



Artificial Intelligence in Weaning Clinical Practice: Finding New Rules in Ventilator Support Care

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ABSTRAK

When patients depend on ventilators for a long period of time, it will increase the risk of complexity and the risk of death. Thus, medical professionals try to help patients to wean off from the ventilator as soon as possible to minimize the adverse effects of the respiratory machine. This study analyzed historical clinical data to evaluate and improve the weaning protocol in operation. This study adopted a retrospective approach by collecting 1,014 weaning cases from Taiwan in 2012. We extracted the crucial rules describing the results of weaning from the ventilator using the machine learning algorithm - C4.5, which help medical professionals revise the existing weaning protocol and as supplementary indicators in a new version of the weaning protocol.

INTRODUCTION

The ventilatory support is used for patients with post-operative, acute, or chronic respiratory failure to support their breathing and prolong their lives by helping them survive under critical situations. However, in approximately 5% to 13% of cases, when the ventilatory support system is used over 72 hours, the patients may be more dependent on the ventilator (Banfi et al., 2019; Knebel et al., 1994). According to clinical results, patients who are overly dependent on the ventilatory support system may result in acute respiratory distress syndrome (ARDS), multiple organ failure (MOF), and ventilator-induced lung injury (VILI), all of which lead to higher mortality rate (Gando et al., 2020; Gatto, Fluck, & Nieman, 2004; Slutsky, 2005; Spence et al., 2006). Prior literature also showed the use of ventilatory support over 48 hours may increase the risk of ventilator-associated pneumonia (VAP) which had a fatality rate of 43% (Chastre et al., 2003; Osman et al., 2020). Eliminating patients' reliance on the ventilatory support systems as soon as possible can minimize family members' suffering associated with patient care, national healthcare expenses, and the workloads of caregivers. Therefore, evaluating the proper time to remove the ventilatory support system is an important issue in critical care medicine.

Physicians usually apply their expertise and experience to estimate when to remove a patient's respiratory support system. Such decision mode may lead to differences in medical care quality and the risk of medical misconduct (Mello, Frakes, Blumenkranz, & Studdert, 2020). To avoid this condition, clinical practice guidelines (CPGs) and clinical protocols are developed to provide physicians with references for medical care. These guidelines can be referenced in the clinical decision-making process to avoid subjectivity in decision making and provide consistent and appropriate medical care to patients (Correa et al., 2020; De Clercq, Kaiser, & Hasman, 2008; Ghai, Subramanian, Jan, Loganathan, & Doumouchtsis, 2021).

With regard to the clinical protocols about the removal of ventilatory support, Randolph, Green, Peacey, and Rogers (2000) pointed out that the current agreement rate is only 66%, and as the protocols are not updated regularly, they cannot satisfy actual requirements. Removal of ventilatory support determined by individual decisions may be unsuccessful due to differences in physicians' experience and the support of medical institutions. The procedure may also deviate from the standard due to colleagues' suggestions and limited medical resources (Girard & Ely, 2008; Kydonaki, Huby, Tocher, & Aitken, 2016; Wennberg, 2002). As such, it is important to regularly update clinical protocols on the removal of ventilatory support system so as to increase compliance and reduce caregivers' workload (Gómez et al., 2020; Pereira Lima Silva et al., 2020).

Considering the clinical decision support system in the Arden Syntax, medical knowledge is mainly expressed via if-then Medical Logic Modules (MLM) (Papadopoulos, Soflano, Chaudy, Adejo, & Connolly, 2022). The rule-based technology provides non-ambiguous and interpretable methods that are

widely used in the evaluation of clinical protocols (Gomoi & Stoicu-Tivadar, 2010; Mani, Shankle, Dick, & Pazzani, 1999; Musen, Middleton, & Greenes, 2021; Papadopoulos et al., 2022). Off-line evaluations of clinical protocols for ventilatory support removal are safe and well-structured and automated analyses. This study used C4.5 decision trees to compare current ventilatory support protocols against the 1,014 weaning cases collected in Taiwan to develop a new comprehensive evaluation for ventilatory support removal.

