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ORIGINAL ARTICLE

Derivation and validation of the ABCDMed clinical score to estimate the probability of extubation failure in intensive care units

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Abstract

Objective: To develop and validate a clinical prediction model to estimate the probability of extubation failure (EF) in the intensive care unit (ICU).

Methods: An observational, analytical, prospective cohort study was conducted to derive and validate a clinical prediction model and a risk prediction score for EF. The study was performed in the ICU of the Mayor Méderi University Hospital in Bogotá, Colombia. All consecutive patients older than 18 years who required mechanical ventilation between June 2017 and April 2019 and were extubated were included. The analysis comprised 800 patients. Cases of extubation according to medical advice and on a planned basis were included. The outcome of the study was EF (dependent variable), which was defined as the need for reintubation in the 48 hours following extubation. The characteristics of the patient before being extubated were the variables of interest. The patients were grouped according to the dependent variable (EF). Using multivariate logistic regression, a prediction model was derived and validated using a purposeful selection strategy and a bootstrapping technique, respectively. Subsequently, a risk prediction score was generated for EF.

Results: EF occurred in 71 (8.9%) patients. A model was generated from five variables: A = acid-base status, B = the rapid shallow breathing index , C = the presence of effective cough, D = probability of death and Med. = medical patient status. The Hosmer-Lemeshow ($\hat{C}$) goodness of fit value was 0.465. The discriminative power determined an area under the curve (AUC) of 0.687. Internal validation with the bootstrapping method showed an AUC of 0.695. A risk score was created, which was divided into four groups using multiples of the baseline risk of EF (8.9%). The observed incidences of EF in patients with low, moderate, high and very high risk were 4.1%, 8.1%, 11.5% and 22.7%, respectively.

Conclusions: The ABCDMed prediction score allows easy estimation of the risk of EF based on five patient variables available at the bedside.

Background

Mechanical ventilation (MV) continues to be the most commonly used support strategy in critically ill patients; however, it is far from being a safe intervention, and its prolonged use is associated with risks such as lung injury,[1,2] diaphragm dysfunction,[3] pulmonary infections, longer hospital stay and increased costs.[4-8] For this reason, once the condition that led to patient intubation is resolved, a timely evaluation is necessary to begin the process of ventilator withdrawal. Ventilator weaning is the transitional period between total support and spontaneous breathing and corresponds to up to 40% of a patient's time under MV.[9]
Extubation failure (EF) is defined as the need to restore MV in the first 48 hours after tube removal, and early failure occurs in the first 24 hours.[10] Risk factors for EF have been described, such as patients with neurological disease, age over 70 years, high mortality scores, continuous sedation, prolonged MV, chronic heart or lung disease, and multiple failed attempts at weaning during spontaneous breathing trials (SBTs).[11,12] Currently, despite a complete evaluation, between 6% and 20% of patients considered eligible for ventilator removal will have EF.[10,13]
The importance of this event is that the need for reintubation is associated with a 4.5-fold increased risk of nosocomial pneumonia[14] and a mortality rate close to 50%.[15] One day on MV has an approximate cost of 2000 dollars, consuming a large part of ICU resources.[16]

In published studies, the variables most frequently used as predictors for EF are respiratory rate, the ratio between partial pressure of oxygen (PaO_2) and fraction of inspired oxygen (FiO_2)(PaO_2/FiO_2 ratio), static compliance at ICU admission,[17] tidal volume, the rapid shallow breathing index (RSBI)[18] and the cuff-leak test.[19,20]

Khamiees et al. showed that an evaluation of cough and the amount of secretions can be important predictors of EF after a positive SBT.[21] In 2014, Miu et al. evaluated different variables during the last SBT and one hour after extubation in 2007 patients. Prediction model factors associated with an increased risk of EF were disease severity determined by the SAPS II (Simplified Acute Physiology Score II) score, minute ventilation and higher secretion suction frequency. This model showed an area under the receiver operating characteristic (ROC) curve of 0.68.[10]

The largest study performed to date to investigate outcomes in patients with planned extubation was performed in the ICU of a medical centre in Taiwan, with the goal of establishing predictors of extubation success. A total of 6.1% of 6583 evaluated patients experienced EF. Three independent factors were found to predict extubation success: the cuff-leak test, maximal expiratory pressure ≥55 cmH_2O and RSBI <68, which represent airway patency, cough strength and respiratory capacity, respectively.[13] The findings of the studies are limited in size or in methodology, and there is still no simple and efficient tool to predict EF.

