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Clinical paper

Development and validation of early prediction for neurological outcome at 90 days after return of spontaneous circulation in out-of-hospital cardiac arrest

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Abstract

Aim: To develop and validate a model for the early prediction of long-term neurological outcome in patients with non-traumatic out-of-hospital cardiac arrest (OHCA).

Methods: We analysed multicentre OHCA registry data of adult patients with non-traumatic OHCA who experienced return of spontaneous circulation (ROSC) and had been admitted to the intensive care unit between 2013 and 2017. We allocated 1329 (2013–2015) and 1025 patients (2016–2017) to the derivation and validation sets, respectively. The primary outcome was the dichotomized cerebral performance category (CPC) at 90 days, defined as good (CPC 1–2) or poor (CPC 3–5). We developed 2 models: model 1 included variables without laboratory data, and model 2 included variables with laboratory data available immediately after ROSC. Logistic regression with least absolute shrinkage and selection operator regularization was employed for model development. Measures of discrimination, accuracy, and calibration (C-statistics, Brier score, calibration plot, and net benefit) were assessed in the validation set.

Results: The C-statistic (95% confidence intervals) of models 1 and 2 in the validation set was 0.947 (0.930–0.964) and 0.950 (0.934–0.966), respectively. The Brier score of models 1 and 2 in the validation set was 0.0622 and 0.0606, respectively. The calibration plot showed that both models were well-calibrated to the observed outcome. Decision curve analysis indicated that model 2 was similar to model 1.

Conclusion: The prediction tool containing detailed in-hospital information showed good performance for predicting neurological outcome at 90 days immediately after ROSC in patients with OHCA.

Keywords: Out-of-hospital cardiac arrest, Prognostication, Prediction, Cerebral performance category, Least absolute shrinkage and selection operator

Introduction

Out-of-hospital cardiac arrest (OHCA) represents a serious public health concern worldwide.[1,2] The importance of in-hospital post-resuscitation after the return of spontaneous circulation (ROSC) was recently highlighted to improve patient outcomes after OHCA.[3,4] However, in-hospital treatment after ROSC requires considerable medical/human resources, especially during the initial critical phase. The neurological outcome remains poor after OHCA, even in patients with successful ROSC, despite improvements in advanced life-support measures and efforts to improve the quality of post-resuscitation care.[5–7] Accurate assessment and identification of patients who are likely to survive with favourable neurological outcomes after rapidly undergoing advanced time-sensitive interventions for post-cardiac syndrome (PCAS) are vital but complex and challenging for clinicians.

Various prediction models have been suggested for patients who achieved ROSC after OHCA.[8–11] However, few models have been rigorously validated, and their discrimination ability in external validation was not high.[12] The utility of previous models for predicting an individual's long-term neurological outcome after OHCA has not been evaluated.

Although machine learning models have been developed recently to predict outcomes of OHCA,[13–16] most cannot be used to determine whether critical interventions should be performed or not in patients after ROSC because they include patient populations with poor prognoses, such as patients without ROSC or those with traumatic OHCA. Furthermore, these models did not utilise detailed in-hospital information available immediately after ROSC as predictors. An accurate predictive model that can estimate the outcome after OHCA in the early stage of resuscitation based on objective parameters available at the bedside will greatly aid physicians with the clinical decision-making process.

The least absolute shrinkage and selection operator (lasso) penalisation is one regularization method to prevent over-fitting and improve the prediction accuracy of the final model.[17,18] The two most popular regularization techniques are ridge regression and lasso regression. Unlike ridge regression, lasso can effectively reduce predictors in the model. We applied lasso regression to a large-scale Japanese prospective OHCA registry. We aimed to develop and validate a prediction model for adult patients with OHCA that could be used to predict neurological outcomes immediately after achieving ROSC using information available at the patient's bedside.

Methods

This study complied with the Transparent Reporting of a Multivariable Prediction Model for Individual Prognosis or Diagnosis statement for reporting methods and results.[19] The ethics committee of Kyoto University approved this study, which waived the need for informed consent because its retrospective nature posed minimal risk to the patients (Approval ID: R1045).