METHODOLOGY

There were 1,014 medical cases collected and used in this research study for the mining analysis of the weaning clinical rules such that the existing weaning protocols could be improved. In this study, we used the C4.5 decision trees algorithm for analysis. The procedures were as follows:

Step1: Collecting the meta-data of medical care activities related to the ventilator support system. Based on a literature review and interviews with medical personnel, the patients' data were collected from the following five perspectives when removing the ventilator support system: demographic characteristics, physiological condition, oxygenation and gas exchange conditions, blood, and psychological state.

Step2: Discretized the collected numeric data attributes for rule mining and rule interpretation. Most attributes related to patients' physiological conditions, oxygenation and gas exchange conditions, and blood test results are numeric attributes. Although the C4.5 decision tree is able to handle the numerical attributes, the cut-point values generated by the C4.5 may not be meaningful for the human experiences in actual clinical practices. Therefore, the numeric attributes were discretized based on the clinical staffs' common practice for convenience of rule interpretation when significant clinical rules were extracted from the clinical cases through the C4.5 decision tree. For example, physicians could judge whether a patient may be eligible for the oxygenation control access based on the following two rules: the oxygen concentration setting value of the ventilator is lower than 50%, and the positive end-expiratory pressure (PEEP) is below 5 cm H₂O. Thus, the values of 50% O₂ and 5cm H₂O were considered as appropriate discretized cut-points for the attributes FiO₂ and PEEP. Setting appropriate parameters for machine learning is very important for discovering algorithms that have improved courtesy of experience derived from the norms of clinical practice. This study also adapt the machine learning platform–Weka as a mining tool, two parameters.

Step3: Interpret the extracted rules and find the characteristics and differences of the rules with existing weaning protocol/plan.

DATA ASSESSMENT AND EMPIRICAL RESULTS

Data Collection

The participants were from the medical and surgical intensive care unit of a teaching hospital located in southern Taiwan, those also had respiratory failure and required ventilatory support. The study got the IRB permission from the Chi-Mei medical center before collecting the data. All collected data were re-coded to unlink their identifications and just keep the descriptive information such as physiological condition, and state during the removal, functions of oxygenation and gas exchange before the removal, and blood analysis. All of the participants met the following two requirements: (1) they were greater than 20 years of age and (2) they used ventilator support due to respiratory failure. The cases were excluded with the following conditions: (1) those who required intubation because of receiving anesthesia for surgery; (2) those who have used a respirator for more than 7 days; (3) Using a ventilator after tracheostomy, and (4) an end-stage malignant tumor.

Based on literature review and consulting with 3 medical experts, we adopt 48 hours as the successful ventilatory support removal criteria (Ashutosh et al., 1991; Grieco et al., 2021; Griffiths et al., 2019). A patient may be viewed as an unsuccessful removal if he/she requires intubation and continued ventilatory support within 48 hours after being weaned from the ventilator. We collected 1,021 cases which met the mentioned criteria from medical case reports from January to December 2012. After deleting the cases with incomplete data, we had 1,014 cases for this study, which 901 successful cases and 113 unsuccessful cases of ventilatory support removal, and the demographic characteristics for the cases was shown in Table 1.

Table 1. Descriptions and Statistics of Variables

No.	Variable Name	Type of data	Statistical Summary
1	Gender	Categorical	Female:364; Male:650
2	Age	Numeric (year)	Range: 20~98 $\mu=64.9$, $\sigma=16.0$
3	Body height(BH)	Numeric (cm)	Range:145~197 $\mu=163.9$, $\sigma=9.2$
4	Body Weight(BW)	Numeric (kg)	Range:33~104 $\mu=62.1$, $\sigma=12.6$
5	Body Mass Index (BMI)	Numeric (kg/m ²)	Range:12.6~37.0 $\mu=23.1$, $\sigma=4.3$ (normal: 18.5–24.0)