The objective of this study was to develop and validate a clinical prediction model to estimate the probability of EF using variables that are readily available in the ICU.

Methods

We followed the TRIPOD (Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis) statement to report multivariable prediction model development and validation.[22] Authorisation for this study was granted by the Institutional Human Research Ethics Committee of Del Rosario University (DVO005 929-CV904). The study was classified according to Colombian legislation as 'Minimum Risk'; general informed consent was used to manage medical history information.

Research design and study site

An observational, analytical, prospective cohort study was conducted to derive and validate a clinical prediction model and a risk prediction score for EF. The study was conducted in the ICU of the Mayor Méderi University Hospital, a high complexity hospital with 780 hospital beds, of which 71 beds were in the adult ICU. Within the ICU, 7 beds were for cardiovascular care, 10 beds for coronary care, 8 beds for neurological care, 24 beds for surgical care and 22 beds for medical care.

Participants

All consecutive patients older than 18 years who required MV between June 2017 and April 2019 and were extubated according to medical advice and on a planned basis were included. The institutional protocol for removal of MV included verification of a checklist that had parameters for oxygenation, ventilatory mechanics, acid-base status, haemodynamic stability, airway management and an SBT with continuous positive airway pressure (CPAP) plus pressure support with positive end-expiratory pressure (PEEP) ≤8 and support ≤8 cmH_2O for at least 30 minutes. Patients who were intubated outside the institution were excluded because most of them did not have a reliable intubation date so the MV time could not be calculated. Likewise, those with accidental or unplanned extubation were not included in the analysis.

Study variables and data collection

Demographic variables (age, sex, predicted body weight,[23] classification as a medical patient or surgical patient according to the cause of ICU admission, admission diagnosis and probability of death in percent determined by APACHE II or Euroscore II in postoperative cardiac patients), oxygenation variables (PaO_2, PaO_2/FiO_2 ratio, oxygen saturation (O_2 saturation), arterial-alveolar ratio (a/A ratio), alveolar-arterial difference (A-a difference), and oxygenation index = FiO_2*mean airway pressure*100/PaO_2), ventilatory mechanics (tidal volume, respiratory rate, RSBI and PEEP), acid-base status (pH), bicarbonate (HCO_3), lactate and partial pressure of carbon dioxide ($PaCO_2$), haemodynamic status (systolic, diastolic and mean blood pressure, heart rate, need for vasopressors and/or inotropes), airway status (cuff-leak percentage) and clinical status (presence of abundant tracheal secretions requiring two or more aspirations in the last two hours, effective cough defined as presence of clearly audible cough during suctioning, with sufficient strength and intensity to expel endotracheal secretions and generate protection of the airway,[24-26] presence of delirium assessed by the CAM-ICU scale, and planning for the use of noninvasive positive pressure ventilation (NPPV) after extubation) were collected. Data were obtained daily from the electronic medical records of each patient, who were followed up during the hospital stay and at 30 days. The data were recorded in a standardised questionnaire and subsequently entered into a Microsoft Excel spreadsheet.

Twelve candidate predictor variables were selected following a review of the literature (oxygenation index, RSBI, respiratory rate, tidal volume, pH, $PaCO_2$, HCO_3, abundant secretions, effective cough, the probability of death predicted by APACHE II or Euroscore II scores according to disease type, medical patient status and NPPV after extubation). The outcome of the study was EF (dependent variable), which was defined as the need for reintubation in the 48 hours following extubation. All continuous variables were retained at their original scales except for pH, which was transformed to its exponential form.

