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Clinical paper

The development of a risk-adjustment strategy to benchmark emergency medical service (EMS) performance in relation to out-of-hospital cardiac arrest in Australia and New Zealand

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Abstract

Introduction: The aim of this study was to develop a risk adjustment strategy, including effect modifiers, for benchmarking emergency medical service (EMS) performance for out-of-hospital cardiac arrest (OHCA) in Australia and New Zealand.

Method: Using 2017–2019 data from the Australasian Resuscitation Outcomes Consortium (Aus-ROC) OHCA Epistry, we included adults who received an EMS attempted resuscitation for a presumed medical OHCA. Logistic regression was applied to develop risk adjustment models for event survival (return of spontaneous circulation at hospital handover) and survival to hospital discharge/30 days. We examined potential effect modifiers, and assessed model discrimination and validity.

Results: Both OHCA survival outcome models included EMS agency and the Utstein variables (age, sex, location of arrest, witnessed arrest, initial rhythm, bystander cardiopulmonary resuscitation, defibrillation prior to EMS arrival, and EMS response time). The model for event survival had good discrimination according to the concordance statistic (0.77) and explained 28% of the variation in survival. The corresponding figures for survival to hospital discharge/30 days were 0.87 and 49%. The addition of effect modifiers did little to improve the performance of either model.

Conclusion: The development of risk adjustment models with good discrimination is an important step in benchmarking EMS performance for OHCA. The Utstein variables are important in risk-adjustment, but only explain a small proportion of the variation in survival. Further research is required to understand what factors contribute to the variation in survival between EMS.

Keywords: Heart arrest, Out of hospital cardiac arrest, Resuscitation, Registries, Emergency medical services

Introduction

Variation in survival outcomes following out-of-hospital cardiac arrest (OHCA) is well documented. This variation has been observed internationally,[1–4] regionally,[5,6] and between emergency medical services (EMS).[4,7] While some of this variation reflects differences in patient and arrest characteristics and early on-scene intervention, it is now accepted that these factors account for only a small proportion of the variation in survival outcomes.[3] EMS have a crucial role in the chain of survival,[8] and agency factors are likely to account for some of the residual, unexplained variation in OHCA outcomes.

EMS are regularly benchmarked by their OHCA survival rates. However, the evaluation of EMS performance is predicated on the concept of comparing "like-with-like" in terms of patient and arrest characteristics. Risk adjustment provides one method of accomplishing this but is inconsistently applied. For example, in Australia, the

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annual Report on Governmental Services[9] observes variation in event survival between EMS, but reports unadjusted data, making it unclear as to the role of EMS factors in driving this variation. A robust risk adjustment model would facilitate less biased EMS comparisons, allowing a better understanding of the modifiable regional determinants of variation in survival.

While the Utstein factors are highly associated with survival and often form the cornerstone of risk prediction algorithms,[10] interplays between these factors (e.g. bystander cardiopulmonary resuscitation [CPR], witnessed arrest and shockable rhythm) have rarely been considered within the context of risk adjustment modelling. Since it's unwise to assume that all predictors have a uniform effect across subgroups, potential effect modifiers must be identified and assessed.

This study aimed to develop a risk adjustment strategy for future benchmarking of OHCA outcome data across EMS in Australia and New Zealand. We also aimed to assess the merits of adding effect modifiers to risk adjustment models.

Method

Study design and setting

This is a retrospective, population-based study of EMS-treated OHCA across Australia and New Zealand for the years 2017–2019. The ten EMS in our countries each service a specific region; in Australia, eight EMS provide coverage at the state/territory level, while in New Zealand, one EMS covers most of the country, with a second servicing the smaller Greater Wellington region. Both countries use the same resuscitation guidelines developed by the Australian and New Zealand Committee on Resuscitation (ANZCOR).[11] This study was approved by the Monash University Ethics Committee.

