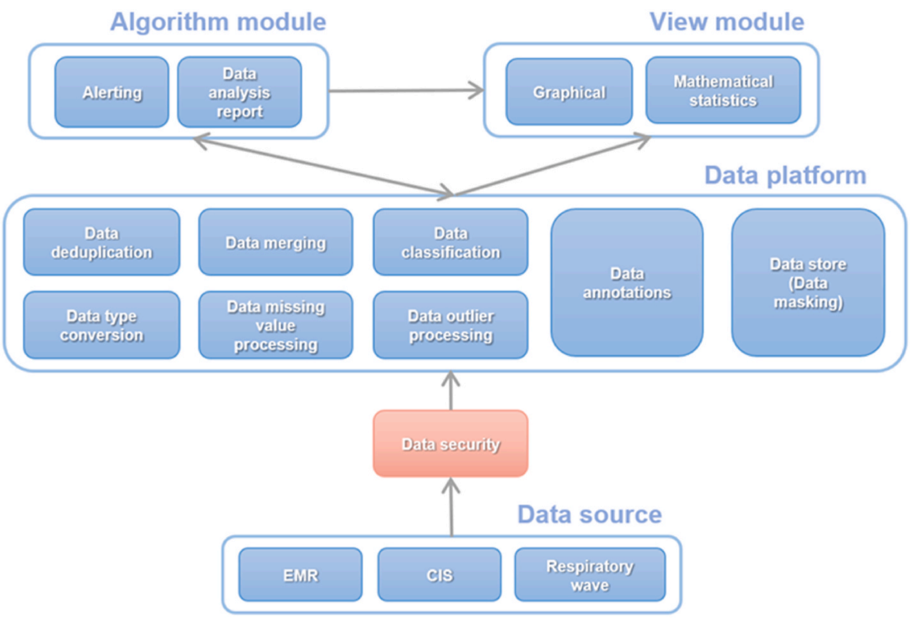


Fig. 2. Flowchart of the PVA-RemoteMonitor system.

exclusive merging involves two sources of data that have no same field except the index, in which data can be directly merged. Cross-merging refers to merging two data sources that share information in several parts.

Data classification is to define the category of data to facilitate accessing, in which data are classified into basic data, admission data, diagnosis and treatment data, and respiratory data. Data type conversion is to convert numerical strings into numerical types and convert segmented data into numerical categories. Data missing processing is to delete the whole record that contains missing data, use the mean or median for complementary, reason rationally based on known data, verify the filling from the rest of the data, and fill the data with a binned plurality. Data outlier processing is the focus of our research in critical care medicine, considering that some of the data belong to the outlier in critically ill patients compared with normal people. Data outlier processing is to delete data that are not characteristic or irregular, and retain data that are typically abnormal as the comparison of experiments to explore the relationship between diseases and symptoms.

Data annotation is to provide the algorithms with better data for learning the features and to provide criteria to evaluate strengths and weaknesses of the algorithms. The data annotation is divided into two parts, which are randomly divided into training set and validation set in the ratio of 8:2. During the operation, the training set data with obvious features are used to train the algorithm model first, so that the algorithm model "learns" to identify the defined anomalous data. Then, the validation set is used to verify the algorithm model, including sensitivity and specificity, in which data are randomly extracted from the validation set as a sub-validation set to assess the robustness and generalization ability of the algorithm model through several times of validation. When the validation results fail to meet expectations, the algorithm model and parameters are continuously adjusted until the sensitivity and specificity can no longer be improved. Using the manually annotated anomalies as a benchmark, the physician-annotated anomalies are the basis for determining whether the algorithm returns correct or incorrect anomaly results.

2.4. Constructure of PVA-RemoteMonitor system

The specific process of constructing the PVA-RemoteMonitor system is shown in Fig. 2. The system acquires multiple critical care medical raw data (including electronic medical records, CIS, and respiratory waveforms); the raw data are transmitted to the data platform in real time through the remote data security network, and the data platform carries out unified and standardized processing to generate the basic data, which can be desensitized and stored or be used as the driving data for the algorithm module. The unified, standardized processing includes data deduplication, data merging, data classification, data type conversion, data missing processing, data outlier processing, and data annotation; the basic data can be used as the input of the algorithm module, and can also be used for mathematical and statistical calculations to be displayed in the view module; the basic data can be used to generate alarms and the data analysis reports through the algorithm module, which are the front-end display in the view module. The view module only receives the data without processing the data. It can interact with physicians to view and analyze data.