Study design and source of data

This study was a secondary analysis of data contained within the Comprehensive Registry of In-Hospital Intensive Care for OHCA Survival (CRITICAL) study, a multicentre prospective repository of pre-hospitalisation and in-hospital data concerning OHCA treatments, whose details have been reported and described previously (Supplementary Appendix 1).[20]

Study population

This study included adult patients aged $\geq$ 18 years with OHCA who achieved ROSC and had been admitted to the intensive care unit (ICU) during the study period from January 1, 2013 to December 31, 2017. We defined ROSC as continuous palpable circulation with a self-beat for > 30 s.[21] The exclusion criteria comprised the following: patients with traumatic cardiac arrest; patients whose first documented rhythm was unknown, patients whose collapses were witnessed by emergency medical services (EMS) personnel, patients with OHCA for whom cardiopulmonary resuscitation was not performed by the physician upon hospital arrival, and patients lacking prehospital data. The data of patients admitted during the initial 3 years (2013–2015) were used for model development (derivation set), and data on those admitted during the following 2 years (2016–2017) were used for model validation (validation set). The validation set was not involved in the development of this model.

Outcomes

The primary outcome of this study was the neurological outcome at 90 days. The physician responsible for treating the patient evaluated the neurological outcome using the cerebral performance category (CPC) scale (category 1, good cerebral performance; category 2, moderate cerebral disability; category 3, severe cerebral disability; category 4, coma or vegetative state; category 5, death/brain death).[22] CPC 1–2 denoted a good outcome and CPC 3–5 denoted a poor outcome.

Predictors of outcome

Potential variables included in the CRITICAL database that were measurable and available immediately after ROSC were included as candidate predictors, based on previous studies and expert opinion.[23–39] We developed two prediction models using different sets of variables: model 1 included demographics, pre-hospitalisation and in-hospital information at the time of ROSC, except for laboratory data, and model 2 included all variables that contained the laboratory data available within 3 h of ROSC. The best level of consciousness to ICU admission was determined using the Glasgow Coma Scale motor score. All candidate variables were chosen from among the parameters obtained in the hours after ROSC (Supplementary Table 1).

Data processing

The no-flow time could not be calculated in patients with unwitnessed OHCA because the time of collapse was unavailable. Thus, we merged the no-flow time and unwitnessed patients into one categorical variable. The categories were divided into no-flow time (mins; 0–4, 5–9, 10–) and unwitnessed patients. A linear relationship with the outcome was found to be a good approximation for the continuous predictors, except for low-flow time, after the assessment of nonlinearity using restricted cubic splines.[40] Since the low-flow time was log-transformed and exhibited a linear relationship with the outcome, the log-transformed value was treated as a continuous variable. Continuous variables were standardised, and the categorical variables were transformed into dummy variables.

Sample size calculation

Overall, 1317 participants were needed to determine the expected R-squared value of 0.15 with an estimated prevalence of 15% for a good outcome using the 24 potential predictor parameters, as per Riley et al.'s criteria.[41] Thus, a sample size of 1329 patients with OHCA was sufficient to develop the models of interest.

Missing values

We used nonparametric missing value imputation based on the "missForest" algorithm with the random forest method.[42] A random forest can generate single point estimates accurately, using bootstrap aggregation of multiple regression trees to reduce the risk of overfitting and combines the estimates from several trees. Its performance is superior to other methods.[43,44] The main outcome values (i.e., CPC at 90 days) were missing for 109 (4.6%) patients due to loss to follow-up, whereas CPC at 30 days was available for these patients. Therefore, we imputed the missing 90-day CPC data in 109 patients predictively with the 30-day CPC and all the predictors using missForest, so as not to compromise the prediction of our outcome measure.[45] The missing predictors were also imputed using all the predictors (including time of sampling and laboratory data after 3 hours of ROSC) and outcomes.

Statistical analysis

Statistical analysis was used for the demographic findings and outcomes. Continuous variables were presented as the median with upper and lower quartiles (interquartile range [IQR]). Categorical variables were presented as numbers and percentages.

All statistical analyses were conducted using R (The R Foundation for Statistical Computing, version 4.0.3).[46] The level of significance was set at a two-sided P-value < 0.05.