Data source

The data were sourced from the Australasian Resuscitation Outcomes Consortium (Aus-ROC) OHCA Epistry, which collates prospectively data from the individual registries of all EMS across Australia and New Zealand. Detailed information concerning patient demographics, arrest characteristics, pre-EMS interventions (bystander CPR and AED use) and OHCA survival are collected in accordance with Utstein definitions.[12] A detailed description of the Epistry can be found elsewhere.[4,11,13]

Study population

We included OHCA patients aged 18 years or older where EMS attempted resuscitation (chest compressions/defibrillation). Patients who had received bystander-initiated defibrillation and achieved return of spontaneous circulation (ROSC) prior to EMS arrival were also included. Arrests due to non-medical aetiologies (i.e. trauma, hanging, drowning, overdose/poisoning, and electrocution) and EMS-witnessed cases were excluded.

Outcomes

The primary outcome was event survival, defined as ROSC at hospital handover. Survival to hospital discharge/30-day survival was assessed as a secondary outcome as these data were only available for 7 of the 10 EMS. Previous research in Western Australia has reported high concordance between survival to discharge and 30-day survival.[14]

Predictor variables

The variables assessed in this study fell into two categories. The first was comprised of factors deemed to be beyond the control of the EMS (unmodifiable factors), and included age, sex, location of arrest, and witnessed status; the second consisted of variables that were at least partially modifiable, including bystander CPR, pre-EMS defibrillation, initial arrest rhythm and EMS response times (in minutes). Age was treated as a continuous variable. Preliminary analysis showed that the associations between age and survival outcomes were non-linear; thus, age was modelled using restricted cubic splines with knots at 50, 80 and 100 years. Location of arrest was categorised as home/private residence, public place or other location. Initial arrest rhythm was classified as shockable (ventricular fibrillation (VF), ventricular tachycardia (VT) or unknown shockable), pulseless electrical activity (PEA), asystole, or unknown non-shockable. Initial arrest rhythm was defined as shockable versus non-shockable in the analysis of survival to discharge/30 days due to low counts across the non-shockable categories.

Statistical analysis

The data were analysed separately for event survival and survival to discharge/30 days. Age and EMS response time were summarised as medians with interquartile range (IQR); categorical variables were presented as counts and percentages. The Kruskal-Wallis test was used to assess survival differences by age and EMS response time; Pearson's Chi-square test was applied to assess differences across categorical and dichotomous predictors.

Logistic regression was applied to develop the risk adjustment models. Variable selection was guided by Hosmer and Lemeshow's purposeful selection approach.[15] This is a two-stage process, whereby a main effects model is first obtained; interactions between the selected variables are then assessed. The process commences with a model which contains all variables with a univariate p-value less than 0.25 and those considered to be clinically important. Non-significant variables are systematically removed from the model unless they are determined to be an important covariate. This is based on the impact of that variable's removal on the estimated coefficients of variables remaining in the model. A change in estimate on any remaining variable that is greater than 20% indicates that the removed variable is important in providing an adjustment for other variables in the model and should be retained as a covariate. At the end of this process, any variables not selected for the original model are entered one at a time and re-evaluated. Once a preliminary, main effects model has been constructed, interaction terms are then assessed. The final model includes all variables that are significant at $p < 0.10$, interaction terms significant at $p < 0.05$, and non-significant variables identified as important due to their influence on other variables.

Model validation

Model performance was assessed using measures of model discrimination and fit. Discrimination was characterised by the concordance statistic as derived from the area under the receiver operating characteristic curve (AUC: c-statistic). A higher AUC indicates better discrimination with a c-statistic of 0.50 indicating that the model is no better than chance at correctly classifying outcomes.

The primary measure of model fit was the McKelvey and Zavoina's R^2 statistic.[16] Of the numerous pseudo R^2 statistics available, the McKelvey and Zavoina's R^2 has the closest correspondence to the R^2 statistic obtained from ordinary least squares linear regression.[17,18] Therefore, it provides a reasonable approximation of variance explained by the model. However, since the magnitude of the R^2 statistic usually increases with the number of variables in the model, the Bayesian Information Criterion (BIC) is also reported, with lower values indicating a better-fitting model.