Validation of the algorithmic model needs to focus on improving the overall recognition ability. Whether the overall recognition ability is improved is judged by observing the indicator weight coefficients of the six PVA: flow insufficiency, premature cycle, delayed cycle, reverse trigger, auto trigger, and overshoot. The indicator weight coefficients are calculated in the following way: counting the number of times the six PVA occur in the overall number of data annotations versus the total number of times, calculating the proportion of each PVA in the total number of times as a weight, multiplying with the sensitivity of the six PVA, respectively, and then adding them up to obtain the sensitivity weight value of the current result. Similarly, the specificity weight value is obtained, and the two weight values are added together as the indicator weight coefficient of the current validation.

After the validation results meet expectations, the algorithmic model is applied to a new data set. These data are not annotated yet and are brand new to the model, predicting whether there is some kind of anomaly in these new data and then manually extracting non-repeated data for review and marking the correctness of the prediction results as an expansion of the next data annotation.

2.5. Questionnaire

The questionnaire survey was carried out in ICU of 9 hospitals in Beijing covered by this platform, including Peking Union Medical College Hospital, Beijing Puren Hospital, Beijing Sixth Hospital, Dongzhimen Hospital, Beijing Hospital, Beijing Hospital of Traditional Chinese Medicine, Beijing Hepingli Hospital, Beijing Longfu Hospital, and Beijing Tongren Hospital. An online questionnaire survey was conducted, distributed and collected using an online tool (www.wjx.cn) with anonymous responses to investigate critical care physicians' opinions of the system. The questionnaires were as follows–

1 Information about the physician and their department, including gender, age, whether they are a critical care physician, hospital level, type of ICU, number of years of working experience in ICU, and whether they have any learning experience in respiratory mechanics or PVA;
2 Willingness to support the configuration of the platform;
3 Satisfaction with each section of the 24-h mechanical ventilation analysis report, including “Diagram of Changes in Ventilation Mode and Setting Parameter”, “Trends Diagram in Lung Protective Ventilation Data”, “Diagram of Changes in PVA Events”, “PVA Events”, “Trend Chart of Respiratory Mechanics Data”, and “Reminder and Discovery”.

Individual interview was conducted with 10 critical care physicians to find out respondents' evaluation of the platform, including 2 chief physicians, 3 associate chief physicians, 3 attending physicians, and 2 resident physicians, to investigate their suggestions and comments on the system. Interview content included.

1 opinions of the system's clinical significance;
2 views and suggestions of the system.

Respiratory therapist is an important position to provide specialized treatment to patients who need respiratory support. However, this questionnaire did not collect responses from respiratory therapists because the ICUs participated in the platform did not set the position.

3. Results

3.1. Recognition of PVA

Based on the results of our previous research [20], our group and Shanghai Shumu Medical Technology Co., Ltd. have further improved the algorithm, which is capable of recognizing the following eight types of PVA: double trigger, ineffective trigger, flow insufficiency, premature cycle, delayed cycle, reverse trigger, auto trigger, and overshoot. A test dataset was used to evaluate the algorithm. The data came from four randomly selected patients, including a 84-year-old male (ventilated for 880.12 h), a 62-year-old male (ventilated for 115.97 h), a 70-year-old male (ventilated for 66.6 h), and 63-year-old male (ventilated for 221.7 h), who had been mechanically ventilated for more than 24 h, totaling 4496 breaths [20].

During ventilation, the ventilator waveforms were recorded by the system, and the abnormal waveforms were marked and categorized by two professional and experienced respiratory therapists (considered as the gold standard). More than 250 events of PVA were manually labeled for each patient. When dyssynchrony occurred, the evaluator or physician did not intervene.