Model development and internal validation

The model development strategy to predict the binary outcome entailed logistic regression with lasso. Lasso regression adds the L1 norm of coefficients as the penalty term to the loss function, thus adding constraints to the coefficients, which effectively selects important predictors and helps reduce the dimensions of the prediction model, thereby minimizing the potential overfitting.[17,18,47] Lasso regularization calculates the optimal regularization parameter (lambda) that computes the minimal misclassification error rate to penalise large coefficients resulting from small sample sizes. Herein, we used 10-fold cross-validation to find lambda using R package's 'glmnet.'[47,48] Furthermore, the internal validity of the constructed model was assessed using bootstrapping analysis (resampling the model 1000 times). We evaluated the confidence intervals (CIs) of the prediction accuracy measures for the prediction models based on the optimism correction methods (i.e., Harrell's bootstrapping bias correction) that were used to compute the 95% CI for the C-statistic of the model in the derivation set using R package's 'preboot.'[49]

Assessment of model performance

External validation was performed through applying the constructed model to the validation set to assess the predictive performance. C-statistics with the 95% CI were used for the assessment of the discriminatory ability. Additionally, we calculated a Brier score for each model to measure model accuracy.[50] This score was defined as the average squared difference between predicted probabilities and observed outcomes, with lower values indicating greater predictive accuracy. Furthermore, the calibration was investigated with a calibration plot through plotting the predicted probability and observed frequency of poor outcome across vigintiles (the values that divide the distribution into twenty groups of equal frequency) of the predicted risk in the validation set.[51] Moreover, we calculated the net-benefit values and depicted the decision curves.[52] Decision curve analysis is a plot of the "net-benefit" against "threshold probabilities", assessing the clinical usefulness of different models at appropriate thresholds for clinical use. Subsequently, we compared the performance of our model with models 1 and 2 using DeLong et al.'s method for calculating the differences in the C-statistics.[53]

Results

Patient characteristics

A total of 11,924 patients with OHCA were registered during the study period. Finally, 2,354 patients admitted to the ICU were included in our analyses, and data imputation was performed for the missing values. Fig. 1 depicts the study's flow diagram. The derivation and validation sets included 1329 and 1025 eligible patients, respectively (median age, 72 and 73 years; men, 887 (66.7%) and 681 (66.4%), respectively). The aetiology of cardiac arrest was cardiogenic [derivation set, 755 (56.8%); validation set,

