Research Article

A Decision for Predicting Successful Extubation of Patients in Intensive Care Unit

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Approximately 40% of patients admitted to the medical intensive care unit (ICU) require mechanical ventilation. An accurate prediction of successful extubation in patients is a key clinical problem in ICU due to the fact that the successful extubation is highly associated with prolonged ICU stay. The prolonged ICU stay is also associated with increasing cost and mortality rate in healthcare system. This study is retrospective in the aspect of ICU. Hence, a total of 41 patients were selected from the largest academic medical center in Taiwan. Our experimental results show that predicting successful rate of 87.8% is obtained from the proposed predicting function. Based on several types of statistics analysis, including logistic regression analysis, discriminant analysis, and bootstrap method, three major successful extubation predictors, namely, rapid shallow breathing index, respiratory rate, and minute ventilation, are revealed. The prediction of successful extubation function is proposed for patients, ICU, physicians, and hospital for reference.

1. Introduction

In recent years, human activities, such as burning of fossil fuels and coal, have led to dust-storm, frog, and haze [1]. Several epidemiological studies have shown the effects of chronic exposure to air pollution (e.g., PM$_{2.5}$, nitrogen dioxide, and NO$_{2}$) on lung function [2]. Air pollution is closely related to both the development and exacerbation of pulmonary disease. In the worst case, approximately 40% of all pulmonary disease patients in medical intensive care unit (ICU) require mechanical ventilation [3, 4]. Many of them are extubated in 2 to 4 days after the start of ventilation, whereas up to 25% require mechanical ventilation for more than 7 days [5]. In spite of weaning protocols, automated systems, daily spontaneous breathing trials, and pressure-support ventilation, it is estimated that 20–30% of patients cannot be extubated upon the first weaning attempt [6]. 29% met the criteria for extubation failure [7], and 40% extubation failure was found in acute ischemic stroke patients [8].

The rapid shallow breathing index (respiratory frequency/tidal volume, $f/V_T$) and spontaneous breathing trials (SBT) have been recognized as useful markers in predicting successful weaning from mechanical ventilation. However, they are imperfect, and clinicians always incorporate other factors for final extubation decision. The traditional extubation decision is solely based on expert clinical judgment. For instance, continuous positive airway pressure could be tolerated at 5 to 7 cm H$_2$O without fatigue for 12 hours, arterial PO$_2$ > 80 mmHg on room air, and bulbar paresis improved. Some studies have predicted the timing of extubation [9]. The factor predicting extubation success in patients in neurocritical care units is addressed [10], and early predictors of extubation success in acute ischemic stroke are studied [8]. Farghaly and Hasan [11] proposed diaphragm ultrasound as a
new method to predict extubation outcome in mechanically ventilated patients. A prospective observational cohort study is performed to predict extubation failure after successful completion of a SBT [12]. Zettervall et al. [13] aimed to evaluate the effect of extubation time on patient’s outcomes after endovascular aneurysm repair and open repair. Miu et al. [14] proposed two prediction models for extubation failure in subjects who have passed an SBT; one for failure at any time and another for failure in the first 24 hours after extubation. Savi et al. [15] evaluated the potential of weaning predictors in mechanical ventilated patients. A prospective observational cohort study included all of above-mentioned methods are not always precise. Therefore, a precise prediction of successful extubation for patients is an important issue and worthy of study. A delay in extubation can increase the risk of ventilator-related complications such as pneumonia, tracheobronchitis, or barotrauma. A premature extubation may lead to the necessity of reintubation with an increased associate in the risk of ventilator-associated pneumonia and airway trauma. The delay or premature extubation may lead to prolonged ICU stay [16]. The prolonged ICU stay is also associated with increased cost and decreased mortality rate in healthcare systems. Therefore, accurate prediction of successful extubation is a key clinical problem. However, no prior work has been done to provide a good prediction function of successful extubation for decision making. In order to provide more precise prediction of successful extubation in ICU, the retrospective study is conducted. Hence, the purpose of this study is to find the key predictors of the successful extubation in critically ill patients. In addition, this study aims to develop a prediction function of successful extubation for effective decision making of extubation.

2. Material and Methods

2.1. Data Collection. This study was conducted at the Chang Gung Memorial Hospital (CGMH) in Taiwan that was approved by the Institutional Review Board (number 103-6085B) of the hospital. CGMH is one of the world’s leading medical centers and currently Taiwan’s largest hospital with 3700 beds. In order to meet the requirements of medical services, CGMH has set up many hospitals in Taiwan and China. For this study, 10 weaning indices are reviewed and analyzed, as shown in Table 1. 41 critically ill patients under ICU weaning protocols are randomly selected. Although the sample size is relatively small, the minimum acceptance level is defined as 30 samples [10, 11]. The mean age was 74 ± 2 years. 27 patients were men (65.8%) and 14 were women (34.1%). Other demographic details are listed in Tables 2 and 3. First, we discussed assessment success factors and weights of extubation with professional doctors. Then, we obtained necessary critical data for all patients from ICU staff screening to facilitate the experimental study. In order to filter out successful extubation predictors, following weaning protocols, we used the Delphi method with face-to-face interviews and consultation with 8 professional doctors in the department of chest diseases at CGMH, who helped to obtain the most important 9 successful extubation predictors, such as (1) gender; (2) Glasgow Coma Scale (GCS): E (eye), V (verbal), and M (motor) score; (3) respiratory rate (RR) (f); (4) minute ventilation (MV); (5) maximal inspiratory pressure (PiMax or MIP); (6) rapid shallow breathing index (RSBI); (7) arterial blood gas (ABS) and PH; (8) arterial carbon dioxide tension (PaCO2); and (9) partial pressure of oxygen (PaO2).