The various types of PVA events returned by the model in this study were compared with the manually labeled results, and the intersection of the two represented the correct judgment of the model, and the final statistics were calculated for each sub-result (Table 1). There were 1204 flow rate insufficiency events, 217 early switching events, 139 delayed switching events, 8 reverse trigger events, 3 auto trigger events, and 47 overshooting events. The sensitivities were 96.60 %, 85.71 %, 83.45 %, 75 %, 66.67 %, and 85.11 %. Corresponding specificity was 90.31 %, 98.76 %, 99.75 %, 99.97 %, 100 %, and 99.69 %. The high sensitivity and specificity for all kinds of PVA meet the application-level requirements.

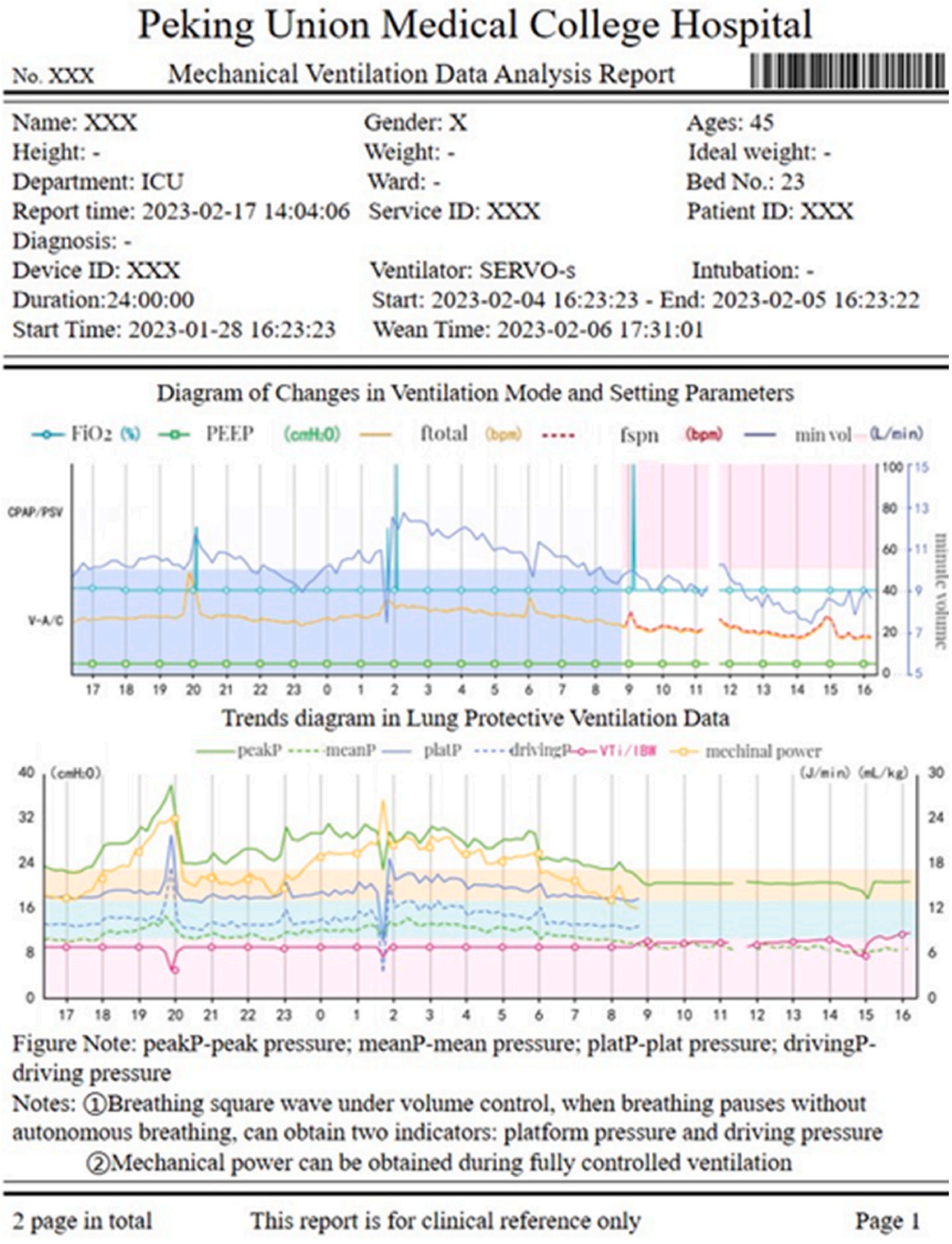
3.2. Analysis report

The statistical calculation and presentation for each section in the data analysis report spans a 24-h duration (Figs. 3 and 4). The report includes several sections: the Basic Information, the Diagram of Changes in Ventilation Mode and Setting Parameter, the Trends Diagram in Lung Protective Ventilation Data, the Diagram of Changes in PVA, the Trend Chart of Respiratory Mechanics Data, and the Reminder and Discovery.