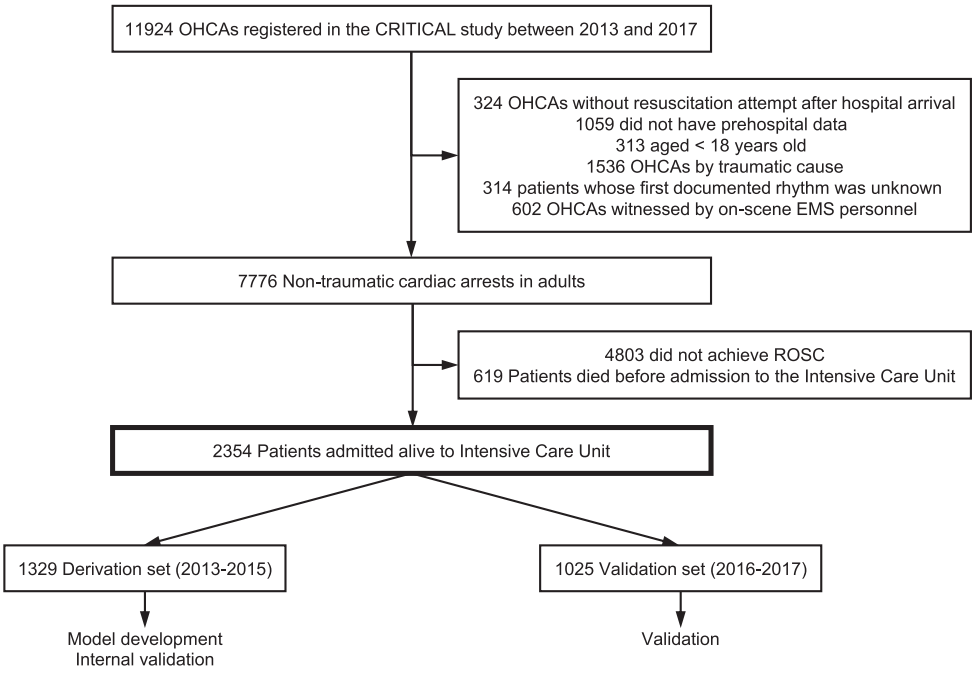

Fig. 1 – Study flowchart. OHCA indicates out-of-hospital cardiac arrest; EMS, emergency medical services; ROSC, return of spontaneous circulation; and CPC, cerebral performance category.

588 (57.4%)] in > 50% of the patients and their collapse was witnessed by a bystander [derivation set, 888 (63.3%); validation set, 681 (66.1%)]. The percentage of patients who were dead or alive at day 90 with an unfavourable neurological outcome was 83.1% (1105) in the derivation set and 84.5% (867) in the validation set. The characteristics of patients in both data sets and patients with missing variables are presented in Table 1 and Supplementary Table 2, respectively.

Predictor selection, model development, and internal validation

In models 1 and 2, 12 predictor variables (17 parameters) and 19 predictor variables (24 parameters) were entered into the variable selection process, respectively. After lasso regression selection with the optimal lambda (Supplementary Fig. 1), 10 predictor variables (12 parameters) for model 1 and 15 predictor variables (17 parameters) for model 2 retained their significance as predictors of poor outcome (Table 2). The C-statistic (95% CI) in the derivation set was 0.946 (0.933–0.960) in model 1 and 0.957 (0.945–0.969) in model 2. The bias-corrected C statistic (95% CI) (Harrell's bias correction) obtained using bootstrapping was 0.939 (0.930–0.955) and 0.950 (0.942–0.965) in models 1 and 2, respectively. The coefficients acquired via the lasso regression can be used to calculate a patient's risk score through multiplying the patient's values by the coefficients and summing the products. The risk score can then be translated to a predicted probability of a poor outcome with the following formula: Prob = exp (score)/(1 + exp [score]). A simple calculator to calculate the risk probabilities for specific patients can be accessed here: https://pcas-prediction.shinyapps.io/pcas_lasso_90d/

Model performance

For discrimination, the C-statistic (95% CI) of model 1 in the validation set was 0.947 (0.930–0.964, Fig. 2). No significant difference was observed between the C-statistic (95% CI) of model 2 and that of model 1 (0.950 [0.934–0.966]; DeLong test: p = 0.344). The average Brier score of models 1 and 2 in the validation set was 0.0622 and 0.0606, respectively. For the visual assessment of the calibration plot (Fig. 3) and the detailed values (predicted probability and observed frequency) by risk vigintile (Supplementary Table 3) in the validation set, both models were well-calibrated to the observed overall range of the predicted poor outcome, although both models partially overestimated the low range of the predicted outcome. The prognostic accuracies of our model in the validation set are shown in Supplementary Tables 4 and 5. The decision curve analysis illustrated in Fig. 4 indicated that the net benefit of model 2 was equal to that of model 1 for most of the threshold probabilities in the validation set.

Discussion

We developed and validated a tool for predicting the long-term neurological outcome of adult patients with non-traumatic cardiac arrest at an early stage after ROSC using data from a large-scale Japanese prospective OHCA registry. The lasso regression model, based on the predictors available during ROSC, showed excellent ability for predicting outcomes during internal validation training and performance on the validation set. Model 2 with laboratory data available immediately after ROSC performed similarly to the model performance of model 1 including no-flow time instead of laboratory data. The web-based application can be used by clinicians to estimate an individual's neurological outcome.

This study has some strengths over previous studies. First, we considered the neurological outcome at 90 days as the longer-term outcome by recent guidelines that recommend reassessment ≥ 3 months after the event.[3,54,55] Most prediction

Table 1 – Patient characteristics.