Bootstrapped estimates and confidence intervals were obtained for all model coefficients and performance metrics using 1,000 replications. While split sampling is most commonly used for model validation, it has been criticised as being inefficient and providing overly pessimistic estimates of model performance.[19] Bootstrapping has since been recommended to estimate internal model validity.[19]

Factors related to variations in survival

Logistic regression models were used to investigate variation in survival that could be attributed to EMS, patient and arrest characteristics, and modifiable factors. Four models were assessed as follows:

Model 1: EMS service.
Model 2: EMS and patient and arrest characteristics (age, sex, arrest location, bystander witnessed arrest).
Model 3: Variables in Model 2 plus initial arrest rhythm.
Model 4: Variables in Model 3 plus potentially modifiable factors (bystander CPR and AED use, EMS response time).

Initial monitored rhythm was modelled separately to other variables as it was considered both unmodifiable (e.g. aetiology) and modifiable due to its high correlation with other variables (e.g. witnessed, bystander CPR and EMS response times). Improvements across models were assessed by model discrimination (c-statistic), McKelvey and Zavoina's R^2 statistic and the range from minimum to maximum probabilities. Estimates of survival probabilities, model performance metrics and their confidence intervals were obtained by bootstrapping with 1,000 replications.

All analyses were completed using Stata version 17.0 (StataCorp, College Station, TX, USA).

Results

Event survival (ROSC on hospital handover)

From 2017 to 2019 there were 26,266 OHCA that met the inclusion criteria. Event survival was 25.9% overall and varied significantly across all predictor variables, except for sex (Table 1). Survival rates were lower in arrests amongst older adults, arrests occurring in non-public locations and unwitnessed arrests. Bystander CPR and AED use and a shockable arrest rhythm were associated with higher survival.

All variables, including sex, emerged as significant predictors of event survival and were retained in the model (Table 2). The model containing effect modifiers is shown in the supplementary file (Table S1). Bystander CPR was a significant effect modifier of associations between event survival and arrest rhythm (p = 0.003), response time (p = 0.001) and witnessed status (p < 0.001). Age (p = 0.01), response time (p < 0.001), witnessed arrest (p < 0.001) and location of arrest (p = 0.01) were modifiers of the association between event survival and arrest rhythm. Pre-EMS defibrillation modified the effect of location (p = 0.01) and witnessed status (p = 0.02) on event survival. Age was an effect modifier of the association between location and event survival (P < 0.001).

The addition of effect modifiers to the main effects model did little to improve model discrimination (c-statistic increased from 0.77 to 0.78). There were modest gains in model fit (McKelvey and Zavoina's R^2 statistic increased from 0.27 to 0.30). The BIC was smaller for the model with interactions; however, the confidence interval for the difference between the two models included zero and cannot be viewed as conclusive support for one model over the other.

The model with EMS alone showed poor discrimination (Table 3: c-statistic = 0.55) and accounted for little of the variation in event survival (McKelvey and Zavoina's R^2 = 0.01). Model discrimination improved with the addition of unmodifiable factors (c-statistic = 0.70) and again with the incremental addition of initial rhythm (c-statistic = 0.76). Variance explained likewise improved, with the McKelvey and Zavoina's R^2 increasing to 0.15 in the model containing unmodifiable factors and to 0.26 after the addition of initial rhythm. Model discrimination and variance improved only slightly following the addition of potentially modifiable factors.

Survival to hospital discharge/30 days

In total, 21,427 OHCA were reported by the seven EMS who provided data for survival to hospital discharge/30 days. Of these, 2,444 (11.4%) survived to hospital discharge/30-days. Survival rates were lower in arrests amongst older persons and females, in unwitnessed arrests and arrests occurring in private residences or other non-public locations (Table 1). Bystander intervention, initial shockable rhythm and shorter EMS response time were linked to an increased likelihood of survival.