The Basic Information area includes report number, name, hospitalization number, report time, monitoring number, device ID, ventilator model, and barcode (located in the upper right corner of the entire report, which can be scanned to quickly read the patient's report information directly on the computer). The Diagram of Changes in Ventilation Mode and Setting Parameter includes five curves of oxygen concentration (%), positive end-expiratory pressure (cmH_2O), total respiratory rate (bpm), spontaneous respiratory rate (bpm), and minute ventilation (L/min); and it includes ventilation modes including, but not limited to, CPAP/PSV, and V-A/C. The Trends Diagram in Lung Protective Ventilation Data includes the peak pressure (cmH_2O), mean pressure (cmH_2O), plateau pressure (cmH_2O), driving pressure (cmH_2O), tidal volume per unit of ideal body weight (VTi/IBW) (mL/kg), and mechanical energy (J/min). The Diagram of Changes in PVA Events includes the frequency of flow insufficiency, premature cycle, delayed cycle, reverse trigger, auto trigger, and overshoot occurring hourly. The PVA Events area comprises the total number of PVA and respiratory cycles. The number and percentage of different PVAs are displayed as well. The Trend Chart of Respiratory Mechanics Data includes two folded lines of airway resistance and compliance; time is used as the horizontal axis, airway resistance ($cmH_2O/L/s$) and compliance (ml/cmH_2O) are used as the vertical axis, and the statistics are conducted in the 1-h unit. The Reminder and Discovery is a generalization of the overall situation of the ventilated patient over 24 h, including mechanical energy, asynchrony index, and changes in airway resistance and compliance. Asynchrony index = number of PVA events/total respiratory rate × 100 % [4,21].

Table 1
Outcomes of algorithm recognizing PVA.

PVA	Frequency	Sensitivity	Specificity	Positive predict value	Negative predict value
Flow insufficiency	1204	96.60 %	90.31 %	78.48 %	98.64 %
Premature cycle	217	85.71 %	98.76 %	77.82 %	99.27 %
Delayed cycle	139	83.45 %	99.75 %	91.34 %	99.47 %
Reverse trigger	8	75 %	99.97 %	85.71 %	99.95 %
Auto-trigger	3	66.67 %	100 %	100 %	99.98 %
Overshoot	47	85.11 %	99.69 %	74.07 %	99.84 %


Peking Union Medical College Hospital

No. XXX Mechanical Ventilation Data Analysis Report

Name: XXX	Gender: X	Ages: 45
Height: -	Weight: -	Ideal weight: -
Department: ICU	Ward: -	Bed No.: 23
Report time: 2023-02-17 14:04:06	Service ID: XXX	Patient ID: XXX
Diagnosis: -		
Device ID: XXX	Ventilator: SERVO-s	Intubation: -
Duration:24:00:00	Start: 2023-02-04 16:23:23 - End: 2023-02-05 16:23:22	
Start Time: 2023-01-28 16:23:23	Wean Time: 2023-02-06 17:31:01	

Diagram of Changes in Ventilation Mode and Setting Parameters

Trends diagram in Lung Protective Ventilation Data

Figure Note: peakP-peak pressure; meanP-mean pressure; platP-plat pressure; drivingP-driving pressure

Notes: ①Breathing square wave under volume control, when breathing pauses without autonomous breathing, can obtain two indicators: platform pressure and driving pressure