	Deriviation set		Validation set	
	Favorable outcome at 90 days (n = 224)	Unfavorable outcome at 90 days (n = 1105)	Favorable outcome at 90 days (n = 158)	Unfavorable outcome at 90 days (n = 867)
Patient information				
Age, median [IQR]	62 [49, 71]	73 [64, 82]	61 [50, 72]	74 [65, 83]
Sex, male, n (%)	182 (81.2)	705 (63.8)	118 (74.7)	563 (64.9)
Cardiac etiology of arrest, n (%)	200 (89.3)	555 (50.2)	143 (90.5)	445 (51.3)
Initial rhythm at the scene, n (%)				
VF /pVT	178 (79.5)	216 (19.5)	117 (74.1)	159 (18.3)
PEA	32 (14.3)	425 (38.5)	32 (20.3)	311 (35.9)
Asystole	14 (6.2)	464 (42.0)	9 (5.7)	396 (45.7)
Bystander CPR, n (%)	106 (47.3)	426 (38.6)	94 (59.5)	421 (48.6)
Bystander automated electrical defibrillation use, n (%)	8 (3.6)	15 (1.4)	26 (16.5)	13 (1.5)
Shock during cardiac arrest, n (%)	185 (82.6)	311 (28.1)	122 (77.2)	227 (26.2)
Administration of adrenaline during cardiac arrest, n (%)	67 (29.9)	963 (87.1)	60 (38.0)	780 (90.0)
Advanced airway management during cardiac arrest, n (%)	183 (81.7)	956 (86.5)	126 (79.7)	750 (86.5)
Initial rhythm on hospital arrival, n (%)				
VF/pVT	51 (22.8)	84 (7.6)	40 (25.3)	70 (8.1)
PEA	12 (5.4)	340 (30.8)	12 (7.6)	281 (32.4)
Asystole	5 (2.2)	454 (41.1)	5 (3.2)	345 (39.8)
ROSC	156 (69.6)	227 (20.5)	100 (63.3)	169 (19.5)
Glasgow Coma Scale motor score < 2, n (%)	171 (76.3)	1083 (98.0)	127 (80.4)	843 (97.2)
No witnessed arrest, n (%)	50 (22.3)	391 (35.4)	26 (16.5)	318 (36.7)
No flow time (Collapse - CPR)[a], min (median [IQR])	5 [2,6]	6 [3,8]	4 [1,7]	6 [3,8]
0–4 min	91 (40.6)	285 (25.8)	69 (43.7)	222 (25.6)
5–9 min	62 (27.7)	251 (22.7)	46 (29.1)	160 (18.5)
10- min	21 (9.4)	178 (16.1)	17 (10.8)	167 (19.3)
Low flow time, min (median [IQR])	12 [7,20]	32 [22,42]	13 [9,24]	33 [22,45]
Extracorporeal membrane oxygenation, n (%)	37 (16.5)	135 (12.2)	29 (18.4)	127 (14.6)
Coronary angiography, n (%)	167 (74.6)	221 (20.0)	113 (71.5)	181 (20.9)
Percutaneous coronary intervention, n (%)	74 (33.0)	102 (9.2)	56 (35.4)	87 (10.0)
Target temperature management, n (%)	142 (63.4)	240 (21.7)	94 (59.5)	150 (17.3)
Laboratory data				
Albumin, g/dL (median [IQR])	3.7 [3.3, 4.0]	3.0 [2.7, 3.4]	3.7 [3.3, 4.0]	3.0 [2.6, 3.3]
Creatinine, mg/dL (median [IQR])	1.07 [0.90, 1.20]	1.10 [0.90, 1.58]	1.06 [0.90, 1.20]	1.12 [0.88, 1.47]
Potassium, mEq/L (median [IQR])	3.8 [3.4, 4.3]	4.7 [3.9, 5.8]	3.70 [3.3, 4.3]	4.6 [3.9, 5.6]
Glucose, mg/dL (median [IQR])	227 [174, 300]	251 [174, 326]	250 [202, 298]	260 [184, 327]
pH (median [IQR])	7.27 [7.17, 7.33]	6.99 [6.87, 7.15]	7.24 [7.11, 7.32]	6.98 [6.86, 7.13]
pCO_2, mmHg (median [IQR])	41.2 [33.7, 48.6]	64.5 [46.7, 86.1]	39.9 [32.8, 48.7]	64.2 [46.9, 84.4]
Lactate, mEq/L (median [IQR])	7.5 [4.8, 9.9]	12.2 [9.0, 15.3]	8.4 [6.4, 11.6]	12.1 [9.4, 15.1]

All variables are shown with their values after imputation.