Table 1. Baseline characteristics and comparison of patients with successful and failed planned extubation as assessed after 48 hours

Variable	Total cohort (n=800)	Failure (n=71)	Success (n=729)	*p-value*
Sex - Male - Female	 457 (57.1%) 343 (42.9%)	 41 (57.7%) 30 (42.3%)	 416 (57.1%) 313 (42.9%)	 0.912
Ideal weight (n=561)ǂ	57 (50-64)	61 (53-70)	57 (50-64)	0.050
Type of patient - Medical - Surgical	 310 (38.8%) 490 (61.2%)	 42 (59.2%) 29 (40.8%)	 268 (36.8%) 461 (63.2%)	
APACHE II (n=507)	17 (13-21)	18 (15-23)	17 (13-21)	0.082
Euroscore II (n=293)	5 (3-7)	6.5 (5-9)	5 (3-7)	0.062
Probability of death (%) - APACHE II - Euroscore II	 26.2 (16.5-38.9) 3.6 (2.2-6.8)	 29.1 (21-46) 6.1 (3.9-13.7)	 26.2 (16.5–38.9) 3.5 (2.2-6.8)	 0.079 0.076
Days of mechanical ventilation	3 (1-5)	4 (2-7)	2 (1-5)	<0.001
PaO_2	81 (70-94)	74 (65-87)	81 (71-94)	0.006
PaO_2/FiO_2 ratio	237 (203-282)	232 (198-265)	237 (205-282)	0.182
O_2 saturation	96 (93-97)	94 (92-96)	96 (94-97)	0.011
a/A ratio	0.63 (0.53-0.74)	0.59 (0.52-0.70)	0.64 (0.53-0.74)	0.297
A-a difference	46 (30-68)	47 (32-67)	45 (30-68)	0.836
Oxygenation index	4.0 (3.0-5.0)	4.25 (3.5-5.1)	4.0 (2.9-4.9)	0.158
RSBI	36 (29-45)	40 (31-50)	36 (28-45)	0.034
PEEP	6 (6-8)	6 (6-8)	6 (6-8)	0.293
Tidal volume	475 (419-55)	457.5 (400-520)	479 (420-556)	0.045
Respiratory rate	18 (15-20)	18 (16-22)	18 (15-20)	0.035
pH	7.40 (0.066)	7.42 (0.067)	7.40 (0.065)	0.001
HCO_3	22 (19-26)	23 (20-27)	21 (19-26)	0.019
$PaCO_2$	36 (32-40)	35 (32-40)	36 (32-40)	0.699
Lactate	1.9 (1.4-2.4)	1.9 (1.5-2.4)	1.9 (1.4-2.4)	0.761
Venous saturation (n=515)ǂ	69 (63-74)	67 (64-73)	69 (63-74)	0.842
Systolic blood pressure	127 (114-142)	131 (118-140)	127 (113-142)	0.395
Diastolic blood pressure	70 (61-80)	72 (65-80)	70 (61-80)	0.215
Mean blood pressure	90 (80-101)	92 (84-103)	89 (79-101)	0.092
Heart rate	83 (75-96)	86 (77-96)	83 (74-96)	0.173
Vasopressors	243 (30.4%)	17 (23.9%)	226 (31.0%)	0.217
Inotropes	103 (12.9%)	8 (11.3%)	95 (13.0%)	0.672
Cuff-leak percentage (n=684)ǂ	64 (50-76)	63 (50-78)	64 (50-76)	0.848
Abundant secretions	50 (6.3%)	8 (11.3%)	42 (5.8%)	0.074
Effective cough	788 (98.5%)	67 (94.4%)	721 (98.9%)	0.016
Delirium	39 (4.9%)	5 (7.0%)	34 (4.7%)	0.381
NPPV after extubation	99 (12.4%)	18 (25.3%)	81 (11.1%)	0.001
Medical patient	310 (38.75)	42 (59.15%)	268 (36.76%)	<0.001

The data distribution was assessed by the Shapiro-Wilk test. All continuous variables were not normally distributed; therefore, the data are expressed as the medians (IQR: interquartile range) except for the pH variable, which is presented as the mean (SD: standard deviation). ǂ with a missing value. EF = extubation failure; APACHE II = Acute Physiology And Chronic Health Evaluation II; PaO_2 = partial pressure of oxygen; PaO_2/FiO_2 ratio = ratio of partial pressure of oxygen to fraction of inspired oxygen; a/A ratio = ratio of arterial oxygen partial pressure to alveolar oxygen partial pressure; A-a difference = difference between the alveolar oxygen partial pressure and arterial oxygen partial pressure; RSBI = rapid shallow breathing rate; PEEP = positive end-expiratory pressure; HCO_3 = bicarbonate; CO_2 = carbon dioxide; NPPV = noninvasive positive pressure ventilation