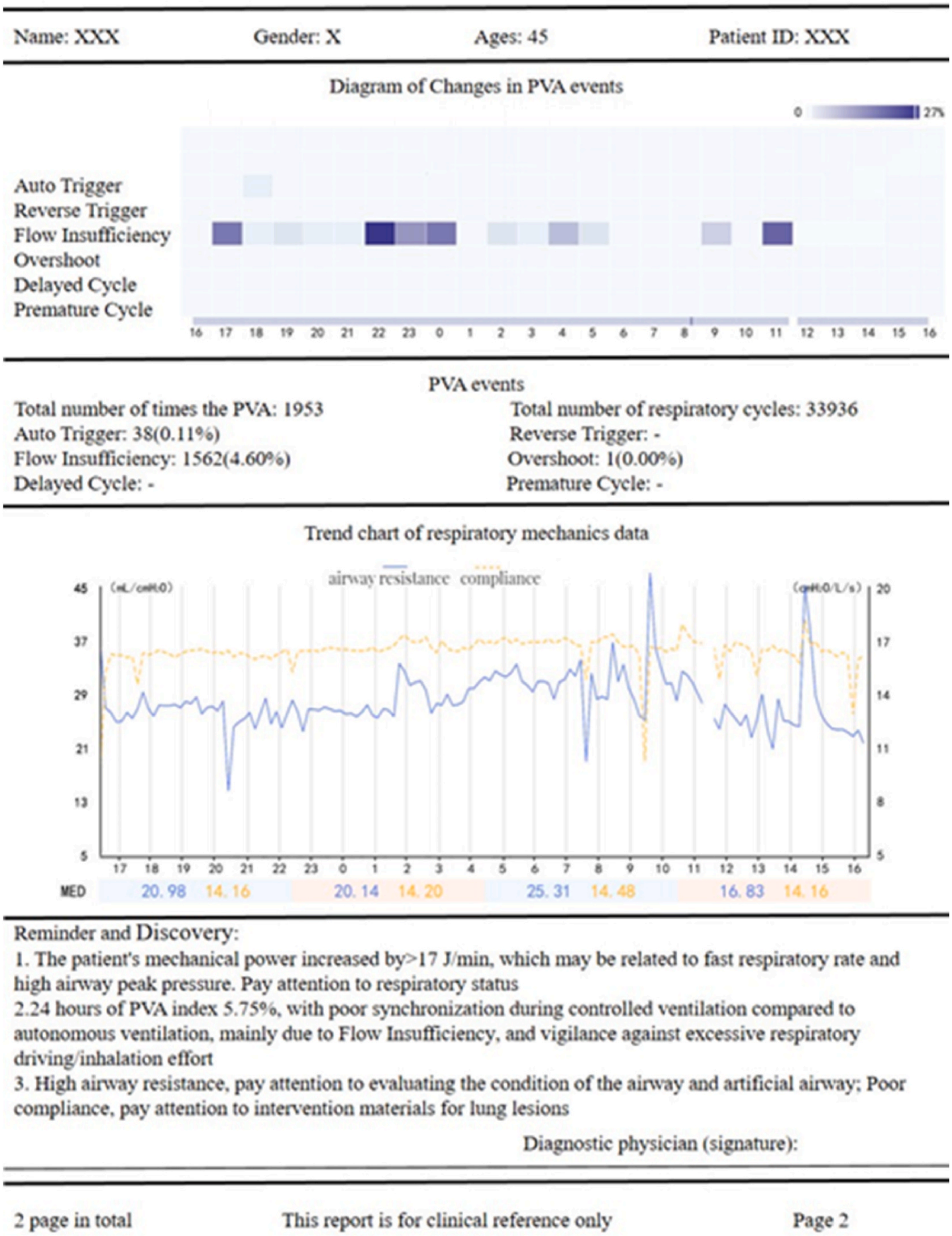
②Mechanical power can be obtained during fully controlled ventilation

2 page in total This report is for clinical reference only Page 1

Fig. 3. 24-hour MV analysis report (part 1/2).