IQR, Interquartile range; VF, ventricular fibrillation; pVT, pulseless ventricular tachycardia; PEA, pulseless electrical activity; ROSC, return of spontaneous circulation;

CPR, cardiopulmonary resuscitation; EMS, emergency medical services.

[a] No flow time was obtained only for patients with witnessed OHCA.

models for OHCA present little information regarding the long-term neurological outcome. The ultimate goal of resuscitation after OHCA should be neurologically intact survival and further neurological recovery can occur after hospital discharge. Moreover, the CRITICAL repository covers most (15 of 16) critical care centres with excellent EMS in Osaka Prefecture, Japan, where emergency medicine and critical care are well developed and termination of resuscitation is rare, and preferential treatment is provided by physicians and EMS personnel for a long duration for most OHCA cases.[7,20] Goldberger et al. reported that efforts to increase the duration of resuscitation could improve survival in some populations,[56] but the duration of resuscitation was generally too short to improve survival. This model that predicts long-term neurological prognosis could provide valuable information for devising best practices to improve outcomes after OHCA.

Second, we applied lasso regression strategies to the prediction process. Most previous models have used conventional logistic regression,[8,9,11] reducing the number of predictive steps; such as stepwise selection or univariable screening, which is problematic due to the instability of selection and biased estimation.[47,56] Lasso regression can eliminate predictors through shrinking their coefficients and alleviate the problem of model overfitting.[18,47] An overfitted model typically overestimates the probability of an event in high-risk patients.[47] Overestimation of poor neurological prognosis of OHCA could lead to inappropriate withdrawal of life-sustaining therapies (WLST), which must be avoided in patients with a chance of recovery. In our prediction model, overestimation at the high predicted poor outcome was rarely observed in the validation set. Although our model alone cannot determine WLST, it may be one more tool available to reduce inappropriate WLST in the early stage. Guidelines recommend delaying neurological prognostication after cardiac arrest for several days following ROSC.[3,54,57] Complementary prognostic information collected over time; such as the cause of cardiac arrest, neurological findings, and imaging studies, should be added to our application to provide a basis for WLST.

Third, we suggested the importance of detailed in-hospital information, including initial rhythm on hospital arrival, to identify rhythm conversion, and laboratory data at the point of ROSC as predictors. Despite the early timing, the discriminatory ability of our model was excellent. Previous machine learning techniques for OHCA included information about treatment (i.e., extracorporeal membrane oxygenation, target temperature management, and percutaneous coro-

Table 2 – LASSO regression coefficients for poor neurological outcome at 90 days.

Variables		Model1	Model2
(Intercept)		−5.2892	11.0535
Age		0.0421	0.0419
Male		0	0
Initial rhythm at the scene (Reference: VF/pVT)			
	PEA	0.6420	0.2733
	Asystole	0.7653	0.3780
Bystander CPR		−0.0478	−0.1027
Bystander automated electrical defibrillation use		0	0
Shock during cardiac arrest		−1.2712	−1.1993
Administration of adrenaline during cardiac arrest		1.4157	1.1486
Advanced airway management during cardiac arrest		0.5051	0.6124
In-hospital first documented cardiac rhythm (Reference: VF/pVT)			
	PEA	1.0990	1.0801
	Asystole	1.7880	1.3109
	ROSC	0	0
Glasgow Coma Scale motor score < 2 (Reference: score ≥ 2)		1.1884	0.8253
Witness / No flow time (Reference: No flow time < 5 min)			
	5–9 min	0	0
	≥10 min	0.1727	0
	No witness	0	0
Low flow time (Log-transformed)		0.5450	0.4319
Albumin		-	−0.8320
Creatinine		-	0
Potassium		-	0.0723
Glucose		-	0.0005
pH		-	−1.8962
pCO_2		-	0.0059
Lactate		-	0.0241

VF, ventricular fibrillation; pVT, pulseless ventricular tachycardia; PEA, pulseless electrical activity; CPR, cardiopulmonary resuscitation; EMS, emergency medical services; ROSC, return of spontaneous circulation.