Sample size and statistical analysis

To ensure the stability of the derived model, we followed the recommendation of Peduzzi et al.[27,28] Ten events for each of the 12 candidate variables were considered in the study. According to previous reports, the incidence of EF is 6-20%.[10,13] We estimated an incidence of 15% (similar to the incidence reported by Thille et al.[11]). Sample size calculation results showed that at least 800 patients who underwent planned extubation needed to be enrolled in the study; we did not use split-sample validation as recommended by Steyerberg.[29]

Exclusion of missing values from the analysis during model development leads to biased effect estimations and decreases the discriminative ability of multivariable model.[22] If any variable had more than 5% missing data, the authors assumed that the missing data occurred at random depending on the clinical variables, and imputation of 10 values was applied using the multivariate normal regression method.

We developed a clinical prediction model with a multivariate logistic regression model using the purposeful selection approach described by Hosmer et al.,[30] which is more demanding for analysis but allows a clinician to derive and evaluate the final model rather than a statistical analysis program command. An evaluation of the presence of collinearity was performed. $\hat{\beta}$ coefficients were determined in the univariate (unadjusted) evaluation. For derivation of the first full multivariate model, we included any variable with a coefficient p-value <0.25.[30] The covariate with the largest p-value greater than 0.05 was eliminated to fit a new model. This process was repeated until the fit of the smaller reduced model was achieved. In step 3 of the selection strategy, any variable not selected from the original multivariable model was added back into the model if the variable had a confounding effect or was required to adjust the effects of the remaining covariates (the percent change for the coefficient or $\Delta\hat{\beta}$>20%). All interaction terms were evaluated in step 6 of the selection strategy. The diagnosis of the model was performed by evaluating influential data (Pearson's χ^2 test and deviance residuals) and measures of influence (determination of leverage and $\Delta\hat{\beta}$). No observation was eliminated after evaluating its biological plausibility. The model was evaluated using the Hosmer-Lemeshow ($\hat{C}$) goodness of fit and Pearson's χ^2 tests. Discriminative capacity was assessed using ROC curves (AUC). The optimal cut-off point and its corresponding Youden Index, sensitivity, specificity, positive and negative predictive value (VP+, VP-) were calculated. To adjust excessive and optimistic performance of the model, the model was validated by bootstrapping techniques (1000 repetitions). The advantages of bootstrap validation are known.[29] A shrinkage procedure was subsequently performed in order to get shrunk coefficients. Finally, the results are presented in two forms for clinical use (as a prediction formula to estimate the probability of EF and as a risk score), developed according to the methodology used in the Framingham studies.[31] The risk score resulted from the sum of the values of individual points. The risk was divided into four groups using multiples (0.5, 1 and 2 times) of the baseline risk.[32] All analyses were conducted using Stata/MP version 15 (Stata Corporation, College Station, Texas, USA).

Results

For 23 months, the required 800 patients were consecutively entered into the study. A total of 457 (57.1%) were male. The median age was 67 years (IQR: 57.5-75), with a minimum age of 18 years and a maximum age of 97 years. The demographic and clinical characteristics and the variables associated with EF at 48 hours are shown in *table 1*. Regarding disease type, 490 (61.2%) were surgical patients, and 310 (38.8%) were medical patients.

EF occurred in 71 (8.9%) patients. Of these patients, 61 (7.6%) required reintubation in the first 24 hours, and 10 additional patients (1.3%) required reintubation between 24 and 48 hours postextubation. Among the causes of EF, the most frequent was hypoxaemic respiratory failure in 25 patients (35.2%), followed by cardiac arrest in 10 patients (14.1%), and increased respiratory effort in 9 patients (12.7%). Other causes included mismanagement of secretions and altered state of consciousness in 8 patients (11.2%), stridor in 7 patients (9.9%), and surgical reoperation in 4 patients (5.6%).

EF increases mortality at 30 days from 15.1% to 49.3%. The longest stay in the ICU was 79 days, and the longest hospital stay was 185 days (*table 2*).