2.2. Statistical Analysis. Among the 41 patients included in this study, 23 (56%) were successfully extubated. All statistical analyses are considered significant when $p < 0.05$ in two-tailed $t$-tests. Statistical calculations are performed using the IBM Statistical Package for the Social Sciences (SPSS) software. The extubation failure is defined as reintubation within 48 hours of extubation. Table 4 shows the successful extubation as well as extubation failure groups. Three predictors, GCS, MV, and RSBI, reach the significance level of 0.05. To find the relative importance weights among the 9 successful extubation predictors, multivariate logistic regression analysis is used to obtain a correlation matrix, as shown in Table 5. Then, unstandardized beta coefficient values $(y)$, $-0.049, 0.569, -0.046, 0.151, -0.092, 0.529, -0.862, 0.302,$ and $-0.307$, and standardized beta coefficients values $(y)$, $-0.047, 0.560, -0.592, 0.930, -0.055, 0.664, -0.094, 0.146,$ and $-0.140$, are used in the multiregression correlation matrix to obtain the rescaled relative weights, as shown in Table 6. Based on the method proposed by Braun and Oswald [33], the standardized beta coefficients and rescaled relative weighting values of RSBI (32.5%), RR (22%), and MV (18%) were found as the top three predictors. Others predictors are gender (10%), PaO2 (8%), PH (6%), GCS (2%), PiMax (1%), and PaCO2 (0%).

2.3. Logistic Regression Analysis. Logistic regression analysis is used to obtain the rate of successful extubation, as shown in Table 7. The overall model is significant, $\chi^2 = 24.516 (p$ value $= 0.004 < 0.05$), while the Hosmer and Lemeshow test $= 16.17 (p$ value $= 0.04 < 0.05)$ reached a significant level. Cox-Snell $R^2 = 0.450$ and Nagelkerke $R^2 = 0.603$. The results show that moderate association exists. The Wald values of GCS, MV, and RSBI are 6.261, 4.094, and 3.009, respectively. The $p$ values of GCS, MV, and RSBI equal 0.012, 0.043, and 0.083 (close to 0.05), respectively. The odds ratios of three key predictors, namely, GCS, MV, and RSBI, are 6.261, 4.094, and 3.009, respectively. The $p$ values of GCS, MV, and RSBI equal 0.012, 0.043, and 0.083 (close to 0.05), respectively. The odds ratios of three key predictors, namely, GCS, MV, and RSBI, are 6.261, 4.094, and 3.009, respectively. Therefore, $\ln \left( \frac{P_1}{1 - P_1} \right) = 0.058 \times \text{Gender} - 3.551$

\[
\begin{align*}
\ln \left( \frac{P_1}{1 - P_1} \right) &= 0.058 \times \text{Gender} - 3.551 \\
&+ 0.758 \times \text{RR} + 2.081 \times \text{MV} \\
&+ 0.471 \times \text{PiMax} + 8.921 \\
&- 0.881 \times \text{PH} + 3.818 \\
&- 2.855 \times \text{PaO}_2 + 23.404,
\end{align*}
\]
| Extubation predictors          | Description                                                                                                                                                                                                 | Sources                                      |
|-------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------|
| Tidal volume ($V_T$)          | Tidal volume is the *lung volume* representing the normal volume of air displaced between normal inhalation and exhalation when extra effort is not applied.                                                | Epstein, 1995 [17] Newth et al., 2009 [18]  |
| Respiratory rate ($f$) (RR)   | The respiratory rate (RR) is also known as the respiration rate, ventilation rate, ventilatory rate, ventilation frequency ($V_f$), respiration frequency ($R_f$), pulmonary ventilation rate, or breathing frequency.                | Yang and Tobin, 1991 [21]                   |
| Minute ventilation (MV)       | The total lung ventilation per minute is the product of tidal volume and respiration rate. It is measured by expired gas collection for a period of 1 to 3 minutes. The normal rate is 5 to 10 liters per minute. | Epstein, 1995 [17]                         |
| Rapid shallow breathing index (RSBI) | The rapid shallow breathing index (RSBI) is a tool that is used in the weaning of MV in *intensive care units*. The RSBI is defined as the ratio of respiratory frequency to tidal volume ($f/V_T$). | Tanios et al., 2006 [23] Chang et al., 2007 [24]  |
| Maximal inspiratory pressure (PiMax or MIP) | Maximum inspiratory pressure (MIP) is a measure of the strength of respiratory muscles, obtained by making the patient inhale as strongly as possible with the mouth against a mouthpiece; the maximum value is near the residual volume. | Nava et al., 1994 [27] de Souza et al., 2013 [28]  |
| Arterial carbon dioxide tension ($PaCO_2$) | A measure of the partial pressure of carbon dioxide in the arterial blood.                                                                                                                                       | Mokhlesi et al., 2007 [9] Nemer et al., 2009 [19] de Souza et al., 2013 [28] |
| Partial pressure of oxygen ($PaO_2$) | When measuring *arterial blood gases*, we sometimes use the term partial pressure of oxygen or $PaO_2$. Partial pressure refers to the pressure exerted by a specific gas in a mixture of other gases. $PaO_2$, put simply, is a measurement of oxygen in arterial blood. The normal range for $PaO_2$ is 75–100 mm Hg. If a patient’s $PaO_2$ is less than this, it means that he/she is not getting enough oxygen. | El Khoury et al., 2010 [29] |
| Static compliance of the respiratory system (Cat, rs) | The static compliance of the respiratory system (Cat, rs) is measured using volume control ventilation.                                                                                                                                                                       | Nemer et al., 2009 [19] |
| Time inspiratory effort (TIE)  | The timed inspiratory effort (TIE) index was developed based on the premise that patients with poor neuromuscular efficiency need more time to develop a maximal effort during the occlusion maneuver.                                                    | de Souza et al., 2013 [28]                  |
| Arterial blood gas (ABS)       | Arterial blood gas (ABG) is a *blood test* that is performed using *blood* from an *artery*.                                                                                                               | Murphy et al., 2006 [30] Zavorsky et al., 2007 [31] Khan et al., 2010 [32] |
Table 2: Demographic details of critically ill patients.