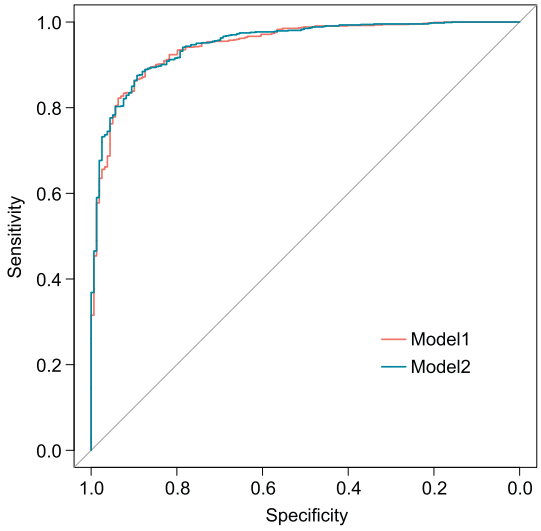

Fig. 2 – Receiver operating characteristic curves in validation set.

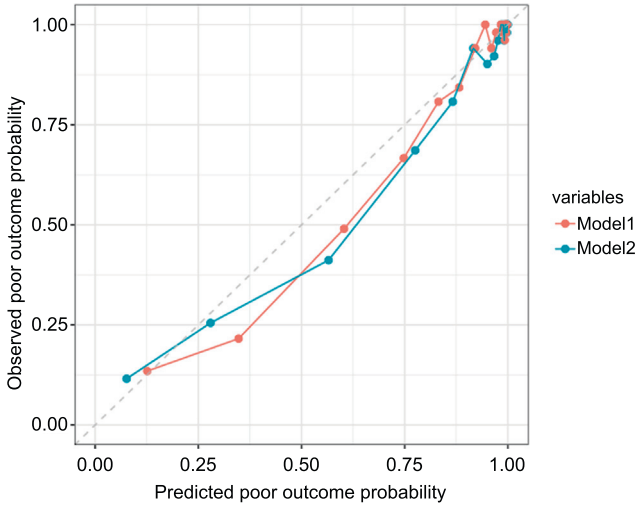

Fig. 3 – Calibration plot of the predicted probability (vigintiles) versus the observed frequency in validation set. The x-axis and the y-axis represents predicted probability, and observed frequency in validation cohort, respectively.

nary intervention) for PCAS,[15] but these variables cannot be included in a model intended to assist decision-making at the point of ROSC as this information would be unavailable while performing the prediction. Moreover, we showed that the model performance that included laboratory data was as good as the model including no-flow time instead of laboratory data. While some pre-hospital information such as time of collapse is unreliable,[58] laboratory data are quickly and objectively available at the hospital. The addition of

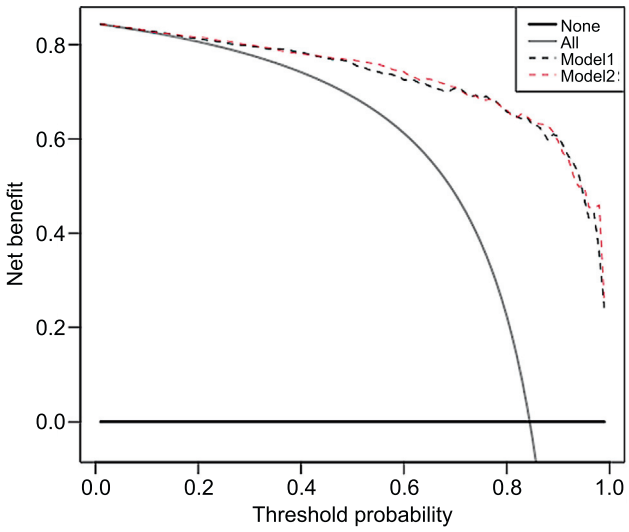

Fig. 4 – Decision curve analysis in validation set. The y-axis represents the net benefit. The red dot line and the black dot line represents model 1 and model 2, respectively. The grey curved line represents the clinical benefit conferred by assuming all patients will perform intensive care (All treatment strategies). The black flat line represents the clinical benefit conferred by assuming all patients will perform no intensive treatment. The x-axis represents the threshold probability, which is where the expected benefit of treatment is equal to the expected benefit of avoiding treatment. The vertical distance from each model represents the net clinical benefit conferred by algorithms at varying risk thresholds.

laboratory data may contribute to better prediction and decision-making through reducing ambiguous predictors from the model.