Table 2. Comparison of clinical outcomes with successful and failed extubation

Variable	Total cohort (n=800)	Failure (n=71)	Success (n=729)	*p-value*
ICU* stay (days)	6 (4-11)	16 (9-23)	6 (4-10)	<0.001
Hospital stay (days)	21.5 (14-32)	32 (20-50)	21 (14-31)	<0.001
ICU mortality (%)	90 (11.2%)	27 (38.0%)	63 (8.6%)	<0.001
Hospital mortality (%)	51 (6.4%)	8 (11.3%)	43 (5.9%)	0.119
Mortality at 30 days (%)	145 (18.1%)	35 (49.3%)	110 (15.1%)	<0.001

Table 3. Unadjusted associations between each predictor and outcome

Variable	OR	95% CI		*p-value*
Oxygenation index	1.082	0.9198139	1.273291	0.341
RSBI	1.024	1.007753	1.040734	0.004
Respiratory rate	1.067	1.009206	1.128748	0.023
Tidal volume	0.998	0.9955969	1.000084	0.059
pH	1.004	1.001797	1.006463	0.001
PaCO2	0.996	0.9618885	1.032122	0.840
HCO3	1.042	0.9974174	1.087519	0.065
Abundant secretions	2.077	0.9343439	4.617501	0.073
Effective cough	0.186	0.0545381	0.6333413	0.007
Probability of death	1.022	1.011052	1.033779	<0.001
Medical patient	2.491	1.516193	4.093365	<0.001
NPPV after extubation	2.717	1.51751	4.864538	0.001

RSBI = rapid shallow respiration index; HCO_3 = bicarbonate; CO_2 = carbon dioxide; NPPV = noninvasive positive pressure ventilation

Table 4. Coefficients of the final model and after internal validation by the bootstrapping method

	Final model (n = 797)			Bootstrapping (1000 repetitions)		
Variable	**Coefficient**	**95% CI**		**Coefficient**	**95% CI**	
EXP(pH)	0.0026	0.0001	0.0052	0.0026	0.0000	0.0053
RSBI	0.0206	0.0037	0.0375	0.0207	0.0021	0.0392
Effective cough	-1.5018	-2.7699	-0.2338	-1.5019	-2.9147	-0.0890
Probability of death	0.0130	-0.00083	0.0263	0.0130	0.0006	0.0254
Medical patient	0.4568	-0.1159	1.0296	0.4568	-0.1655	1.0792

RSBI = rapid shallow breathing index

The RSBI was significantly different between the extubation failure and successful extubation groups. Discriminative capacity not adjusted for the other variables was 0.5766 (*figure 1*).

Univariate analysis

Of the 12 variables evaluated, $PaCO_2$, oxygenation index, abundant secretions, HCO_3, and tidal volume did not show a significant association with EF (*table 3*). The variable with the highest unadjusted odds ratio (OR) was medical patient. The variable oxygenation index had missing values for 134 patients (16.7%). Imputation of values was performed using lactate and PEEP as auxiliary variables in addition to the already established variables. However, the imputed values did not improve the significance of the variables (p=0.341 to 0.446).

When evaluating the correlation of continuous variables, there was a strong correlation between HCO_3 variable and pH and $PaCO_2$ (0.5978 and 0.6698, respectively) and a strong correlation between RSBI and the variables respiratory rate and tidal volume (0.5464 and -0.5636, respectively), which are plausible due to their biological interrelation in the former and the mathematical relationship in the latter.

Multivariate analysis

During the first step of the intentional selection strategy, the first multivariable prediction model was generated without including the $PaCO_2$ and oxygenation index variables (p>0.25). Subsequently, the variables tidal volume (p=0.715), respiratory rate (p=0.475), HCO_3 (p=0.157), medical patient (p=0.164), abundant secretions (p=0.103) and NPPV use after extubation were consecutively eliminated (p=0.060). At the end of this stage, the first reduced multivariable model was obtained with the variables pH, effective cough, RSBI and probability of death. Despite not being significant, the variable medical patient was re-entered after determining that it fit the probability of death variable (presenting an increased $\Delta\hat{\beta}$ % value of 31.1%). The assumption of linearity was evaluated according to the logit, and the significance of interaction variables was determined without additional changes to the model. Finally, the adjusted multivariate logistic model obtained by the intentional selection strategy included the variables RSBI, Exponential(EXP) (pH), effective cough, the probability of death and medical patient.

