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PREHOSPITAL AND RETRIEVAL MEDICINE

Retrieval Rapid Emergency Medical Score in retrieval medicine

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Abstract

Objective: Prognostic models are commonly used in the clinical setting. The objective of the study is to evaluate the prognostic accuracy of the Rapid Emergency Medical Score (REMS) or alternate models.

Methods: A retrospective cohort study of critical care patients who underwent retrieval service transfer to an ICU in a single state-wide service in Victoria, Australia. All patients aged 18 years and over transferred to an ICU between 1 January 2010 and 30 June 2013. Retrieval and ICU datasets were probabilistically linked. Multivariable logistic regression modelling was used to investigate the capacity of physiological markers and patient characteristics to predict in-hospital mortality in the ICU population. The prediction performance was evaluated using measures of discrimination (C-statistic) and calibration (Hosmer–Lemeshow [H-L statistic]).

Results: There were 1776 ICU patients who were transferred and 1749 (98.5%) had complete data. Of the 1749 patients with complete data, 257 (14.7%) died in-hospital. The REMS calculated at the time of retrieval referral demonstrated borderline predictive capability (C-statistic 0.69, 95% CI 0.62–0.76). Following logistic regression analysis of the REMS components, final variables included in the Retrieval REMS model were age, mean arterial pressure and Glasgow Coma Scale score. This model demonstrated acceptable predictive capability (C-statistic 0.72, 95% CI 0.64–0.79). The median (interquartile range [IQR]) Retrieval REMS for survivors and non-survivors, respectively, were 7 (5, 10) and 9 (7, 11), $P < 0.01$.

Conclusions: The availability of a validated tool such as Retrieval REMS assists recognition of high-risk patients and consideration of this risk in retrieval mission planning and response.

Key words: *decision support, prognostic scoring, REMS, retrieval.*

Key findings

- The Retrieval REMS score provides adequate prognostic capability in critical care inter-hospital retrieval practice.
- Prognostic tools may assist in application of appropriate crew skill sets to retrieval missions.
- The Retrieval REMS may assist in decision support tools in coordination of retrieval cases.

Introduction

'Retrieval can be defined dependant on jurisdiction, however it generally includes the inter-hospital transportation of critically ill patients using specialised clinical staff, transport platforms and equipment'.[1] Inter-hospital transfer is an independent risk factor for mortality in the ICU population, placing those patients at higher risk of death.[2] Transferred ICU patients are more likely to have an increased length of stay morbidity.[2,3] This has triggered interest in risk reduction by improving stabilisation of the patient before transfer, and optimisation of case coordination.[4]

Prognostic models are commonly used in clinical practice. The Rapid Emergency Medical Score (REMS) was first published by Olsson and Lind.[5] The REMS has been validated in emergency patient settings as a predictor of survival; however, its applicability is yet to be assessed in the retrieval population. Retrieval patients are often at the most undifferentiated and highest risk point of their illness.[2] A validated, objective tool that establishes mortality risk in this population might assist clinical and logistic decision-making in retrieval. Prognostic models have also been used to benchmark cost-effectiveness and resource consumption of medical services.[6] A tool or measure that would enable retrieval services to assess individual performance against clinical outcome risk might further improve service delivery as has been seen in the hospital setting.[7] Prognostic tools can also be

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TABLE 1. *Scoring system for the parameters in the Rapid Emergency Medical Score (REMS)*

Variable	High abnormal range						Low abnormal range				
	+6	+5	+4	+3	+2	+1	0	+1	+2	+3	+4
MAP	–	–	>159	130–159	110–129	–	70–109	–	50–69	–	<50
HR	–	–	>179	140–179	110–139	–	70–109	–	55–69	40–54	<39
RR	–	–	>49	35–49	–	25–34	12–24	10–11	6–9	–	<5
SpO_2 (%)	–	–	–	–	–		>89	86–89	–	75–85	<75
GCS	–	–	–	–	–	–	>13	11–13	8–10	5–7	<5
Age (years)	>74	66–74	–	55–64	45–54	–	<45	–	–	–	–

GCS, Glasgow Coma Scale; HR, heart rate; MAP, mean arterial pressure; RR, respiratory rate; SpO_2, peripheral oxygen saturation.