The main effects risk adjustment model included all demographic and arrest characteristic measures (Table 2). Age (p < 0.001), bystander CPR (p < 0.001), EMS response time (p < 0.001) and witnessed status (p < 0.001) were identified as significant effect modifiers of the association between survival and initial rhythm (Supplementary file: Table S2); age (p = 0.04), pre-EMS defibrillation (p = 0.02) and EMS response time (p < 0.001) were effect modifiers of the association between survival and location of arrest. Bystander CPR (p < 0.001) and pre-EMS defibrillation (p = 0.01) were effect modifiers of the association between witnessed status and survival. No other interaction terms were significant. The addition of effect modifiers improved model fit with respect to the BIC but not the McKelvey and Zavoina's R^2; it did not improve model discrimination.

The model with only EMS showed poor discrimination (Table 3) (c-statistic = 0.54) and accounted for little of the variance in survival to discharge/30-days (McKelvey and Zavoina's R^2 = 0.01). The addition of unmodifiable factors improved both metrics (c-statistic = 0.79; McKelvey and Zavoina's R^2 = 0.32); further gains were obtained by the inclusion of initial rhythm (c-statistic = 0.87; McKelvey and Zavoina's R^2 = 0.45) but not modifiable factors.

Discussion

We have described the development of risk adjustment models for event survival and survival to hospital discharge/30-days in EMS-treated OHCA cases in Australia and New Zealand. Demographic variables (age, sex), arrest characteristics (location of arrest, witnessed arrest and initial [monitored] rhythm), bystander intervention (bystander CPR and defibrillation) and EMS response times were identified as key factors in both models. Significant effect modifiers were identified for both models, although the value of adding these to risk adjustment algorithms appears limited. The model for survival

Table 1 – Demographics and arrest features for event survival and survival to hospital discharge/30 days.

	Survived event (ROSC on hospital handover)				Survived to hospital discharge/30 days			
	Total	Yes	No	*p*-value	Total	Yes	No	*p*-value
	26266	6813	19453		21427	2444	18983	
Age group (*n*, %))								<0.001
18-29	538	189 (35.1)	349 (64.9)	<0.001	437	93 (21.3)	344 (78.7)	
30-39	1059	334 (31.5)	725 (68.5)		845	158 (18.7)	687 (81.3)	
40-49	2363	687 (29.1)	1676 (70.9)		1889	316 (16.7)	1573 (83.3)	
50-59	4169	1307 (31.3)	2862 (68.7)		3373	606 (18.0)	2767 (82.0)	
60-69	5611	1569 (28.0)	4042 (72.0)		4558	610 (13.4)	3948 (86.6)	
70-79	6319	1580 (25.0)	4739 (75.0)		5154	460 (8.9)	4694 (91.1)	
80-89	4897	980 (20.0)	3917 (80.0)		4087	178 (4.4)	3909 (95.6)	
90+	1310	167 (12.7)	1143 (87.3)		1084	23 (2.1)	1061 (97.9)	
Age (years) (median (IQR))	69 (56, 79)	65 (54, 76)	70 (57, 80)	<0.001	69 (57, 79)	60 (50, 70)	70 (58, 80)	<0.001
Sex (*n* (%))								<0.001
Male	17944	4665 (26.0)	13279 (74.0)	0.75	14708	1882 (12.8)	12826 (87.2)	
Female	8322	2148 (25.8)	6174 (74.2)		6719	562 (8.4)	6157 (91.6)	
Location (*n* (%))								<0.001
Private residence	19119	4330 (22.6)	14789 (77.4)	<0.001	15546	1217 (7.8)	14329 (92.2)	
Public Place	4654	1996 (42.9)	2658 (57.1)		3870	1100 (28.4)	2770 (71.6)	
Other	2493	487 (19.5)	2006 (80.5)		2011	127 (6.3)	1884 (93.7)	
Witnessed arrest (*n* (%))								<0.001
Bystander	14851	5194 (35.0)	9657 (65.0)	<0.001	12157	2099 (17.3)	10058 (82.7)	
Unwitnessed	11415	1619 (14.2)	9796 (85.8)		9270	345 (3.7)	8925 (96.3)	
Bystander CPR (*n* (%)								<0.001
No	6597	1338 (20.3)	5259 (79.7)	<0.001	5362	281 (5.2)	5081 (94.8)	
Yes	19669	5475 (27.8)	14194 (72.2)		16065	2163 (13.5)	13902 (86.5)	
Defib before EMS arrival (*n* (%))								<0.001
No	25169	6216 (24.7)	18953 (75.3)	<0.001	20447	2027 (9.9)	18420 (90.1)	
Yes	1097	597 (54.4)	500 (45.6)		980	417 (42.5)	563 (57.5)	
Initial rhythm (*n* (%))				<0.001				<0.001
Shockable	8754	4002 (45.7)	4752 (54.3)		7203[1]	2112 (29.3)	5091 (70.7)	
Non-shockable[1]					14224	332 (2.3)	13892 (97.7)	
PEA	4351	1300 (29.9)	3051 (70.1)					
Asystole	12353	1266 (10.2)	11087 (89.8)					
Unknown non-shockable	808	245 (30.3)	563 (69.7)					
Response time (mins) (Median (IQR)	8 (6, 11)	8 (6, 10)	8 (6, 12)	<0.001	8 (6, 11)	7 (6,10)	8 (6, 11)	<0.001