The diagnosis of the model was performed by reviewing poorly adjusted or more influential co-variable patterns. No co-variable

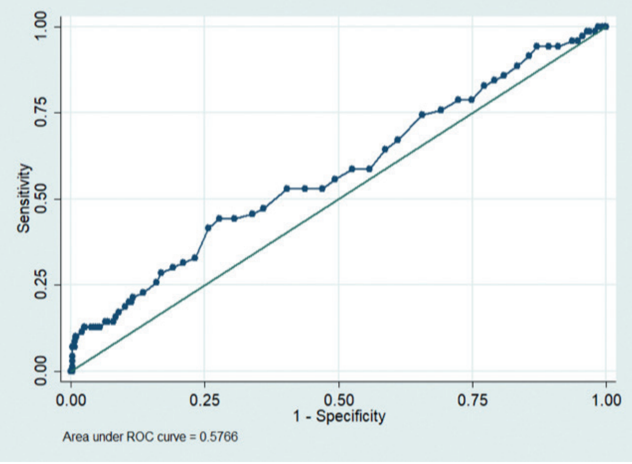

Figure 1. ROC curve of the Rapid Shallow Breathing Index

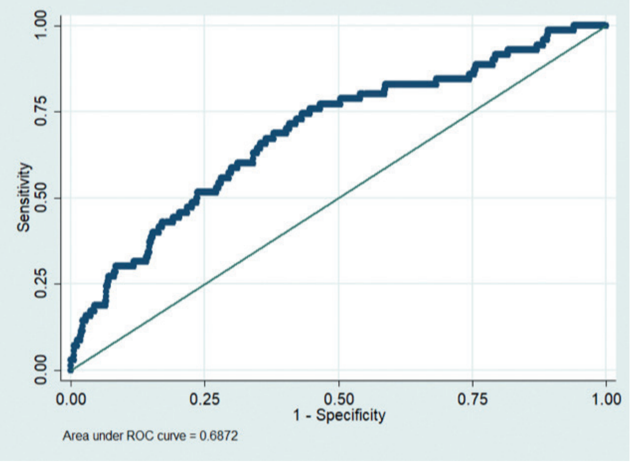

Figure 2. ROC curve of the prediction model

pattern was eliminated, and at the end of the diagnostic process, the model was kept without modifications. With respect to the Hosmer-Lemeshow ($\hat{C}$) and Pearson's χ^2 goodness of fit tests, they were not significant (p 0.465 and 0.296, respectively), which means that the model is well calibrated. The evaluation of the discriminative capacity of the multivariate model revealed an AUC of 0.687. The optimal cut-off point 0.0879 and Youden Index: 30.7, sensitivity: 67.1 (95% CI 55.5 to 77.0), specificity: 63.5% (95% CI 60.0 to 67.0), PV+: 15.1, and PV-: 95.3) (*figure 2*). Internal validation was performed with the bootstrapping method. Coefficients similar to those obtained by the initial model were obtained (*table 4*). Finally, the average area under the ROC curve obtained when performing 1000 samples was 0.695 (SD: 0.034).

The shrunk coefficient is the product of the bootstrapping coefficient multiplied by a shrinkage factor (0.8478). Shrunk coefficients were used to generate the regression formula (Equation 1) for EF prediction as follows:

Equation 1

Probability of EF = 1/[1+EXP –(-6.6 + RSBI*0.0175 + EXP (pH)*0.0022 -1.2733(if cough is effective) + probability of death*0.0110 + 0.3873(if the patient is a medical patient)]

The prediction score for EF is shown in *table 5*. A factor to determine the regression units was the increase in probability of death every 10% (0.110), to which 1 point was assigned for the risk scale. The authors called this scale the ABCDMed score, which corresponds to a letter of each variable used in the prediction model as follows: A: acid-base status, B: rapid shallow breathing index, C: effective cough, D: probability of death, Med: medical patient. *Figure 3* shows the probability of EF vs. prediction score, showing a direct relationship between the two.