| Total number of patients | 41 |
|--------------------------|----|
| Age (mean ± SD), years   | 74 ± 2.495 |
| Gender (M/F)             | 27/14 |
| Successful, failed extubation | 23/18 |
| Glasgow Coma Scale (GCS) E (mean ± SD) | 3.71 ± 0.106 |
| Glasgow Coma Scale (GCS) V (mean ± SD) | 4.44 ± 0.148 |
| Glasgow Coma Scale (GCS) M (mean ± SD) | 5.54 ± 0.149 |
| RR (f) (mean ± SD)       | 23 ± 1.021 |
| Tidal volume (mean ± SD) | 0.312 ± 0.0283 |
| Minute ventilation (mean ± SD) | 6.568 ± 0.4845 |
| PiMax (MIP, NIF) (mean ± SD) | −37.88 ± 2.202 |
| RSBI (f/TV) (mean ± SD)  | 99.98 ± 10.355 |
| Arterial blood gas pH (mean ± SD) | 7.44 ± 0.0085 |
| PaO₂ (mean ± SD)         | 112.076 ± 4.279 |
| PaCO₂ (mean ± SD)        | 41.944 ± 1.5901 |

Table 3: Underlying diseases patient characteristics.

| Chronic obstructive pulmonary disease (COPD) | 6 (15%) |
| End stage renal disease (ESRD)              | 2 (5%) |
| Old stroke                                  | 8 (20%) |
| Cervical cancer                             | 1 (2%) |
| Cirrhosis                                   | 2 (5%) |
| Hepatitis B virus (HBV)                     | 1 (2%) |
| Heart failure                               | 3 (7%) |
| Esophageal cancer                           | 2 (5%) |
| Prostate cancer                             | 2 (5%) |
| Hypertension                                | 1 (2%) |
| Pneumoconiosis                              | 1 (2%) |
| Hepatocellular carcinoma (HCC)              | 1 (2%) |
| Congestive heart failure (CHF)              | 1 (2%) |
| Cerebral palsy                              | 1 (2%) |
| Systemic lupus erythematosus (SLE)          | 2 (5%) |
| Colon cancer                                | 1 (2%) |
| Deep vein thrombosis (DVT)                  | 1 (2%) |
| Old tuberculosis (TB)                       | 1 (2%) |
| Pulmonary tuberculosis (TB)                 | 1 (2%) |
| Renal cell carcinoma (RCC)                  | 1 (2%) |
| Nil                                         | 2 (5%) |
| Total                                       | 41 (100%) |

The PSEF is solved using IBM SPSS software syntax to obtain the successful rate of the observation as 87.8%, as shown in Table 9. As a result, a high accuracy rate of the PSEF is obtained. Only 5 observations are misjudged. The reasons for classification of logistic regression analysis are shown in Table 8. The values of sensitivity, specificity, positive predictive, negative predictive, false positive rate, and false negative rate can be obtained as 0.957, 0.778, 0.846, 0.933, 0.153, and 0.066, respectively. This indicates that the PSEF has a high rate of successful classification.

2.4. Comparing the Classification Rates of the Two Methods. The summary of classifications of 9 extubation predictors by discriminant analysis and logistic regression analysis is used to validate the classification results, as shown in Table 10. The logistic regression analysis offers a successful classification rate of 80.5% and discriminant analysis gives a successful classification rate of 87.8% for prediction of extubation.

2.5. Discriminant Classification Function. The factor of the successful extubation predictors for the classification of Fisher’s linear discriminant functions (see Table 11) affects the PSEF. The fail function of classifying groups is given as follows:

\[ D_1 = f(x) = -152.053 \times \text{Gender} + 100.671 \times \text{GCS} + 3.258 \times \text{RR} + 16.664 \times \text{MV} + 172.336 \times \text{PiMax} \]

\[ + 45.964 \times \text{RSBI} + 3305.766 \times \text{PH} - 3.363 \]

and the success function of the classifying groups is given as

\[ D_2 = f(x) = -152.399 \times \text{Gender} + 104.655 \times \text{GCS} + 2.940 \times \text{RR} + 17.718 \times \text{MV} + 171.695 \times \text{PiMax} \]

\[ + 49.667 \times \text{RSBI} + 3299.738 \times \text{PH} - 1.253 \]

\[ - 154.393 \times \text{PaO₂} - 31057.793 \]

IBM SPSS software with Fisher’s linear discriminant function is used to obtain the probability values. Figure 2 shows the scatter plot of the probability of classification for top three predictors in different functions, when the default cut-off point is 0.5 and the prediction probability is greater than 0.5. Top three predictors reveal very little difference in the distance (0 and 1). It is observed that the classification function can be accurately predicted. Figure 3 shows the 8 misjudged observations and 33 correctly predicted observations in discriminant classification function. In order to verify the correctness of the classification of Fisher’s linear discriminant functions, we use Press’ Q formula to test the predictability of the clustering results and get a Press’ Q value = 15.24 > 3.84. Indeed, it is a good classification. As seen in Figure 4, there are four misclassified samples (which actually should be attributed to fail extubation group). There are four other misclassified samples, which actually should be attributed to the successful extubation group [34].
Data collection
41 random critically ill patients under ICU weaning protocols are selected.