[1] Initial rhythm was categorised as shockable versus non-shockable for survival to hospital discharge/30-days.

Table 2 – Risk adjustment models for event survival and survival to hospital discharge/30 days (interaction terms not shown).

	Event survival			Survival to hospital discharge/30 days		
Variable	Odds ratio	95% CI	*p*	Odds ratio	95% CI	*p*
Age						
Cubic spline amongst 18–50 years	0.99	0.99, 1.00	<0.001	0.98	0.97, 0.98	<0.001
Cubic spline amongst 51+ years	0.98	0.98, 0.99	<0.001	0.97	0.95, 0.98	<0.001
Sex						
Male	1.00			1.00		
Female	1.49	1.39, 1.60	<0.001	1.18	1.05, 1.32	0.01
Location						
Private residence	1.00			1.00		
Public place	1.38	1.28, 1.49	<0.001	1.90	1.70, 2.12	<0.001
Other	0.83	0.74, 0.93	0.002	0.88	0.71, 1.10	0.27
Witnessed arrest						
Unwitnessed	1.00			1.00		
Bystander witnessed	2.12	1.97, 2.28	<0.001	2.88	2.54, 3.27	<0.001
Bystander CPR						
No	1.00			1.00		
Yes	1.08	1.00, 1.17	0.05	1.36	1.17, 1.58	<0.001
Defibrillation prior to EMS arrival						
No	1.00			1.00		<
Yes	1.40	1.22, 1.61	<0.001	1.66	1.42, 1.94	0.001
Initial rhythm						
Shockable (VF/VT/shockable)	1.00			1.00		
Non-shockable rhythm				0.10[1]	0.09, 0.12	<0.001
PEA	0.63	0.58, 0.68	<0.001			
Asystole	0.20	0.18, 0.21	<0.001			
Unknown non-shockable	0.67	0.58, 0.79	<0.001			
Response time	0.95	0.94, 0.96	<0.001	0.92	0.91, 0.94	<0.001
Model performance metrics						
Main effects risk adjustment models (Model 1)						
Concordance c-statistic	0.77 (0.76, 0.78)			0.87 (0.86, 0.88)		
McKelvey & Zavoina R^2	0.27 (0.26, 0.29)			0.48 (0.45, 0.52)		
Bayesian Information Criteria (BIC)	−4668.28 (−5002.07, −4333.24)			−4497.58 (−4864.85, −4130.83)		
Risk adjustment models with effect modifiers (Model 2)						
Concordance c-statistic	0.78 (0.77, 0.79)			0.88 (0.87, 0.89)		
McKelvey & Zavoina R^2	0.30 (0.28, 0.32)			0.47 (0.44, 0.51)		
BIC	−4752.98 (−5075.89, −4384.95)			−4577.47 (−4953.60, −4223.21)		
Change in BIC: (Model 1-Model 2)	57.70 (−33.09, 163.40)			97.89 (17.29, 193.65)		