Clinicians have to perform risk stratification during the initial stage of resuscitation based on readily available parameters to identify patients who are likely to benefit from expensive and labour-intensive life-sustaining therapeutic options. The decision-making process for the allocation of these resources remains a complex challenge for physicians. A web-based application with the variables available at the patient's bedside can interactively visualize the possibility of neurological recovery in real-time.

Limitations

This study had some limitations. First, interpretation of potential predictors by the medical staff in charge of the patient might have influenced the decision-making process for the resuscitation strategies. Their interpretation could have intrinsically compromised the outcome in patients with poor prognostic factors, akin to a self-fulfilling prophecy. Although the medical staff were blinded to the study's objective and the patients in our model admitted to the ICU rarely reached the state of WLST, our study may have overestimated the model's discriminatory ability. Second, the registry did not contain complete information on comorbidities or setting factors that could have helped outcome prediction. The inclusion of these currently unavailable data may improve the accuracy of the models if they are obtained immediately after ROSC. Third, some predictor variables and outcomes were missing. We performed an algorithm to impute the missing values using missForest. However, missForest may lead to underperformance with a substantial amount of missing data.[59] In this study, missing data, especially missing laboratory data, may have led to a biased assessment. Finally, there was a lack of generalisability of the model owing to insufficient external validation. This model was validated using bootstrapping and the validation set. However, the predictive performance for new cases was not fully assessed because the derivation and validation sets were derived from the same registry. All data for the development and validation sets were collected from a Japanese urban area, which limited the generalisability of our model to other regions. Studies validating our model using a registry obtained from another area should be conducted to confirm the model's generalisability.

Conclusions

We developed and validated a tool to predict the long-term neurological outcome immediately after ROSC in patients with OHCA based on lasso regression. This application calculates the probable neurological outcome at 90 days and could help identify the need for critical interventions.

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CRediT authorship contribution statement

Norihiro Nishioka: Conceptualization, Methodology, Software, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Daisuke Kobayashi:** Methodology, Resources, Writing – review & editing. **Takeyuki Kiguchi:** Conceptualization, Methodology, Writing – review & editing, Visualization. **Taro Irisawa:** Investigation, Resources, Project administration. **Tomoki Yamada:** Investigation, Resources, Supervision. **Kazuhisa Yoshiya:** Investigation, Resources, Project administration. **Changhwi Park:** Investigation, Resources. **Tetsuro Nishimura:** Investigation, Resources, Writing – review & editing. **Takuya Ishibe:** Investigation, Resources. **Yoshiki Yagi:** Investigation, Resources. **Sung-Ho Kim:** Investigation, Resources. **Yasuyuki Hayashi:** Investigation, Resources. **Taku Sogabe:** Investigation, Resources. **Takaya Morooka:** Investigation, Resources. **Haruko Sakamoto:** Investigation, Resources. **Keitaro Suzuki:** Investigation, Resources. **Fumiko Nakamura:** Investigation, Resources. **Tasuku Matsuyama:** Formal analysis, Data curation. **Yohei Okada:** Formal analysis, Data curation. **Satoshi Matsui:** Formal analysis, Data curation. **Satoshi Yoshimura:** Formal analysis, Data curation. **Shunsuke Kimata:** Formal analysis, Data curation. **Shunsuke Kawai:** Formal analysis, Data curation. **Yuto Makino:** Formal analysis, Data curation. **Tetsuhisa Kitamura:** Validation, Data curation, Writing – review & editing, Funding acquisition. **Taku Iwami:** Conceptualization, Writing – review & editing, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.resuscitation.2021.09.027.

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