Filtering the successful extubation index
Delphi method with face-to-face interviews and consultation with 8 professional doctors are performed to obtain 9 extubation predictors.

Methodologies
(1) Logistic regression analysis is used to correctly predict the probability of extubation success.
(2) Discriminant analysis (DA) is used to classify extubation functions.
(3) Bootstrap method is used to prove the robust consistency of the results.

Extubation classification function
(1) Nine extubation success predictors are used to predict probability functions.
(2) Groups of successful functions are classified.
(3) Groups of failed functions are classified.

To aid extubation judgment
(1) Key predictors of successful extubation are obtained.
(2) The prediction of successful extubation function is developed.

**Figure 1:** Experimental procedure.

**Figure 2:** Scatter plot for the top three predictors of the classification functions.
**Table 4:** Tests of successful and failed extubation groups.

| Extubation index | Successful extubation (n = 23) | Failed extubation (n = 18) | p value (two-tailed) |
|------------------|---------------------------------|-----------------------------|---------------------|
| Gender           | 0.78 ± 0.088                    | 0.50 ± 0.121                | 0.06                |
| GCS              | 0.83 ± 0.081                    | 0.33 ± 0.114                | 0.001***            |
| RR               | 22.70 ± 1.335                   | 23.39 ± 1.591               | 0.741               |
| MV               | 7.497 ± 0.723                   | 5.381 ± 0.495               | 0.028*              |
| PiMax            | −40.61 ± 3.378                  | −34.39 ± 2.417              | 0.126               |
| RSBI             | 85.48 ± 11.559                  | 118.50 ± 17.825             | 0.05*               |
| PH               | 7.44 ± 0.010                    | 7.46 ± 0.014                | 0.296               |
| PaO₂             | 112.81 ± 6.162                  | 111.13 ± 5.939              | 0.968               |
| PaCO₂            | 39.89 ± 1.706                   | 44.567 ± 2.83               | 0.170               |

* p < 0.05; ** p < 0.01.

**Table 5:** Multivariate regression correlation matrix.

|        | PaCO₂ | PH | RSBI | PaO₂ | GCS | Gender | PiMax | MV | RR |
|--------|-------|----|------|------|-----|--------|-------|----|----|
| PaCO₂  | 1     |    |      |      |     |        |       |    |    |
| PH     | 0.126 | 1  |      |      |     |        |       |    |    |
| RSBI   | −0.109| −0.078| 1 |      |     |        |       |    |    |
| PaO₂   | −0.050| −0.148| 0.175| 1 |     |        |       |    |    |
| GCS    | 0.209* | 0.250| 0.205*| −0.078| 1 |        |       |    |    |
| Gender | −0.229* | −0.339| −0.015| 0.140| −0.566*| 1 |     |    |    |
| PiMax  | −0.082| 0.167| −0.015| 0.035| −0.273| 0.326| 1 |    |    |
| MV     | 0.001* | 0.006| 0.879*| 0.212| 0.341*| −0.293*| −0.270| 1 |    |
| RR     | 0.118| 0.143| −0.939| −0.174| −0.101| −0.004| 0.098| −0.870| 1 |

* p < 0.05.

**Table 6:** Rescaled relative weights of successful extubation indexes.

| Rescaled relative weights (%) | Gender | GCS | RR | MV | PiMax | RSBI | PH | PaO₂ | PaCO₂ |
|-------------------------------|--------|-----|----|----|-------|------|----|------|-------|
| Unstandardized beta coefficients | 21.100 | 2.651 | 9.973 | 8.578 | 25.889 | 10.727 | 19.960 | 0.728 | 0.391 |
| Standardized beta coefficients | 10.147 | 2.319 | 22.078 | 17.828 | 0.664 | 32.545 | 6.129 | 7.939 | 0.346 |

**Table 7:** The results of logistic regression analysis.

| Variable name | B   | SE  | Wald value | Odds ratio | Effect value |
|---------------|-----|-----|------------|------------|--------------|
| Gender        | 0.058 | 1.429 | 0.002 | 1.059 |              |
| GCS           | −3.551 | 1.419 | 6.261 | 0.029 |              |
| RR            | −0.758 | 0.447 | 2.881 | 0.468 |              |
| MV            | 2.081 | 1.028 | 4.094 | 8.011 |              |
| PiMax         | 0.471 | 2.233 | 0.045 | 1.602 |              |
| RSBI          | 8.921 | 5.143 | 3.009 | 7487.943 |              |
| PH            | −8.891 | 12.157 | 0.535 | 0.000 |              |
| PaO₂          | 3.818 | 2.661 | 2.059 | 45.520 |              |
| PaCO₂         | −2.855 | 2.388 | 1.430 | 0.058 |              |
| Constant      | 23.404 | 100.915 | 0.054 | 14596256529 | \(\chi^2 = 24.516\) |

Overall pattern match verification \(\chi^2 = 24.516\)