incorporated into electronic decision support tools that assist clinicians in balancing resource, risk and logistic options in complex patient transfer scenarios. Mortality prediction models have been used effectively in the ICU population for many years.[8] One common tool is the Adult Physiology and Chronic Health Score (APACHE) score that included an evaluation of health status preadmission and a physiological score related to degree of acute illness. The APACHE II is a validated and revised version of the tool.[9]

The Rapid Acute Physiology Score (RAPS) is an abbreviated version of the APACHE II. The RAPS is considered to be a simpler tool for prognostication in the ED, enabling more rapid assessment of patient acuity.[5] In the pre-hospital setting, a validation study reported that the RAPS was a poor predictor of illness severity and physiological stability before and after patient transport between hospital services.[10,11]

REMS was developed to further abbreviate the already validated APACHE II.[5] As described in Table 1, the REMS is a 6-item data scale: age, heart rate (HR), respiratory rate (RR), mean arterial pressure (MAP), Glasgow Coma Scale (GCS) score and peripheral oxygen saturation (SpO_2).[5] REMS is a sum of the values with a maximum score of 26.[12]

The REMS was modelled initially on ED and ICU patient data.[5] Validation studies assessing the REMS found acceptable to excellent levels of discrimination, ranging from an area under the curve (AUC) of 0.74[13] to 0.91[12] in ED and trauma populations, respectively. When compared with other prognostic models, the REMS was found to have a similar discriminatory power to the APACHE score[5] and superior discrimination compared with the RAPS.[12–14]

The primary aim of the present study was to investigate the ability of the REMS score to predict in-hospital mortality in the retrieval patients who were transferred by Adult Retrieval Victoria (ARV), and who were admitted to ICU. The secondary aim was to assess which components of the REMS are the most important predictors of in-hospital mortality in this retrieval population.

Methods

Setting

ARV is a statewide retrieval service established in 2007. ARV case processes are based around structured telephone or tele-health consultation between a referring site and a medical coordinator, who is a critical care specialist medical practitioner. The service manages over 4000 cases per annum and 2500 critical care retrieval transfers.[15]

The State of Victoria, Australia, has a population of 5.8 million people,[16] of whom 76% reside in the capital, Melbourne. The catchment area of ARV covers over 250 000 km^2 and spans a radius of 450 km.

Datasets

The ARV dataset includes demographic and clinical information. The Australian and New Zealand Intensive Care Society (ANZICS)[17] is the custodian of ICU data in Victoria and its Centre for Outcome and Resource Centre Adult Patient Database (CORE APD) captures data about in-hospital and ICU mortality, interventions, physiological and biochemical markers, and patient outcomes.

Inclusion criteria

All adult (18 years or over) patients transferred by ARV, who were admitted to an ICU between 1 January 2010 and 30 June 2013, were included.

Data linkage

ARV and ANZICS databases were linked probabilistically. Similar methods of data linkage have been validated and are commonly used in public health linkage projects.[18] The cases were linked based on five identifiers: hospital site, hospital admission date, age, sex and presenting diagnosis. This data linkage method has been applied to these datasets previously, with a known linkage accuracy of 84%.[19] During the study period, ARV retrieved 4934 patients. A total of 1776 patients were linked between the ARV and ANZICS datasets, representing patients retrieved to an ICU. This corresponds to an ICU admission rate of 36%, which is consistent with previous data in ARV annual reporting.[19]

Variables

Variables extracted from the datasets included age, date, sex, time of arrival, hospital service level, vital signs and