3.3. *Outcomes of the questionnaire*

Table 2 illustrated the baseline of responders. Of the 87 valid questionnaires received, 75 physicians (86.2 %) expressed a desire/support for ICUs to be equipped with the platform. The six modules of the 24-h mechanical ventilation analysis report include "graphs of changes in ventilation mode and setting parameters", "Trend graph of lung protective ventilation data", "Change graph of human-machine asynchronous events", "Human-machine asynchronous events", "Trend graph of respiratory mechanics data " and "Tips and Findings", which were well received by most physicians (Fig. 5). The "Trend graph of respiratory mechanics data " and "Tips and



Name: XXX Gender: X Ages: 45 Patient ID: XXX

Diagram of Changes in PVA events

PVA events

Total number of times the PVA: 1953
Total number of respiratory cycles: 33936
Auto Trigger: 38(0.11%)
Reverse Trigger: -
Flow Insufficiency: 1562(4.60%)
Overshoot: 1(0.00%)
Delayed Cycle: -
Premature Cycle: -

Trend chart of respiratory mechanics data

Reminder and Discovery:

1. The patient's mechanical power increased by>17 J/min, which may be related to fast respiratory rate and high airway peak pressure. Pay attention to respiratory status
2.24 hours of PVA index 5.75%, with poor synchronization during controlled ventilation compared to autonomous ventilation, mainly due to Flow Insufficiency, and vigilance against excessive respiratory driving/inhalation effort
3. High airway resistance, pay attention to evaluating the condition of the airway and artificial airway; Poor compliance, pay attention to intervention materials for lung lesions

Diagnostic physician (signature):

2 page in total This report is for clinical reference only Page 2

Fig. 4. 24-hour MV analysis report (part 2/2).

Findings" sections received more unsatisfactory feedback, with 9 responses.

Interviews with 10 critical care physicians revealed that the clinical significance of the system was recognized by 3 of the physicians interviewed, 3 questioned it, and 4 were neutral. The evaluations and recommendations of the 10 physicians interviewed can be summarized as follows: difficulty in interpreting parameters and the need for reports to indicate substantial treatment guidance; concern about excessive storage space requirements; insufficiently validated parameters of PVA not to be used as a basis for guiding treatment; and lack of timeliness in reporting 24-h reports due to rapid changes in the patient's condition.

Table 2
Baseline characteristics of responders.

		Number (Percentage)
Hospitals		
Peking Union Medical College Hospital		30 (34.5 %)
Beijing Puren Hospital, Beijing Sixth Hospital		9 (10.3 %)
Dongzhimen Hospital		6 (6.9 %)
Beijing Hospital		12 (13.8 %)
Beijing Hospital of Traditional Chinese Medicine		7 (8.0 %)
Beijing Hepingli Hospital		7 (8.0 %)
Beijing Longfu Hospital		8 (9.2 %)
Beijing Tongren Hospital		8 (9.2 %)
Sexuality		
	Male	38 (43.7 %)
	Female	49 (56.3 %)
Age		
	18–25	5 (5.7 %)
	26–30	15 (17.2 %)
	32–40	55 (63.2 %)
	41–50	11 (12.6 %)
	51–60	1 (1.1 %)
ICU physician		
	Yes	74 (85.1 %)
	No	13 (14.9 %)
Rank of hospital		
	Tertiary care hospital	82 (94.3 %)
	Second care hospital	5 (5.7 %)
Subspecialty		
General ICU		65 (74.7 %)
Surgical ICU		14 (16.1 %)
Medical ICU		2 (2.3 %)
Cardiology ICU		2 (2.3 %)
Emergency ICU		3 (3.4 %)
Respiratory ICU		1 (1.1 %)
Years of work in ICU		
≤5 years		27 (31.0 %)
6–10 years		31 (35.6 %)
11–20 years		22 (25.3 %)
≥21 years		7 (8.0 %)
Learning Experience in respiratory mechanics or PVA		
Yes		60 (69.0 %)
No		27 (31.0 %)

4. Discussion

This study proposed a remote monitoring system to provide prompt alerts and generate detailed data analysis reports on the front-end interface. Our algorithmic model achieved automatic detection of PVA, reaching a level of clinical application. Positive feedback from the questionnaire emphasizes the favorable reception and recognition of the system by critical care physicians.