 Hosmer and Lemeshow test = 16.17 significance
### Table 8: The reasons for classification of the logistic regression analysis.

| Patient number | $y = \text{extubation}$ | Forecast groups | Predicting probability | Classification score | Misjudgment Analysis of reasons |
|----------------|--------------------------|-----------------|------------------------|----------------------|--------------------------------|
| (1)            | 1                        | 1               | 0.756                  | −2.36                |                                |
| (2)            | 1                        | 1               | 0.545                  | 3.8                  |                                |
| (3)            | 0                        | 0               | 0.19                   | 1.5                  |                                |
| (4)            | 1                        | 1               | 0.669                  | −2.78                |                                |
| (5)            | 1                        | 1               | 0.716                  | −2.67                |                                |
| (6)            | 1                        | 0               | 0.064                  | 0.82                 | Misjudgment Positive values should be classified in successful groups |
| (7)            | 1                        | 1               | 0.806                  | −2.17                |                                |
| (8)            | 0                        | 0               | 0.350                  | −4.1                 |                                |
| (9)            | 0                        | 1               | 0.947                  | −0.59                | Misjudgment Negative values should be judged as failed groups |
| (10)           | 1                        | 1               | 0.884                  | −1.45                |                                |
| (11)           | 0                        | 0               | 0.224                  | −4.85                |                                |
| (12)           | 1                        | 1               | 0.949                  | −0.56                |                                |
| (13)           | 1                        | 1               | 0.906                  | −1.22                |                                |
| (14)           | 1                        | 1               | 0.941                  | −0.71                |                                |
| (15)           | 0                        | 0               | 0.009                  | −1.16                |                                |
| (16)           | 0                        | 0               | 0.202                  | 2.25                 |                                |
| (17)           | 1                        | 1               | 1.000                  | 15.31                |                                |
| (18)           | 0                        | 0               | 0.306                  | −4.3                 |                                |
| (19)           | 1                        | 1               | 0.937                  | −0.79                |                                |
| (20)           | 0                        | 1               | 0.514                  | −3.43                | Misjudgment Negative values should be judged as failed groups |
| (21)           | 0                        | 1               | 0.705                  | −2.61                | Misjudgment Negative values should be judged as failed groups |
| (22)           | 0                        | 0               | 0.048                  | 0.64                 |                                |
| (23)           | 1                        | 1               | 0.829                  | −1.9                 |                                |
| (24)           | 0                        | 1               | 0.746                  | 4.58                 | Misjudgment Positive values should be classified into successful groups |
| (25)           | 0                        | 0               | 0.113                  | 1.44                 |                                |
| (26)           | 1                        | 1               | 0.680                  | −2.73                |                                |
| (27)           | 0                        | 0               | 0.210                  | 2.18                 |                                |
| (28)           | 0                        | 0               | 0.022                  | −0.28                |                                |
| (29)           | 1                        | 1               | 0.998                  | 2.9                  |                                |
| (30)           | 1                        | 1               | 0.896                  | −1.33                |                                |
| (31)           | 1                        | 1               | 0.881                  | −1.6                 |                                |
| (32)           | 1                        | 1               | 0.917                  | −1.2                 |                                |
| (33)           | 1                        | 1               | 0.979                  | 0.34                 |                                |
| (34)           | 0                        | 0               | 0.016                  | −0.49                |                                |
| (35)           | 1                        | 1               | 0.599                  | 4.02                 |                                |
| (36)           | 1                        | 1               | 0.810                  | −2.04                |                                |
| (37)           | 0                        | 0               | 0.169                  | 1.91                 |                                |
| (38)           | 1                        | 1               | 0.523                  | −3.39                |                                |
| (39)           | 1                        | 1               | 0.877                  | −1.52                |                                |
| (40)           | 0                        | 0               | 0.003                  | −2.39                |                                |
| (41)           | 0                        | 0               | 0.135                  | 1.77                 |                                |
Therefore, the bootstrap method is used to reduce the gap between the sample data and the general population by estimating path coefficients repeatedly [35]. Bootstrapping is also undertaken to confirm the robustness of the findings. To do this, our study uses the IBM SPSS of bootstrap method [36] to generate 1000 random numbers. Bootstrap samples were built by resampling with replacement of the original sample. Finally, the repeating presentation pattern of the sampling results shows robust consistency. The bootstrapping method is commonly used to calculate confidence intervals around the success indexer estimates. The summary results for bootstrapping are provided in Table 12. The critically ill patient’s data of 41 repeated samples (using the bootstrap method) are as follows: GCS = 0.009, MV = 0.023, and RSBI = 0.053. Only three successful extubation predictors RR, MV, and RSBI are significant. 15 critically ill patient’s data types are used again by the bootstrap method to obtain the following: RR = 0.014; MV = 0.014; RSBI = 0.014; PH = 0.014; PaO\textsubscript{2} = 0.014; PaCO\textsubscript{2} = 0.014. 6 successful extubation predictors RR, MV, RSBI, PH, PaO\textsubscript{2}, and PaCO\textsubscript{2} are significant.