TABLE 2. *Demographics of survivors and non-survivors*

REMS components	Survived (n = 1492)	Died (n = 257)
Age		
Mean (SD)	54.7 (18.1)	65.2 (14.4)
Median (IQR)	56 (41–69)	67 (56–76)
GCS, n (%)		
3–8	545 (36.6)	128 (49.8)
9–12	113 (7.6)	22 (8.6)
13–15	833 (55.9)	107 (41.6)
Respiratory rate, mean (SD)	19.1 (8.1)	18.2 (6.9)
Heart rate, mean (SD)	92.8 (24.1)	91.7 (24.8)
MAP, mean (SD)	89.5 (22.8)	89.7 (24.7)
SpO_2, mean (SD)	96.5 (7.8)	96.5 (7.6)
Patient characteristics		
Gender, n (%)		
Male	911 (61.1)	163 (63.4)
Diagnosis type, n (%)		
Other†	387 (90.1)	40 (9.4)
Neuro	296 (75.3)	97 (24.7)
Trauma	281 (92.4)	23 (7.6)
Cardiac	211 (81.2)	49 (18.9)
Respiratory	196 (88.3)	26 (11.7)
Sepsis	121 (84.6)	22 (15.4)

†Diagnostic type; Other, includes diagnostic categories endocrine, Ear Nose and Throat,[14] gastrointestinal, genitourinary, gynaecology, haematology, immune/allergy, multi-organ failure, oncology, renal, shock, toxicology, vascular and other. GCS, Glasgow Coma Scale; IQR, interquartile range; MAP, mean arterial pressure; REMS, Rapid Emergency Medical Score; SpO_2, peripheral oxygen saturation.

diagnostic category at the time of retrieval referral. The vital signs included were HR, RR, SpO_2, GCS, MAP, systolic and diastolic blood pressure (SBP, DBP). Additional variables extracted from the ANZICS data included the time of arrival at ICU, APACHE III score, discharge destination, death, and all items of the APACHE III and the linkage variables. The diagnostic categories collected from the ARV dataset were collapsed into six groups due to the low frequency of cases in some diagnostic categories. The groups were cardiac, neurology and neurosurgery, trauma, respiratory, sepsis and other.

Ethics

Ethical approval for this project was obtained from Monash University Human Research Ethics Committee. The project was approved by the research committees of Ambulance Victoria and the ANZICS CORE.

Descriptive statistics and modeling

We separately described the characteristics of survivors and patients who died. Where appropriate, continuous variables were described using the mean and standard deviations (SD) or the median and interquartile range (IQR). Categorical data were described using frequencies and percentages.

We established three different model forms:

1. the REMS calculated from patient values collected at the referral hospital at the time of retrieval referral call;
2. the scores for the individual components of the score; and
3. a revised (Retrieval) REMS based on the significant component elements.

We assessed the out-of-sample performance using 200 random splits of the data for each of the three model forms (a total of 600 models were performed). Data were randomly allocated into two subsets to be used for model building (80%) and validation (20%).

The coefficients estimated by the model derived from the building subset were applied to the validation set to estimate mortality risk. We assessed discrimination between death and survival by calculating the C-statistic; comparing the predicted mortality to the observed mortality using the AUC of the receiver operating characteristic (ROC) plot of sensitivity *versus* 1-specificity. The mean and distribution of the C-statistic were used to assess discrimination and construct an uncertainty interval.

The final model coefficients and standard error estimates for each model were calculated by bootstrapping with 200 repetitions using the entire dataset. We used the Hosmer–Lemeshow goodness of fit test to evaluate calibration across the deciles of risk.

All analyses were conducted using Stata 12.1 (StataCorp LP, College Station, TX, USA).

Results

There were 1776 ICU patients who were transferred by ARV between January 2010 and June 2013. For the present study, 1749 (98.5%) had complete data. Of these, 257 (14.7%) died in-hospital.

There was no association between sex and in-hospital mortality. Age and diagnostic group were associated with in-hospital mortality (Table 2). The proportion of in-hospital deaths increased with age group. Neurology or neurosurgical patients had the highest proportion of in-hospital deaths (Table 2).