Finally, patients were divided into four risk groups using multiples of baseline risk.[31] The base probability for EF was 8.9%. The risk sheet divided patients into four groups, as

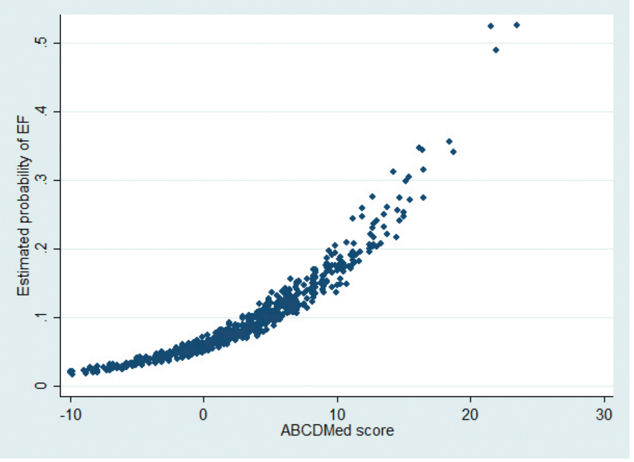

Figure 3. Direct relationship between the probability of extubation failure and the ABCDMed score

follows: 1. low risk: <0.5 times the baseline risk; 2. moderate risk: 0.5 to <1 times the baseline risk; 3. high risk: 1 to 2 times the baseline risk; and 4. very high risk: > 2 times the baseline risk. The observed incidence rates of EF in patients with low, moderate, high and very high risk were 4.1%, 8.1%, 11.5% and 22.7%, respectively (*table 6*).

Discussion

This study is the largest prospective cohort performed to evaluate the outcomes of patients with planned extubation. The EF rate was 8.9%, thus generally lower than the reports in the literature,[10,11,33,34] with the exception of two studies, the cohort published by Lai et al.,[13] who reported an EF rate of 6.1% but with longer MV times than previous reports,[35,36] and a Dutch cohort studied by IJzendoorn et al.,[37] where 2.4% of reintubation was found after unplanned extubation. Both studies suggest that a delay in extubation may be responsible for the low EF rate.

Table 5. ABCDMed score for extubation failure

Variable	Category	Score
Acid/base status (pH)	7.20/7.250	0*
	7.8%	8.1%
	7.251/7.30	1.7
	7.301/7.35	3.5
	7.351/7.40	5.4
	7.401/7.45	7.4
	7.451/7.50	9.5
	7.511/7.55	11.7
	7.551/7.60	14
Rapid Shallow **B**reathing Index	≤19	0
	20/29	1.5
	30/39	3
	40/49	4.5
	50/59	6.25
	60/69	8
	70/79	9.5
	80/89	11
	90/99	12.75
	≥100	14.25
Effective **c**ough	Yes	- 11.5
Probability of **d**eath (%) (APACHE II/Euroscore II)	≤10	0
	10.1/20	1
	20.1/30	2.25
	30.1/40	3.25
	40.1/50	4.5
	50.1/60	5.5
	60.1/70	6.5
	70.1/80	7.75
	>80.1	8.75
Medical patient	Yes	3.5

*Do not continue weaning until evaluation of the cause of acidosis and correction

In the univariate evaluation, a low PaO_2 and O_2 saturation, a high RSBI, a low tidal volume, a high respiratory rate, an abnormal pH, elevated HCO_3, the absence of effective cough, and the use of NPPV after extubation were found to be significantly associated with EF. The most common cause of EF in this cohort was hypoxaemia, and postextubation stridor was present in 10% of the reintubated patients.

The RSBI developed by Yang and Tobin in 1991[18] is commonly used as a predictor of EF, with a cut-off point of 105 breaths per minute / litre (bpm /l) during SBT. Smina et al.[38] reported RSBI values of 88 vs. 66 bpm/l in patients with failed or successful extubation, respectively. In our cohort, the RSBI was higher in patients with EF compared with patients with successful extubation, 40 vs. 36 bpm /l, p<0.034, which is consistent with previous literature reports,[21,38,39] however with values lower than those reported in the original study by Yang and Tobin.[18,33] We believe that this finding is a consequence of the quantification of this index in an SBT with PEEP and pressure support (PS). In the Yang and Tobin study the candidates for ventilatory weaning were disconnected from the mechanical ventilator and SBT was performed in a T-tube. Using a spirometer, the RSBI was calculated. A value around 100 had good sensitivity (97%) and specificity (64%) to predict successful extubation.[18,40] El-Khatib et al.[41] calculated the RSBI under various ventilatory support settings: pressure support ventilation (PSV) (PS of 5 cmH_2O, PEEP of 5 cmH_2O), CPAP (PS of 0 cmH_2O, PEEP of 5 cmH_2O), and T-tube. The index was significantly lower during PS (46±8 bpm/l) and CPAP (63±13 bpm/l) vs. T-tube (100±23 bpm/l). Similar findings have been reported by different authors.[42-44] This is explained because the use of PS leads to a higher tidal volume and this reduces the value of the RSBI. In our study, the RSBI was even lower than those previously mentioned, probably because our institutional protocol uses PEEP of 6 cmH_2O and PS between 6 and 8 cmH_2O during SBT.