### 3. Discussion

RSBI < 105 has 90% sensitivity, whereas 18% specificity was found. Artificial neural network has been used to predict extubation outcome although its result varies in different studies [37, 38]. Miu et al. [14] proposed a few important risk factors for extubation failure. For instance, oxygenation was an important component of early failure. Lower diastolic blood pressure and repeatedly failed SBT are significant contributorsto extubation failure at any time. Two prediction models for extubation failure are found in subjects who have passed an SBT: one for failure at any time and another for failure in the first 24 hours after extubation. Approximately, both models showed 70% accuracy when correct predicting was obtained. Nguyen et al. [10] found that lower negative inspiratory force and higher vital capacity are corrected with successful extubation. SBT is the major diagnostic test to determine whether patients can be successfully extubated [39]. Lioutas et al. [8] indicated that conventional respiratory parameters have no effect on extubation success in acute ischemic stroke patients. The PaCO\textsubscript{2} appears as a strong predictor of extubation failure [12]. However, all of the above-mentioned methods are not always precise and do not provide a decision function for aiding the decision making of extubation.

Except weaning predictors, some clinical rules such as mental status and endotracheal secretions are used to predict extubation failure [40]. Muscle weakness resulting from critical illness polyneuropathy or myopathy causes failure to wean from the ventilator. Farghaly and Hasan [11] proposed

![Figure 3: Misjudgment analysis in discriminant classification function.](image)

![Figure 4: Predictive clustering scatter plot by discriminant analysis.](image)
Table 10: Summary of classifications of nine successful extubation indexes by two methods.

| Group          | Discriminant classification | Logistic regression classification |
|----------------|----------------------------|---------------------------------|
|                | S  | F  | Classification rate (%) | S  | F  | Classification rate (%) |
| Case Extubation| S  | 87.0 | 13.0 | 80.5 | 95.65 | 4.35 | 87.8 |
|                | F  | 278 | 72.2 | 77.78 | 22.22 | 77.78 |

Table 11: The classification of Fisher's linear discriminant functions.

| Indexes | Successful (failed) extubation |
|---------|--------------------------------|
|         | Failed                        | Successful                     |
| Gender  | -152.053                     | -152.399                      |
| GCS     | 100.671                       | 104.655                       |
| RR      | 3.258                         | 2.940                         |
| MV      | 16.664                        | 17.718                        |
| PiMax   | 172.336                       | 171.695                       |
| PH      | 3305.766                      | 3299.738                      |
| PaO₂    | -3.363                        | -1.253                        |
| PaCO₂   | 156.543                       | 154.393                       |
| Constant| -13085.090                   | -13057.793                   |

diaphragm ultrasound as a new method to predict extubation outcome in mechanically ventilated patients. Besides, prolonged mechanical ventilation is defined as greater than 21 days of mechanical ventilation for at least 6 hours per day. Failed weaning had a lower hypercapnic ventilatory response than successfully weaned subjects [41].

In this retrospective study, we found a more precise function for prediction of successful extubation in ICU of CGMH. Our experimental results show that predicting successful rate of 87.8% is obtained from the proposed predicting function. Multiple statistical methods are used to obtain the prediction of successful extubation function, $D_2$. In addition, the bootstrap method is used to confirm the robustness of the findings. Top three predictors, namely, RSBI (32.5%), RR (22%), and MV (18%), are found for successful extubation in ICU of CGMH. The prediction of successful extubation function is also provided for aiding the clinicians to make a more precise extubation decision for patients in ICU to avoid delay or premature extubation against the potential harms and costs of failed extubation. The prediction of successful extubation function was derived, which can easily be used to aid clinical extubation judgment. Our study is a monocentric retrospective pilot trial involving limited number of critically ill patients. Further studies are needed in terms of larger and more heterogeneous patient groups to precisely revise the coefficients of PSEF.

5. Conclusion

The results show several strengths of relative weights. First, relative weights add up to $R^2$ [36]. Additionally, relative weights are easy to explain to researchers [43]. Second, three major predictors of success of extubation are found in both discriminant analysis and logistic analysis. A successful classification rate of 87.8% was obtained to avoid delay or premature extubation against the potential harms and costs of failed extubation. The prediction of successful extubation function was derived, which can easily be used to aid clinical extubation judgment. Our study is a monocentric retrospective pilot trial involving limited number of critically ill patients. Further studies are needed in terms of larger and more heterogeneous patient groups to precisely revise the coefficients of PSEF.

Additional Points

Highlight. (1) Approximately 40% of patients admitted to the medical intensive care units require mechanical ventilation. (2) Extubation decision solely based on clinical judgment of experts is not always precisely. (3) Our experimental results show that a predicting successful rate of 87% is obtained by the proposed predicting function. Research Question. (1) Can a good predicting function for extubation decision be obtained? (2) In practice, what are the successful extubation factors? (3) What is the improvement method for finding more precise predicting function for extubation decisions.

Disclosure

Chih-Hao Chang is an equal first author.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Authors’ Contributions

Chang-Shu Tu planned the study; Chih-Hao Chang, Shu-Chin Chang, and Chung-shu Lee conducted a survey; Ching-Ter Chang coordinated all works in the study.
**Table 12: Bootstrap method with sample analysis of 15 and 41 patients.**