No.	Variable Name	Type of data	Statistical Summary
6	Patient's symptom Diagnosis (Diagnosis)	L: Pneumonia, pulmonary edema, chronic obstructive pulmonary disease, airway obstruction H: heart failure, Myocardial infarction, coronary artery disease I: Infection, Septic shock O: Non-end-stage hematological malignancies S: Trauma surgery, Poor ventilation after surgery	L: 265; H: 105; I: 400; O: 228; S: 16
7	ICU stay days (ICU_day)	Numeric (days)	Range:3~44 $\mu=7.9$, $\sigma=4.6$
8	Usage time of ventilator (TV_hour)	Numeric (hour)	Range:16~466 $\mu=103.3$, $\sigma=57.3$
9	Acute Physiology and Chronic Health Evaluation (APACHE II)	Numeric	Range:8~45 $\mu=21.8$, $\sigma=5.8$
10	Therapeutic intervention scoring system (TISS)	Numeric	Range:9~45 $\mu=21.8$, $\sigma=5.4$
11	Glasgow Coma Scale(GCS)	Numeric	Range:4~15 $\mu=13.6$, $\sigma=2.8$ (normal: 15)
12	Body Temperature (BT)	Numeric ($^{\circ}$ C)	Range: 35.0~39.3 $\mu=36.8$, $\sigma=0.7$ (normal:36~37.5 $^{\circ}$ C)
13	Heart Rate (HR)	Numeric (beats/min)	Range: 53~133 $\mu=88.2$, $\sigma=18.2$ (normal: 60-100)
14	Respiratory Rate (RR)	Numeric (breath/min)	Range: 7~31 $\mu=17.6$, $\sigma=4.8$ (normal: 12-20)
15	Mean Arterial Pressure (MAP)	Numeric (mm Hg)	Range: 46~121 $\mu=80.7$, $\sigma=16.1$ (normal: 70- 05)
16	Cough Function	Categorical (Yes or No)	Yes: 929; No: 85
17	Urine Output	Numeric (ml/hour)	Range: 0~400 $\mu=82.1$, $\sigma=60.5$

No.	Variable Name	Type of data	Statistical Summary
18	Use of Sedation (Sedation)	Categorical (Yes or No)	Yes: 172 ; No: 842
19	Partial pressure of O ₂ in arterial blood (PaO ₂)	Numeric (mm Hg)	Range:53.8~96.9 $\mu=93.7$, $\sigma=2.7$ (normal: 80-100)
20	Partial pressure of carbon dioxide in arterial blood (PaCO ₂)	Numeric (mm Hg)	Range:19.7~72.6 $\mu=38.9$, $\sigma=6.7$ (normal: 35-45)
21	Fraction of inspired oxygen in arterial blood (FiO ₂)	Numeric (%)	Range:25~35 $\mu=26.6$, $\sigma=2.4$
22	Positive end expiratory Pressure in the lungs (PEEP)	Numeric (cm H ₂ O)	Range:0~6 $\mu=4.0$, $\sigma=2.0$ (normal: 0- 5)
23	Ratio of partial pressure arterial oxygen to fraction of inspired oxygen (PaO ₂ /FiO ₂)	Numeric (mm Hg)	Range:215.2~387.6 $\mu=355.4$, $\sigma=31.1$ (normal: > 350)
24	Index of rapid shallow breathing (RSI)	Numeric (breaths/min/L)	Range:10~144 $\mu=54.6$, $\sigma=36.1$ (normal: <105)
25	Pressure support level (PSL)	Numeric (cm H ₂ O)	Range:6~12 $\mu=9.1$, $\sigma=1.2$
26	Maximum inspiratory Pressure (MIP)	Numeric	Range:-80~-10 $\mu=-37.2$, $\sigma=14.7$
27	Maximum expiratory Pressure (MEP)	Numeric	Range:8~141 $\mu=68.6$, $\sigma=36.6$
28	Ventilatory mode	Categorical (PSP or PSV)	PSP: 988; PSV:26
29	Patients' hemoglobin of blood (Hb)	Numeric (mg/dL)	Range:6.5~21.8 $\mu=10.7$, $\sigma=1.7$ (normal: 10-17)
30	Patients' hematocrit of blood (HCT)	Numeric	Range:19.5~65.4 $\mu=32.0$, $\sigma=5.0$ (normal: 7.35-7.45)
31	Patients' blood PH level (PH)	Numeric	Range:7.3~7.6 $\mu=7.4$, $\sigma=0.05$ (normal: 7.35-7.45)
32	Patients' blood sugar level (Sugar)	Numeric (mg/dL)	Range:67~355 $\mu=184.1$, $\sigma=67.0$ (normal: 60-110)