An analysis of the Predictive model for REMS, REMS components and Retrieval REMS and comparison of prediction tools by survivors and non-survivors is presented in Tables 3 and 4. Although it demonstrated adequate goodness of fit across the deciles of risk, the REMS (model 1) demonstrated modest predictive performance (C-statistic = 0.69, Table 3). Each unit

TABLE 3. *Predictive model for REMS, REMS components and Retrieval REMS*

		Coefficient (95% CI)	Odds ratio (95% CI)	*P*-value	C-statistic (95% uncertainty interval)	Goodness of fit, *P*-value
Model 1	REMS	0.203 (0.163 to 0.243)	1.225 (1.177 to 1.275)	<0.001	0.69 (0.62–0.76)	0.38
	Constant	−3.255 (−3.600 to −2.911)		<0.001		
Model 2†	Heart rate	0.042 (−0.088 to 0.171)	1.043 (0.916 to 1.187)	0.528	0.72 (0.64–0.78)	0.83
	MAP	0.212 (0.098 to 0.326)	1.236 (1.103 to 1.385)	<0.001		
	Respiratory rate	−0.008 (−0.211 to 0.194)	0.992 (0.810 to 1.214)	0.936		
	GCS	0.263 (0.183 to 0.343)	1.301 (1.201 to 1.410)	<0.001		
	Age	0.344 (0.269 to 0.418)	1.410 (1.309 to 1.519)	<0.001		
	SpO_2	−0.066 (−0.307 to 0.176)	0.936 (0.736 to 1.192)	0.593		
	Constant	−3.626 (−4.069 to −3.182)		<0.001		
Model 3‡	Retrieval REMS	0.291 (0.233 to 0.350)	1.338 (1.262 to 1.419)	<0.001	0.72 (0.64–0.79)	0.92
	Constant	−3.532 (−3.936 to −3.129)		<0.001		

Components are modelled using their score; † and ‡ include MAP score, GCS score and age score. GCS, Glasgow Coma Scale; MAP, mean arterial pressure; REMS, Rapid Emergency Medical Score; SpO_2, peripheral oxygen saturation.

TABLE 4. *Comparison of prediction tools by survivors and non-survivors*

		Survived ($n = 1443$)	Died ($n = 239$)	Test statistic
REMS	Median (IQR)	6 (4, 9)	9 (6, 11)	$P < 0.01$
Retrieval REMS	Median (IQR)	7 (5, 10)	9 (7, 11)	$P < 0.01$

IQR, interquartile range; REMS, Rapid Emergency Medical Score.

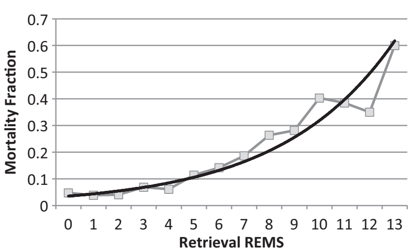

Figure 1. *Retrieval Rapid Emergency Medical Score (REMS)* versus *mortality fraction.*

increase in the REMS score was associated with 1.2 times the relative odds of in-hospital death. When we modelled the components of the REMS score (model 2), we found that the scores for HR, RR and SpO_2 were not significantly predictive of mortality in this population (Table 3). The MAP score, GCS score and age score were all significantly associated with increased odds of in-hospital mortality, with respective odds ratios of 1.2, 1.3 and 1.4. The more parsimonious model (model 3) included only those component scores that were significant in model 2 (Table 3). This model demonstrated acceptable predictive performance, similar to model 2 with each unit increase in the revised composite score associated with a 1.3 times relative odds of in-hospital mortality.

Figure 1 demonstrates the relationship between Retrieval REMS and mortality rate.

Discussion

There has been controversy about application of prognostication tools in health. Some argue that they provide an effective method of risk stratification.[20] Despite apparent validity, they are not commonly applied in clinical settings.

Many factors might contribute to this under-use, including the large number of models, poor knowledge of the existence of a model, or how it might be applied to a population, complexity of model, and resistance to use the tool.[20] The utility of a predictive tool is related to its simplicity, specificity, reliability and applicability, such that it influences the clinician to alter a course of action, a clinical choice, a system structure or process. Wyatt and Altman[21] stated that all patient data included in a prognostic model should be tested and be clinically reasonable. The model should be simple and the predictions should make sense to health practitioners. There are numerous models that have been developed to predict the risk of in-hospital mortality.[13,22,23]

The main aim of the present study was to validate the REMS score in the critically unwell retrieval population admitted to the ICU. The population studied uniquely represents a range of the most unwell patients who require interhospital transfer.