| Successful index | Solving bootstrap for sample analysis of 15 patients | Solving bootstrap for sample analysis of 41 patients |
|------------------|------------------------------------------------------|-----------------------------------------------------|
|                  | Beta estimates | SE | Significant (two-tailed) | Beta estimates | SE | Significant (two-tailed) |
| Gender           | −0.281         | 5942.222 | 0.135                  | 0.058         | 148.105 | 0.750                  |
| GCS              | −0.785         | 3821.522 | 0.095                  | −3.551        | 208.851 | 0.009                  |
| RR               | −0.839         | 956.320  | 0.014                  | −0.758        | 122.741 | 0.061                  |
| MV               | 2.263          | 1528.980 | 0.014                  | 2.081         | 272.902 | 0.023                  |
| PiMax            | −2.801         | 2569.122 | 0.014                  | 0.471         | 582.832 | 0.657                  |
| RSBI             | 9.443          | 8954.303 | 0.014                  | 8.921         | 1178.506 | 0.053                  |
| PH               | −28.325        | 16465.99 | 0.014                  | −8.891        | 2084.391 | 0.387                  |
| PaO₂             | 5.455          | 1613.969 | 0.014                  | 3.818         | 333.872 | 0.076                  |
| PaCO₂            | −4.553         | 2601.498 | 0.014                  | −2.855        | 1184.107 | 0.131                  |
| Cox & Snell $R^2$ | 0.350          | 0.450    |                        |              | 0.603    |                        |
| Nagelkerke $R^2$ | 0.486          | 0.603    |                        |              |          |                        |

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**References**

[1] H. Kan, R. Chen, and S. Tong, "Ambient air pollution, climate change, and population health in China," *Environment International*, vol. 42, pp. 10–19, 2012.

[2] S.-S. Tsai, C.-C. Chang, and C.-Y. Yang, "Fine particulate air pollution and hospital admissions for chronic obstructive pulmonary disease: A case-crossover study in Taipei," *International Journal of Environmental Research and Public Health*, vol. 10, no. 11, pp. 6015–6026, 2013.

[3] P. Santus, A. Russo, E. Madonini et al., "How air pollution influences clinical management of respiratory diseases. A case-crossover study in Milan," *Respiratory Research*, vol. 13, article no. 95, 2012.

[4] Z. Zhang, J. Wang, L. Chen et al., "Impact of haze and air pollution-related hazards on hospital admissions in Guangzhou, China," *Environmental Science and Pollution Research*, vol. 21, no. 6, pp. 4236–4244, 2014.

[5] N. R. MacIntyre, S. K. Epstein, S. Carson, D. Scheinhorn, K. Christopher, and S. Muldoon, "Management of patients requiring prolonged mechanical ventilation: report of a NAMDRC consensus conference," *CHEST*, vol. 128, no. 6, pp. 3937–3954, 2005.

[6] J. Sellares, M. Ferrer, E. Cano, H. Loureiro, M. Valencia, and A. Torres, "Predictors of prolonged weaning and survival during ventilator weaning in a respiratory ICU," *Intensive Care Medicine*, vol. 37, no. 5, pp. 775–784, 2011.

[7] F. Frutos-Vivar, A. Esteban, C. Apezteguia et al., "Outcome of reintubated patients after scheduled extubation," *Journal of Critical Care*, vol. 26, no. 5, pp. 502–509, 2011.

[8] V.-A. Lioutas, K. A. Hanafi, and S. Kumar, "Predictors of extubation success in acute ischemic stroke patients," *Journal of the Neurological Sciences*, vol. 368, pp. 191–194, 2016.

[9] B. Mokhlesi, A. Tulaimat, T. J. Gluckman et al., "Predicting extubation failure after successful completion of a spontaneous breathing trial," *Respir Care*, vol. 52, pp. 1710–1717, 2007.

[10] T. N. Nguyen, N. Badjatia, A. Malhotra, F. K. Gibbons, M. M. Qureshi, and S. A. Greenberg, "Factors predicting extubation success in patients with Guillain–Barré syndrome," *Neurocritical Care*, vol. 5, no. 3, pp. 230–234, 2006.

[11] S. Farghaly and A. A. Hasen, "Diaphragm ultrasound as a new method to predict extubation outcome in mechanically ventilated patients," *Australian Critical Care*, vol. 30, no. 1, pp. 37–43, 2017.

[12] B. Mokhlesi, A. Tulaimat et al., "Predicting extubation failure after successful completion of a spontaneous breathing trial," *Respiratory Care*, vol. 52, pp. 1710–1717, 2007.

[13] S. L. Zettervall, P. A. Soden, K. E. Shean et al., "Early extubation reduces respiratory complications and hospital length of stay following repair of abdominal aortic aneurysms," *Journal of Vascular Surgery*, vol. 65, no. 1, pp. 58–64.e1, 2017.

[14] T. Miu, A. M. Joffe, N. D. Yanez et al., "Predictors of reintubation in critically ill patients," *Respiratory Care*, vol. 59, no. 2, pp. 178–185, 2014.

[15] A. Savi, C. Teixeira, J. M. Silva et al., "Weaning predictors do not predict extubation failure in simple-to-weak patients," *Journal of Critical Care*, vol. 27, no. 2, pp. 221–e8, 2012.

[16] P. H. Yang, J. Y. Hung, C. J. Yang et al., "Successful weaning predictors in a respiratory care center in Taiwan," *Kaohsiung Journal of Medical Sciences*, vol. 24, pp. 85–91, 2008.

[17] S. K. Epstein, "Etiology of extubation failure and the predictive value of the rapid shallow breathing index," *American Journal of Respiratory and Critical Care Medicine*, vol. 152, no. 2, pp. 545–549, 1995.

[18] C. J. L. Newth, S. Venkataraman, D. F. Willson et al., "Weaning and extubation readiness in pediatric patients," *Pediatric Critical Care Medicine*, vol. 10, no. 1, pp. 1–11, 2009.

[19] S. N. Nemer, C. S. V. Barbas, J. B. Caldeira et al., "New integrative weaning index of discontinuation from mechanical ventilation," *Crit Care*, vol. 13, no. R152, 2009.