No.	Variable Name	Type of data	Statistical Summary
33	Patients' blood albumin level (Alb)	Numeric (mg/dL)	Range:1.1~10.7 $\mu=2.76$, $\sigma=0.56$ (normal: 3.5-5.5)
34	Patients' blood urea nitrogen level (BUN)	Numeric (mg/dL)	Range:2.1~150 $\mu=27.6$, $\sigma=21.9$ (normal: 8- 25)
35	Patients' blood creatinine level (Cr)	Numeric (mg/dL)	Range:0.2~11.0 $\mu=1.6$, $\sigma=1.8$ (normal: 0.6-1.5)
36	Patients' blood magnesium level (Mg)	Numeric (mg/dL)	Range:0.8~4.4 $\mu=2.2$, $\sigma=0.4$ (normal: 1.3- 2.5)
37	Patients' blood phosphorus level (P)	Numeric (mg/dL)	Range:0.7~10.0 $\mu=3.0$, $\sigma=1.1$ (normal: 2.1- 4.7)
38	Patients' blood potassium level (K)	Numeric (mg/dL)	Range:2.0~7.4 $\mu=3.8$, $\sigma=0.5$ (normal: 3.5-5.0)
39	Patients' blood sodium level (Na)	Numeric (mg/dL)	Range:105.7~160.4 $\mu=139.6$, $\sigma=5.03$ (normal: 135-145)
40	Patients' blood calcium level (Ca)	Numeric (mg/dL)	Range:5.7~13.2 $\mu=8.1$, $\sigma=0.7$ (normal: 8.4-10.6)
41	Irritable	Categorical (Yes or No)	Yes: 168; No: 846
42	Cold sweat	Categorical (Yes or No)	Yes: 16; No: 998
43	Successfully weaning from mechanical ventilation (Success)	Categorical (Yes or No)	Yes: 901; No: 113

Variable Categorization

There were eight categorical variables (i.e., sex, diagnosis, cough function, sedation, mode, irritability, cold sweat, and weaning result) and 35 numerical variables, which were shown in table 1. To interpret and apply the generated decision tree rules, the numeric values of 35 attributes were discretized and converted into categorical variables. The 25 variables of 35 attributes were converted into 3-level value (i.e., L1, L2, and L3) categorical variables. L1 indicated the attribute value was lower than the clinical norm or average value, L2 indicated the attribute had the clinical norm or average value, and L3

indicated the attribute value was higher than the clinical norm or average value. For example, the attribute Ca was recoded as: 1 for low value, 2 for normal value, and 3 represents high value.

There are 6 attributes (i.e., BMI, BH, ICU_day, RR, Hb, and Sugar) were converted into 4-level categorical value. For example, normal value of variable Hb (Hemoglobin) is 13-17 g/dl, but the value 10 g/dl is also often used in clinical judgement. Thus, we converted the Hb into a 4-level value categorical variable and its variable value meanings were shown as followings: L1 was low value (Hb<10), L2 was acceptable value (Hb=10-13), L3 was normal value (Hb=13-17), and L4 was high value (Hb>17). For convenience of interpretation, the 3 variables (age, urine output, and body weight) were converted into six-level value categorical variables. However, the attribute RSI was converted into 2-level categorical value. Regardless of number of attribute value in a categorized variable, the higher-level value represented higher-numeric value.

Parameter Tuning and Rule Generating

We adopted the C4.5 algorithm of machine learning platform Weka 3.8.1 (Ng, Ling, Chew, & Lau, 2021) to build a C4.5 decision tree for extracting the clinical experience on ventilator support removal. To build an accurate decision tree model, we had to tune two parameters, C and M, for C4.5 decision tree. The C parameter referred to a confidence factor for tree pruning and subtree raising during tree generation, and the M parameter referred to the minimum number of objects in the leaf nodes. The default values for C and M were 0.25 and 2, respectively. This study implemented 10-fold cross-validation procedure. Three performance metrics widely were used in clinical studies, namely, sensitivity, specificity, and accuracy, to evaluate the performance of the classification tree for developing an effective diagnostic model. Sensitivity measured the predictive performance of the successful removal of ventilatory support. Specificity measured the predictive performance of the unsuccessful removal of ventilatory support. Accuracy measured the extent to which prediction for each case was accurate. To develop an accurate model, C value was set from 0.15 to 0.35 in increments of 0.05, and M value was set from 1 to 15 in increments of 2. The model evaluation results indicated that sensitivity ranges between 93.0% and 98.9%, specificity ranges between 92.6% and 98.9%, and accuracy ranges between 92.5% and 99.0% while changing C and M according to mentioned parameter tuning procedure. The classification model reaches the best performance when the C was set at 0.35 and M was set at 7. The performance of a decision tree model was shown in Table 2.