Systems and algorithms are being proposed as the need of monitoring mechanical ventilation—particularly monitoring of asynchrony—increases. Chen et al. developed a computer algorithm that detects ineffective trigger by analyzing the distributions of flow and pressure deflection [17]. With an area under the curve (AUC) of 0.98 and 0.97 when esophageal balloon was the reference standard, their method produced remarkable results. It's worth noting that this algorithm was primarily designed to identify ineffective trigger. Susceptibility to contamination by airway secretions and cardiac shock further hinders its application. Blanch et al. validated software designed to identify ineffective inspiratory effort during expiration. This software processed output data from various ventilators and categorized the parameters represented by each waveform. Their algorithm achieved an AUC of 0.96 in identifying ineffective effort, using expert judgment as the gold standard [18]. Though they applied this technique to 50 ventilated patients and reported the incidence of PVA [9], it's essential to acknowledge that this study monitored only ineffective inspiratory effort during expiration, double trigger, aborted inspirations, and short and prolonged cycling. Sinderby et al. introduced recognition algorithms that utilize the electrical activity of the diaphragm (EAdi) and ventilator graphics. They proposed a new NeuroSync index for detecting neural respiratory movement and PVA [19]. The proposed algorithms required the acquisition of EAdi, which may not always be readily available and can increase clinician workload. Sottile et al. designed a machine learning algorithm that detects double-triggered, flow-limited, premature-ventilator terminated, and ineffective-triggered breaths. They reported that double-triggered and flow-limited breaths could lead to large tidal volumes greater than 10 ml/kg and highlighted that deep sedation reduces the occurrence of PVA but does not eliminate them [16].

Compared to the above studies, our system excels in identifying eight distinct types of PVA while continuously monitoring MV. It offers timely alarms and analysis reports displayed on the front-end interface, aiding physicians in promptly recognizing and

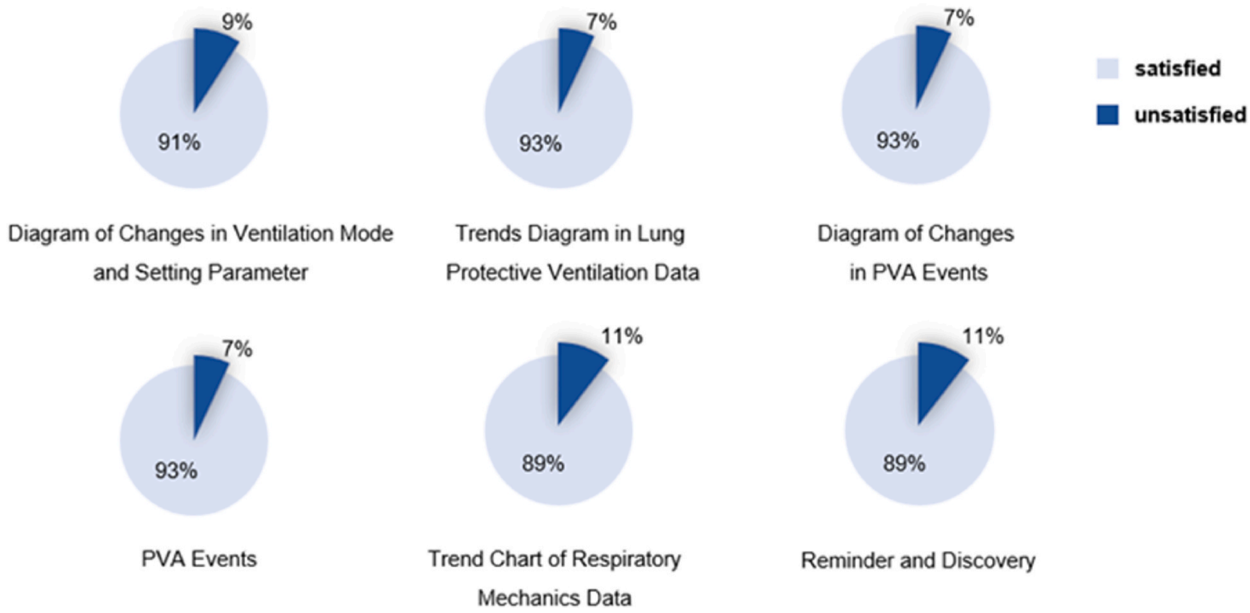


Fig. 5. Physicians' satisfaction of 24-h MV analysis report.

addressing anomalies, thereby reducing or eliminating harm caused by PVA. Testing experiments indicate that the algorithmic model can detect flow insufficiency, premature cycle, delayed cycle, reverse trigger, auto trigger, and overshoot, with sensitivities ranging from 66.67 % to 96.60 % and specificities from 90.31 % to 100 %, ensuring reliable detection and minimal false positives across various asynchrony types. The system has reached a clinical application level and now offers round-the-clock online services.