[1] Initial rhythm was modelled as shockable versus non-shockable.

Table 3 – Fit statistics for OHCA survival models.

	EMS service	EMS + patient age and sex, location of arrest, witnessed arrest status	EMS + patient age and sex, location of arrest, witnessed arrest status + initial rhythm	EMS + patient age and sex, location of arrest, witnessed arrest status + initial rhythm + bystander CPR, pre-EMS defibrillation, EMS response time
Survived event				
AUC c-statistic	0.55 (0.54, 0.56)	0.70 (0.69, 0.71)	0.76 (0.76, 0.78)	0.77 (0.76, 0.78)
McKelvey & Zavoina R^2	0.01 (0.01, 0.02)	0.15 (0.14, 0.17)	0.26 (0.24, 0.28)	0.28 (0.26, 0.30)
Survival to discharge/30 days				
AUC c-statistic	0.54 (0.52, 0.55)	0.79 (0.78, 0.80)	0.87 (0.86, 0.88)	0.87 (0.86, 0.88)
McKelvey & Zavoina R^2	0.01 (0.00, 0.01)	0.32 (0.29, 0.35)	0.45 (0.43, 0.48)	0.49 (0.45, 0.52)

EMS: Emergency Medical Services.

to hospital discharge/30 days had excellent discrimination (AUC = 0.87); the performance of the model for event survival was modest by comparison, but it still showed good discrimination (AUC = 0.77).

While both risk adjustment models performed well, performance was better for survival to hospital discharge/30 days than for event survival. It is unclear why the risk adjustment model would work better for survival to hospital discharge/30 days; however, it points to the importance of on-scene factors as drivers of hospital survival. While in-hospital factors may account for much of the unexplained variance in survival to discharge/30 days, early on-scene intervention (bystander CPR and defibrillation) may influence the later success of hospital treatment.

Our risk adjustment algorithms accounted for only 27% of the variation in event survival and 48% of the variation in survival to discharge/30 days. This suggests that important factors, not captured by the AUS-ROC Epistry, have been left out of the models. Patient factors may account for some of the unexplained variation. For example, patient comorbidities, symptom recognition and delays in contacting EMS have been linked to survival to hospital discharge in EMS-witnessed arrests.[20–23] Socioeconomic status (SES) may also be important, with links between lower SES status and poorer hospital survival reported,[24–26] including ethnic disparities in New Zealand.[27] Regional characteristics have also been linked to OHCA survival with poorer outcomes in rural locations when compared to metropolitan regions.[28] Arguably, area remoteness impacts on the availability of witnesses, bystander interventions and access to hospital treatment. We could not explore the effect of remoteness on survival outcomes in this study, due to cross-national differences in the definitions and measurement of area remoteness, but we plan to examine this effect next.

Available evidence suggests that Utstein factors account for only a small proportion of EMS agency variation in survival outcomes.[3] This has ranged from 17-51% depending on the OHCA population studied. At least one study has reported that initial rhythm accounts for most of the interagency variation in OHCA survival,[29] which is consistent with our findings. Adding initial rhythm to models that included EMS agency, patient characteristics and arrest features led to improvements in model performance for both event survival and survival to hospital discharge/30 days (Table 3). The incremental improvement following additional adjustment for potentially modifiable factors was modest in comparison.