Table 2. Performance Assessment of a Decision Tree Model with M=7

M	C	Sensitivity (%)	Specificity (%)	Accuracy (%)
7	0.15	98.5	98.5	98.5
7	0.20	98.8	98.8	98.8
7	0.25	98.9	98.9	99.0
7	0.30	98.9	98.9	99.0
7	0.35	98.9	98.9	99.0

We employed the tuned best parameter values to generate a decision tree and to extract clinical weaning practice rules. The generated decision tree was shown in Figure 1. The decision tree was constructed based on the following eight attributes: ICU_day, TV_hour, Cold sweat, Cough Function, Sedation, APACHE II, MIP, and RSI. The decision tree had a six-level structure. When tracking the decision tree from root nodes to leaf nodes, we extracted 17 rules that included 10 rules for describing the practice of successful ventilator removal cases and 7 rules for describing the unsuccessful removal ones. The coding schema of variable categorization for the tree variables was shown in Table 3.

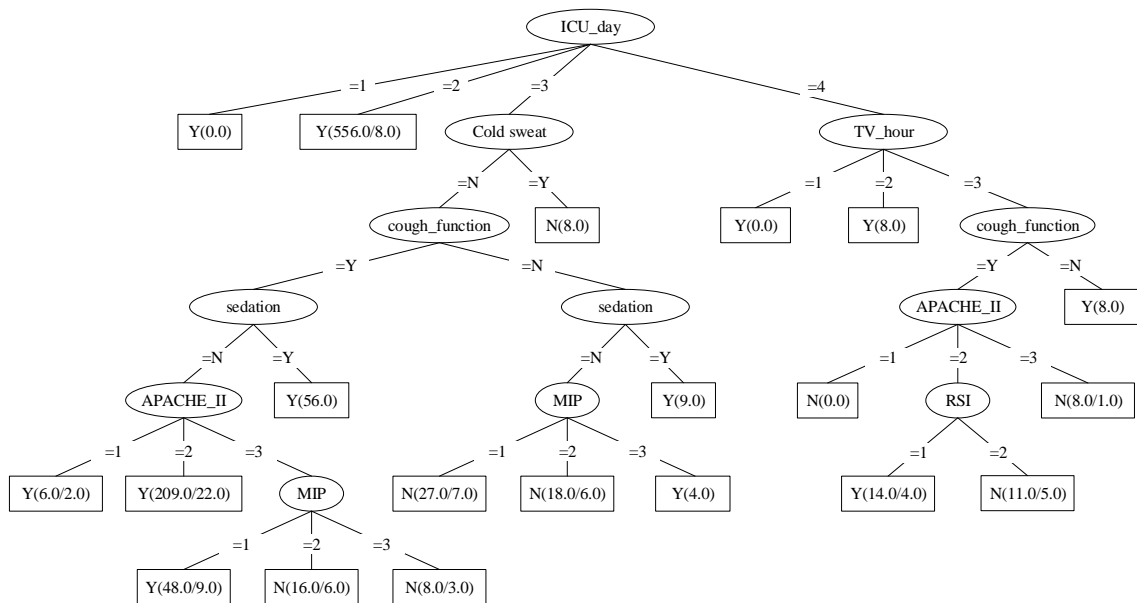


Fig1. Generated Decision Tree based on C = 0.35 and M = 7

Table 3. Coding Schema of Variable Categorization for the Tree Variables

Factor	1	2	3	4
ICU_Day	< 2	2~7	8~14	>14
TV_hour	< 24	24~72	> 72	
APACHE II	< 15	15~25	> 25	
MIP	< -30	-30~-20	> -20	
RSI	≤ 105	> 105		

In Figure 1, each tree leaf node was shown as (S/E), S referred the total classified cases and E referred the misclassified cases. For example, an extracted rule: ICU_day=2 \rightarrow Y (556.0/8.0), S was 556 and E was 8.0. We adopted the rule criteria of "Support" and "Confidence" of association rule technique to evaluate the significance of each decision tree rule. The support value of a tree rule was S/N (N referred all cases in the tree). The confidence value of a rule was (S - E)/S. The support of the mentioned rule (ICU_day=2 \rightarrow Y) was calculated as 556/1014=0.548, and its confidence was calculated to (556-8)/556=0.986. The support and confidence values for each extracted tree rule were shown in Table 4.