The REMS collected at the time of retrieval referral was a borderline predictor of mortality; however, components of the REMS were significantly associated with mortality, and when re-modelled using these variables, the Retrieval REMS provided acceptable predictive ability.[24]

The Retrieval REMS using existing REMS weightings, included the variables MAP, age and GCS. The maximum possible score was 14.

RR, HR and SpO_2 were excluded from the final model, as they did not independently predict mortality.

The poor performance of these parameters could be due to poor collection methods, faulty equipment and time limitations.[25] In addition, RR is traditionally 'estimated' at the bed side more often than carefully measured; HR might be influenced by many factors in the early dynamic phase of a critical illness (such as pain, awareness, anxiety), none of which are necessarily associated with survival; and SpO_2 in the acute phase of assessment and stabilisation for transfer might be dynamically effected by variation or optimisation of inspired oxygen concentration or early ventilator settings. It is likely that the more reliably predictive variables of MAP and GCS are less susceptible to early variability related to intervention, collection or measurement factors.

The need for critical care interhospital retrieval is not always related to, or driven by the severity of illness. Health system factors are also associated with transfers. These factors might include geographical distribution of hospitals and ambulance services, economic drivers such as bed availability at a referral service, and availability of specialist treatment in a limited number of hospitals within a system.[26] The degree to which such non-clinical factors drive transfer of lower risk intensive care patients is unknown, but might influence the reliability of a clinical measurement-based outcome predictive tool. The vast majority (95.7%) of ARV transfers are driven by lack of availability of a specialised clinical specialty or service at the point of referral rather than lack of local infrastructure (ICU beds or available medical or nursing staff).[19]

In retrieval practice, critical care 'early warning tools' might be limited in their ability to provide strong predictions as they are not specifically designed for application to complex systems and less differentiated clinical problems.[27] The present study has demonstrated that the Retrieval REMS score is an acceptable, although not strong indicator of ICU mortality within the defined population. Its application as an objective tool in real-life circumstances might assist retrieval clinicians who also balance subjective measures and logistic limitations in the management of high-risk transfers. Retrieval missions are commonly performed by different staff types with varying clinical skillsets, capability and experience (consultants, registrars, paramedics); and tasking of particular crew-mixes is often discretionary. The availability of a simple score (Retrieval REMS) that suggests a 1.3 times increased risk of in-hospital mortality per 1 point increase in score might have direct application to retrieval practice. When considered alongside the median Retrieval REMS score of 7 in survivors and 9 in non-survivors, this knowledge might allow retrieval coordinators to identify patients at highest risk and for whom higher levels of crew skill set should be considered. Similar influence might occur in regard to transport platforms and urgency of response, leading for instance to tasking of crews by helicopter rather than road ambulance for highest risk patients. Patients with a Retrieval REMS of 7 or more should be considered at increased risk of death. Clearly, other factors such as clinical complexity might also drive decision-making in regard to crew mix or skill set that might be required in any particular retrieval mission. The REMS score has been incorporated into ARV computer-based decision support tools as one of several factors used by retrieval coordinators when considering case complexity and crew-mix requirements in retrieval case formulation and planning. It is likely that as additional study is performed into the relationship between physiological and other measures and outcome, such tools will be further refined and provide greater utility.

Limitations

Although the Retrieval REMS showed acceptable predictive ability in the test population, stronger performance might be seen with a larger sample size.[28] The REMS and Retrieval REMS were only evaluated in adult patients transferred to a Victorian ICU by ARV, within the Victorian retrieval system. Assessment of the score in other settings might have positive or negative effects on statistical model performance and C-statistic.

Conclusion

The management of critically ill patients is complex. Mortality prediction tools have been developed in an attempt to stratify those most at risk. The availability of a validated tool such as Retrieval REMS assists recognition of high-risk patients and consideration of this risk in mission planning, crew allocation and response.

Author contributions

MPK, KW and BJG: substantial contribution to the conception or design of the work, the acquisition, analysis, and interpretation of data for the work; drafting the work or revising it critically for important intellectual content; and final approval and accountability of the version to be published. LS and MB contributed to the design of the work, the analysis and interpretation of data for the work; drafting the work or revising it critically for important intellectual content; and final approval and accountability of the version to be published.

Competing interests

None declared.

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