Assessment of EMS performance requires adjustment for all patient case-mix characteristics, arrest features and hospital factors that are known to influence survival and vary across EMS. Beyond this, any residual variation should be due to EMS agency factors. EMS care is an important element in the chain of survival.[30] EMS personnel generally manage patients according to regional protocols, which determine on-scene practices surrounding the initiation and termination of resuscitation and advanced life support. Our previous survey suggests some of these vary across EMS jurisdictions.[11] For example, the EMS resources allocated to respond vary regionally. The skills and experiences of EMS personnel may also be important. Higher exposure to attempted resuscitation is associated with improved OHCA patient outcomes, with variation in exposure likely to occur both within and across agencies.[31] EMS commitment to quality improvement may reduce disparities in patient OHCA outcomes. The implementation of a state-wide resuscitation quality improvement program in Victoria (Australia) led to significant improvement in OHCA outcomes.[32]

Patient transport protocols may also contribute. Survival outcomes are consistently higher amongst patients transported to 24-hour PCI capability.[33–36] However, while direct transport to an advanced care facility is optimal, it's unclear whether this supports a hospital bypass policy; available evidence, while mixed, points to a survival benefit in bypass, provided that the additional transport time does not exceed 14 minutes.[33,35] Given the time-critical nature of diversion to a PCI-capable facility, this may not be an option in rural and remote regions where the availability of such facilities may be limited.

The limitations of our data have been reported elsewhere.[4] While the Epistry undergoes regular review to identify gaps and standardise definitions and data collection, there may be differences in case definitions, case inclusion and the interpretation of core Utstein items.[4] In particular, the reporting of longer-term survival outcomes lacks consistency, although previous research in Western Australia reported high concordance between survival to discharge and 30-days.[14] Whilst we restricted our study cohort to OHCAs due to 'medical causes' we acknowledge that this is still a heterogenous group. Furthermore, we were unable to assess post-resuscitation and neurological outcome as this data is not available on our Epistry.

Conclusion

This study used a robust methodology to identify key OHCA arrest characteristics that were associated with survival. Reports aiming to compare OHCA outcomes across EMS need to use risk adjustment to provide fairer and more meaningful comparisons. We found no compelling reasons to include effect modifiers to risk adjustment algorithms as a matter of course. However, this should not discourage future researchers from exploring other effect modifiers when developing risk adjustment algorithms. Our next aim is to validate and refine our risk adjustment strategy using 2022 data when it becomes available. We also aim to use these models as a basis for adjusted comparisons between EMS and to explore other system factors (e.g. use of different responder programs and EMS transport practices within our EMS)[11] related to OHCA survival.

CRediT authorship contribution statement

Stuart Howell: Formal analysis, Methodology, Project administration, Writing – original draft, Writing – review & editing, Investigation. **Karen Smith:** Conceptualization, Methodology, Writing – review & editing, Data curation. **Judith Finn:** Conceptualization, Funding acquisition, Methodology, Writing – review & editing, Data curation. **Peter Cameron:** Conceptualization, Methodology, Writing – review & editing, Funding acquisition. **Stephen Ball:** Data curation, Methodology, Writing – review & editing. **Emma Bosley:** Data curation, Methodology, Writing – review & editing. **Tan Doan:** Data curation, Methodology, Writing – review & editing. **Bridget Dicker:** Data curation, Methodology, Writing – review & editing. **Steven Faddy:** Data curation, Methodology, Writing – review & editing. **Ziad Nehme:** Methodology, Writing – review & editing. **Andy Swain:** Data curation, Writing – review & editing. **Melanie Thorrowgood:** Data curation, Writing – review & editing. **Andrew Thomas:** Data curation, Writing – review & editing. **Samuel Perillo:** Data curation, Writing – review & editing. **Mike McDermott:** Data curation, Writing – review & editing. **Tony Smith:** Data curation, Writing – review & editing. **Janet Bray:** Conceptualization, Data curation, Funding acquisition, Methodology, Project administration, Supervision, Writing – review & editing.

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

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