Table 4. Support and Confidence of Each Extracted Rule

No	Rule	Success	Leaf node	Support	Confidence
1	ICU_day = 2~7 day	Y	556/8	0.548	0.986
2	ICU_day=8-14 day, Cold_Sweat=N, Cough_function=Y, Sedation=N, APACHE II \leq 15	Y	6/2	0.006	0.667
3	ICU_day=8-14 day, Cold_Sweat=N, Cough_function=Y, Sedation=N, APACHE II=15-25	Y	209/22	0.206	0.895
4	ICU day= 8-14 day, Cold_Sweat=N, Cough_function=Y, Sedation=N, APACHE II >25, MIP<-30	Y	48/9	0.047	0.813
5	ICU_day=8-14 day, Cold_Sweat=N, Cough_function=Y, Sedation=Y	Y	56/0	0.055	1.000
6	ICU_day= 8-14 day, Cold_Sweat=N, Cough_function=N, Sedation=N, MIP > - 20	Y	4/0	0.004	1.000
7	ICU_day=8-14 day, Cold_Sweat=N, Cough_function=N, Sedation=Y	Y	9/0	0.009	1.000

No	Rule	Success	Leaf node	Support	Confidence
8	ICU_day >14 day, TV_hour=24-72 hours	Y	8/0	0.008	1.000
9	ICU_day >14 day, TV_hour) >72 hours, Cough_function=Y, APACHE II=15-25, RSI≤105	Y	14/4	0.014	0.714
10	ICU_day >14 day, TV_hour >72 hours, Cough_function=N	Y	8/0	0.008	1.000
11	ICU_day =8-14 day, Cold_Sweat=N, Cough_function=Y, Sedation=N, APACHE II<15 MIP= -30 ~ -20	N	16/6	0.016	0.625
12	ICU_day=8-14 day, Cold_Sweat=N, Cough_function=Y, Sedation=N, APACHE II<15 MIP > -20	N	8/3	0.008	0.625
13	ICU_day = 8-14 day, Cold_Sweat=N Cough_function=N, Sedation=N, MIP < -30	N	27/7	0.027	0.741
14	ICU_day =8-14 day, Cold_Sweat=N, Cough_function=N, Sedation=N, MIP= -30 ~ -20	N	18/6	0.018	0.667
15	ICU_day= 8-14 day, Cold_Sweat=Y	N	8/0	0.008	1.000
16	ICU_day >14 day, TV_hour) >72 hour, Cough_function=Y, APACHE II=15-25, RSI >105	N	11/5	0.011	0.545
17	ICU_day >14 day, TV_hour > 72 hour Cough_function=Y, APACHE II > 25	N	8/1	0.008	0.875

With the assistance of the clinical staff and rule evaluation results, we extracted the No. 1, 3 and 5 rule for the successful weaning cases and No. 13 rule for the failure case. The confidence of the extracted rules was greater than 0.7. In the study, this hospital had a flowchart weaning protocol for removing ventilatory support. However, the flowchart-like protocol cannot fully meet the immediate needs of on-site clinical care due to the protocol were too complicated. Therefore, the medical staff developed a lean and simple weaning plan as follows to monitor patients' status and improve weaning-care performance:

1. PaO₂/FiO₂ ≥ 200
2. PEEP ≤ 8 cmH₂O

3. Fraction of inspired oxygen in arterial blood (FiO_2) $\leq 40\%$
4. Respiratory Rate (RR) ≤ 35
5. Pressure support level (PSL) ≤ 12
6. Maximum inspiratory pressure (MIP) > -20
7. Index of rapid shallow breathing (RSI) ≤ 105
8. Spontaneous tidal volume (TV) = 5-8 ml/kg

Besides the original simple weaning plan, the extracted decision rules were used to improve weaning-care. The study found rule 1 and rule 2 with a support value greater than 0.2 were the most common successful rules, and these extracted decision tree rules could provide important clinic assessment criteria (i.e., duration of ICU_day, Cold_Sweat, and Cough_function, etc.). Comparing the successful rule 2 and failure rule 4, we found the cough function and APACHE II were important factors for successful weaning. Comparing rule 3 and rule 4, cough function and Sedation were two important factors to determine patients' weaning condition.