Currently, ventilator waveform monitoring techniques provide increasingly valuable data, yet none have been widely adopted in clinical practice. Physicians may have limited awareness of MV monitoring and PVA management, which could hinder the platform's adoption. However, results of our survey are promising: over 80 % of respondents supported the application of the platform, and approximately 90 % approved of the daily report. Our findings highlight the clinical need for PVA monitoring platforms.

Given the intricacy and diversity of monitoring methods, the demand for specialized knowledge, and the associated high costs, physicians face the challenge of analyzing and interpreting substantial data volumes in their demanding clinical roles. This necessitates the development of individualized treatment plans based on MV monitoring results, requiring physicians to possess advanced knowledge and clinical competence [15]. Medical training assumes paramount significance. Rotations and training programs have the potential to enhance physicians' proficiency in mechanical ventilation and their capacity to interpret ventilator waveforms [22–24]. Training and technology will complement each other to significantly improve and enhance physicians' ability to recognize and manage PVA [25,26]. The PVA-RemoteMonitor system developed in this study may enhance monitoring while increasing physician knowledge of PVA and improving management of mechanically ventilated patients.

Certainly, we have also received criticisms and concerns. The questionnaire results indicated that 86.2 % support equipping ICUs with this platform. Non-supporters' comments can be referred to the results of the interviews. The opposing opinions included difficulties in interpreting parameters, concerns about excessive data storage requirements, insufficient validation of PVA parameters for clinical decision-making, and delays in 24-h report timeliness. We have addressed these feedback points as follows:

Firstly, difficulties in understanding relevant parameters highlight a knowledge gap regarding PVA among some physicians. If physicians do not have knowledge of PVA, the data provided by the monitoring platform cannot be used to guide treatment. This emphasizes the need for enhanced training of physicians in the management of asynchrony along with the application of monitoring tools. Secondly, regarding data storage requirements, our system is cloud-based, eliminating the need for local data storage hardware and thus mitigating user concerns. Thirdly, while the clinical value of PVA parameters is debated, current research has not definitively established a causal relationship between PVA and patient outcomes. However, multiple studies indicate a correlation between high levels of asynchrony and adverse outcomes. It is imperative to avoid unmanaged asynchrony; standardized monitoring and management of PVA may benefit patients and represents a future trend. And based on the increasing application of monitoring techniques, future studies could explore the mechanisms between asynchrony and prognosis. Lastly, concerns about timeliness are addressed by our system's dual approach: it includes both 24-h reports and real-time monitoring data. Future versions of the platform will feature real-time alerts to prompt immediate physician intervention and improve patient-ventilator interaction.

5. Conclusion

The PVA-RemoteMonitor system we developed accurately identified PVA. The analysis report generated by the system can provide guidance for physicians to monitor and control the occurrence of PVA in clinic. According to our questionnaire, the system was welcomed by most of physicians. Our platform can effectively assist ICU physicians in the management of ventilated patients.

Ethics and consent statement

This study was reviewed and approved by the Ethics Committee of Peking Union Medical College Hospital, Chinese Academy of Medical Sciences with the approval number: K298303. All physicians involved in the study were informed that consent to participate in the study and publish their data would be assumed on completion and submission of the study questionnaire.

Consent for publication

All authors were aware of and approved the publication.

Data availability statement

The datasets used and analyzed during the current study available from the corresponding author on reasonable request.

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CRediT authorship contribution statement

Xiangyu Chen: Writing – original draft, Investigation. **Junping Fan:** Investigation. **Wenxian Zhao:** Investigation. **Ruochun Shi:** Investigation. **Nan Guo:** Investigation. **Zhigang Chang:** Investigation. **Maifen Song:** Investigation. **Xuedong Wang:** Investigation. **Yan Chen:** Investigation. **Tong Li:** Investigation. **Guang-gang Li:** Investigation. **Longxiang Su:** Resources, Methodology, Data curation. **Yun Long:** Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no competing interests.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e33692.

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