[20] N. Adiguzel, G. Gümüş, and M. J. Tobin, "Hippocrates is alive and weaning in Brazil," *Crit Care*, vol. 13, no. 142, 2009.

[21] K. L. Yang and M. J. Tobin, "A prospective study of indexes predicting the outcome of trials of weaning from mechanical ventilation," *The New England Journal of Medicine*, vol. 324, no. 21, pp. 1445–1450, 1991.
[22] C. S. H. Sassoon and C. K. Mahutte, “Airway occlusion pressure and breathing pattern as predictors of weaning outcome,” *American Review of Respiratory Disease*, vol. 148, no. 4, pp. 860–866, 1993.

[23] M. A. Tanious, M. L. Nevins, K. P. Hendra et al., “A randomized, controlled trial of the role of weaning predictors in clinical decision making,” *Critical Care Medicine*, vol. 34, no. 10, pp. 2530–2535, 2006.

[24] C. H. Chang, Y. W. Hong, and S. k. Koh, “Weaning approach with weaning index for postoperative patients with mechanical ventilator support in the ICU,” *Korean Journal of Anesthesiology*, vol. 53, pp. 47–51, 2007.

[25] C. M. Rodriguez and J. Varon, “The science behind weaning from mechanical ventilation,” *Crit Care & Shock*, vol. 11, pp. 48–53, 2008.

[26] A. Fadaii, S. S. Amini, B. Bagheri, and B. Taherkhanchi, “Assessment of Rapid Shallow Breathing Index as a Predictor for Weaning in Respiratory Care Unit,” *Tanaffos*, vol. 11, pp. 28–31, 2012.

[27] S. Nava, F. Rubini, E. Zanotti et al., “Survival and prediction of successful ventilator weaning in COPD patients requiring mechanical ventilation for more than 21 days,” *European Respiratory Journal*, vol. 7, no. 9, pp. 1645–1652, 1994.

[28] L. C. de Souza, F. S. Guimaraes, and J. R. Lugon, “Evaluation of a new index of mechanical ventilation weaning: the timed inspiratory effort,” *Journal of Intensive Care Medicine*, vol. 10, pp. 10–1177, 2013.

[29] M. Y. El Khoury, R. J. Panos, J. Ying, and K. F. Almoosa, “Value of the PaO2:FiO2 ratio and Rapid Shallow Breathing Index in predicting successful extubation in hypoxemic respiratory failure,” *Heart & Lung: The Journal of Acute and Critical Care*, 2010.

[30] R. Murphy, S. Thethy, S. Raby et al., “Capillary blood gases in acute exacerbations of COPD,” *Respiratory Medicine*, vol. 100, no. 4, pp. 682–686, 2006.

[31] G. S. Zavorsky, J. Cao, N. E. Mayo, R. Gabbay, and J. M. Murias, “Arterial versus capillary blood gases: A meta-analysis,” *Respir Physi & Neurobiology*, vol. 155, pp. 268–279, 2007.

[32] Z. H. Khan, S. Samadi, M. Sadeghi et al., “Prospective study to determine possible correlation between arterial and venous blood gas values,” *Acta Anaesthesiologica Taiwanica*, vol. 48, no. 3, pp. 136–139, 2010.

[33] M. T. Braun and F. L. Oswald, “Exploratory regression analysis: A tool for selecting models and determining predictor importance,” *Behavior Research Methods*, vol. 43, no. 2, pp. 331–339, 2011.

[34] RM. Warner, *Applied statistics: from bivariate through multivariate techniques*, Sage, Thousand Oaks, CA, 2008.

[35] R. Davidson and J. G. Mackinnon, *Econometric Theory and Methods*, Oxford university, Oxford, England, 2004.

[36] S. Tonidandel and J. M. LeBreton, “Relative Importance Analysis: A Useful Supplement to Regression Analysis,” *Journal of Business and Psychology*, vol. 26, no. 1, pp. 1–9, 2011.

[37] H. G. Okuno and M. Ali, *New Trends in Applied Artificial Intelligence*, vol. 4570, Springer Berlin Heidelberg, Berlin, Heidelberg, 2007.

[38] H.-J. Kuo, H.-W. Chiu, C.-N. Lee, T.-T. Chen, C.-C. Chang, and M.-Y. Bien, “Improvement in the prediction of ventilator weaning outcomes by an artificial neural network in a medical ICU,” *Respiratory Care*, vol. 60, no. 11, pp. 1560–1569, 2015.

[39] J.-M. Boles, J. Bion, A. Connors et al., “Weaning from mechanical ventilation,” *European Respiratory Journal*, vol. 29, no. 5, pp. 1033–1056, 2007.

[40] B. Mokhlesi, A. Tulaimat, T. J. Gluckman et al., “Predicting extubation failure after successful completion of a spontaneous breathing trial,” *Respiratory Care*, vol. 52, no. 12, pp. 1710–1717, 2007.

[41] C. S. Lee, N. H. Chen, L. P. Chuang et al., “Hypercapnic ventilatory response in the weaning of patients with prolonged mechanical ventilation,” *Canadian Respiratory Journal*, Article ID 7381424, 2017.

[42] S. E. Bleeker, H. A. Moll, E. W. Steyerberg et al., “External validation is necessary in prediction research: A clinical example,” *Journal of Clinical Epidemiology*, vol. 56, no. 9, pp. 826–832, 2003.

[43] J. W. Johnson and J. M. LeBreton, “History and use of relative importance indices in organizational research,” *Organizational Research Methods*, vol. 7, no. 3, pp. 238–257, 2004.