DISCUSSION AND CONCLUSIONS

Currently in-use clinical protocols may not be able to provide precise medical recommendations as they cannot be regularly updated; thus, more precise recommendations may be delayed once an issue is discovered in an existing protocol. This becomes a major issue for junior doctors who might keep using an old clinical protocol to evaluate the rules of removing ventilatory support. For even higher precision, medical records should also be integrated into personal decision-making experience. This results of this study provide a model to update existing clinical protocols. Based on actual medical cases, updating existing clinical protocols can increase new protocol compliance, reduce debates among physicians, and provide more stable quality of care. That is why there is a growing trend of the development of automated clinical protocols based on medical record databases and a logical architecture (López-Espuela et al., 2022).

This study adopted the C4.5 machine learning method for analysing medical records related to describing the removal of ventilatory support. The study aimed to identify statistically significant correlations among removal-related indices mentioned in the cases. Awareness of these relationships could help care providers judge the correct time for weaning patients from the ventilator, reduce patients' dependence on ventilatory support, and increase patients' quality of life. In addition, medical institutions can allocate reasonable medical resources. The main findings of this study were as follows: First, the large number of numeric variables derived from the practical data may cause difficulties in their interpretation in both research and clinical practice. Thus, these variables were discretized based on clinical definitions in order to provide more easily understood rules to fit clinical needs. By using the C4.5 algorithm for decision tree generation, a classification model was constructed which

provided simplified rules, allowing improved applicability and timeliness in clinical practice. Second, C4.5-generated rules for the removal of ventilatory support included eight attributes: duration of ICU stay (in days), duration of ventilatory support (in hours), severity of disease according to APACHE II, sedation, cough function, RSBI, MIP, and cold sweat. The rules generated in this study could be applied by care providers when evaluating the appropriate time for weaning patients who had stayed in the ICU for 8 to 14 days from ventilatory support. Application of these rules could help decrease the time of mechanical ventilation and increase the probability of successful removal.

LIMITATIONS AND FURTHER STUDY

Limitations of this study and suggestions for future research are described as followings: First, this study collected 1,014 clinical records from a tertiary and teaching hospital in southern Taiwan. Diagnoses for each case were complex and it was difficult to determine whether all the attributes were considered. Second, the 43 variables collected were based on the assumption of their relation to the removal of ventilatory support in past literature. Further analysis using different classification approaches could be conducted to identify potential or extraneous variables in order to improve the efficiency and quality of the classification model. Third, this study only discussed two variables regarding the psychological state of patients weaned from ventilatory support, namely, irritability and cold sweat, and did not provide a complete description of patients' psychological states. It is suggested that future studies use an objective psychological scale and evaluate patients' physiological reactions to create an objective reference for predicting procedural outcomes. Fourth, indicators such as minute ventilation volume (MVV) and tidal volume (Vt) were not considered in this study; Thus, their relation to the removal of ventilatory support could not be confirmed. In the future, more accurate rules for the removal of ventilatory support can be generated with larger datasets.

Compliance with Ethical Standards

1. **Conflict of Interest Statement:** All of the authors declare that they have no conflict of interest.
2. **Role of Funding Source:** This work was supported by the Ministry of Science and Technology [Grant no. NSC102-2410-H-218-018]
3. **Ethical Approval:** All subjects gave their informed consent for inclusion before they participated in the study. The study was conducted in accordance with the Declaration of Helsinki.
4. **Informed Consent:** Written informed consent was obtained from all subjects before the study.
5. **Authors' Contributions:** Tsang-Hsiang Cheng: Conceptualization, Methodology, Formal analysis, and Review and editing; Shih-Chih Chen: Methodology, Data curation, and Review and editing; Mei-Lan Su: Data curation; Mai-Lun Chiu: Project administration, Methodology, Formal

analysis, and Review and editing. All authors have read and agreed to the published version of the manuscript.

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