In the univariate analysis, the following variables were associated with EF: RSBI, respiratory rate, pH, absence of effective cough, probability of death, being a medical patient and use of NPPV postextubation. Lai et al. found a significant OR for the RSBI and APACHE II;[13] however, comparison with the adjusted OR reported in the Lai study is not possible because our study is a prediction model and not an association model.

A prediction model was developed with five defined variables (pH, effective cough, RSBI, probability of death and medical patient). The evaluation of the discriminative capacity of the multivariate model determined an area under the ROC curve of 0.687, a value similar to previous models.[10] However, this is the first study to develop a prediction score that is easily applicable in clinical practice and allows the stratification of patients scheduled for extubation into four risk categories, showing a correlation between the proposed score and the probability of reintubation. In the variables evaluated in the model, pH values <7.25 do not increase the risk of EF. This is explained by the fact that patients with EF had a median pH of 7.43 (IQR 7.38-7.48) with a minimum value of 7.21 and those with successful extubation had a median pH 7.40 (IQR 7.35-7.44) with a minimum value of 7.26, concluding that in this work patients with severe acidosis (pH <7.25) were not considered candidates for programmed extubation. Also the HCO_3 levels were higher in patients with EF, 23 (IQR 20-27) vs. 21 (IQR 19-26) in those with successful extubation, findings consistent with the fact that metabolic alkalosis may interfere with successful extubation.[45,46]

Table 6. ABCDMed score classification and estimated and observed probabilities of extubation failure

ABCDMed score	Estimated mean Probability	Observed probability	Risk group	Patients in the scoring category
≤ 0	4.1%	4.1%	Low <5%	337 (42.3%)
0.1 – 4.5	7.8%	8.1%	Moderate 5% a 10%	198 (24.8%)
4.6 – 9	12.3%	11.5%	High 10% a 15%	174(21.8%)
>9.1	22.0%	22.7%	Very high >15%	88 (11.1%)

This study has several limitations. It was conducted in a single centre, and the population under study, management patterns and level of staff training cannot be generalised to other institutions. Although there is an institutional extubation protocol, this decision is still largely made by the attending physician, which can sometimes delay extubation. As study strengths, the information was collected prospectively over a period of approximately two years with a significant sample size, which provides useful and representative information for institutions with characteristics similar to ours. We estimated an incidence of 15% according to previous reports;[10,13] however, the observed incidence was 8.9%. Therefore, the required sample size may be larger. We did not conduct a corresponding sensitivity study. Evaluating this risk score in other institutions is recommended.

Conclusions

EF is an important clinical problem and its presence is associated with poor clinical outcomes. The ABCDMed prediction score is proposed to estimate the risk of EF in an objective manner based on five variables available at the bedside of the patient. These risk prediction models serve as accurate but simple tools that can be used to stratify patients into EF risk groups and guide ICU healthcare professionals during further management. It is recommended to advance extubation in patients in low and moderate risk groups and avoid extubation in patients in high and very high-risk groups; however, clinical judgment and individual characteristics must accompany this decision.

Future studies are required for an external validation of the model and to evaluate whether additional variables such as fluid balance and diaphragmatic function can improve the performance of the model.

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Disclosures

The datasets used and analysed during the current study are available from the corresponding author on reasonable request. The authors declare no conflicts of interest. The resources used for this study were granted by the research department of Mayor Méderi University Hospital.

Dataset

https://www.njcc.nl/sites/nvic.nl/files/njcc/ABCDMed.xlsx

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