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Original Article

Critical care outcome prediction equation model, version 7

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ABSTRACT

Objective: Mortality prediction models are used for benchmarking, audit, research, and epidemiology. This report describes the development and validation methodology, for version 7 of the critical care outcome prediction equation for monitoring adult intensive care unit (ICU) mortality risk.
Design: This was a multiphase study incorporating data extraction, curation, aggregation, modelling, and validation applied to jurisdictional administrative datasets to model 90-day survival.
Setting: The study was conducted across 28 public and 19 private hospitals in state of Victoria, Australia, with an adult population of 5.28 million.
Participants: A total of 215,148 consecutive adult hospital separations receiving intensive care over 5 years, July 2019–June 2024, were included in the study.
Main outcome measures: The main outcome measures included the case fatality rate (CFR) and standardised 90-day mortality ratio (SMR) at the provider level with model fit assessed for calibration (Brier score; Hosmer–Lemeshow statistic [H_{10}]), discrimination (area under the receiver-operator characteristic and precision-recall curves), classification (CFR and SMR results for ICU-years classified within ±3 standard deviation [SD]), and dispersion (dispersion value [ϕ]; SD random effect [τ]) characteristics.
Results: The CFR was found to be 12.0 (95% confidence interval: 11.8–12.1) per 100 separations and 16.1 (95% confidence interval: 15.7–16.4) per 100 persons. A total of 7771 (53.7%) admission diagnoses were aggregated into 24 clinical diagnosis groups and eight demographic (final) model variables. The following results were obtained: mean Brier score = 0.08; H_{10} = 15.95; area under the receiver-operator characteristic curve = 0.85; area under the precision-recall curve = 0.43. A total of 126 (54.1%) CFR results and 220 (94.4%) SMR values were within ±3 SD. A total of 105 (45.3%) CFR-outlier ICU-years were reclassified as SMR inliers, with no CFR inlier reclassified as an SMR outlier. Overdispersion metrics: $\phi = 2.80$; $\tau = 0.15$.
Conclusions: Critical care outcome prediction equation, version 7 is a parsimonious hospital mortality prediction model for adult intensive care admissions, derived from administrative data common to all jurisdictions.

1. Introduction

Critical care medicine in Australia and New Zealand is fortunate to have several clinical registries[1] and metrics for monitoring

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patient safety and quality of care.[2–4] In the state of Victoria, the critical care outcome prediction equation (COPE[5]), now in its seventh iteration, has been used for over 15 years to monitor the same Victorian adult population using similar metrics (hospital mortality, morbidity, and length of stay) derived from an administrative dataset independent of the treating team. Multiple data sources and metrics provide clinicians and managers with a greater depth and insight and facilitate triangulation of any signals of interest.

An ideal outcome prediction model includes all adult patients, all diagnoses, and all providers and adjusts for patient-related factors outside the control of the hospital and clinical service under review. Mortality prediction models have many applications: monitoring clinical performance, clinical research, and epidemiology. The purpose of this report is to describe the revised methodology of the COPE version 7 (COPE7) model and its application to hospital monitoring. This model is used in quarterly jurisdictional patient safety reports but has not previously been described for clinicians and managers who access these reports. Our primary intent is methodological rather than diagnostic or comparative, although these are important topics.

2. Methods

2.1. Data collection

Following each hospital discharge (separation), relevant demographic and clinical data are extracted from the medical record by clinical coders and health information managers in accordance with national[6] and state[7] coding rules. Diagnoses and procedures are coded according to the 12th edition of the Australian modification of the International Classification of Disease and Health-Related Problems, version 10 (ICD10-AM) and the Australian Classification of Health Interventions.[8] These data are primarily collected for activity-based funding and epidemiology. A deidentified copy of these data is supplied by the Department of Health (Victoria) to its Intensive Care Data Committee within SaferCare Victoria[9] for the purpose of monitoring and reporting intensive care outcomes.

Model development required several phases to condense thousands of candidate variables into a statistically manageable number of clinically relevant groups: phase 1, data curation; phase 2, aggregation of ICD10-AM diagnoses; phase 3, risk ranking; phase 4, model development; and phase 5, model validation.

This project was approved by the Department of Health and by the Eastern Health Human Research Ethics Committee (LR19/062), and the need for patient consent was waived. We used the Stata/MP™ v18.0 (2023, College Station, TX) statistical software. A Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis[10] checklist is provided in Table E1 (online Supplement).

2.2. Phase 1: Data curation

For this report, we collated the data from all reported public and private sector adult intensive care unit (ICU) separations for the 5-year period, July 2019–June 2024, in the state of Victoria (Australia). Each record describes a unique period of hospital care and includes patient demographics (age, sex, ethnicity, hospital admission source, and urgency), up to 40 diagnoses and 40 procedure codes, and outcomes such as length of ICU and hospital stay and survival. Of note, the "condition-onset' flag[6] attached to each diagnosis permitted the exclusion of postadmission diagnoses (complications) and retention of on-admission diagnoses. Records were excluded if an admission diagnosis or admission and discharge dates were missing.

Encrypted patient and hospital identifiers permitted estimation of hospital readmissions and linkage with the Victorian Death Index for long-term survival, censored on 31st December 2024. Ninety-day (rather than hospital or ICU) survival was selected as the outcome of interest. Each hospital was assigned to one peer-group category: public sector tertiary-referral, major metropolitan, and major regional; and private sector tertiary or other. One new hospital commenced tertiary ICU services during the observation period.

2.3. Phase 2: Aggregation of ICD-10-AM codes

All admission ICD10-AM diagnosis codes were identified and allocated to one of 406 unique clinical diagnosis groups (CDGs) according to the published algorithm, detailed elsewhere.[11] A CDG is defined as a group of one or more ICD10-AM diagnosis codes that describe a similar pathophysiologic state; for example, community-acquired pneumonia or cardiac failure. All CDG sets capture over 10000 ICD10-AM diagnosis codes aggregated into 240 acute diagnoses, 53 chronic conditions, 57 clinical signs, 18 laboratory test abnormalities, and 16 (prehospital) procedural complications.

2.4. Phase 3: Ranking of CDG

The purpose of phase 3 was to identify which CDG sets were significantly associated with death at 90 days post admission and the strength of that association, as assessed by the multivariable risk-adjusted odds ratio (OR). To this end, we fitted a mixed-effect regression model to 90-day survival and included patient demographic and the CDG variables identified in phase 1. To this model we added a categorical (fixed-effect) variable for each fiscal year to adjust for temporal trends in case mix, triage, and therapeutic advances and a random intercept for each ICU service to adjust for hospital factors such as variations in activity, services, and models of care. The variance between hospitals and peer groups was assessed by their intraclass correlation coefficient (ICC).[12]

Using a manual iterative process, nonsignificant candidate variables were removed. Candidate variables were retained if they explained variance in the outcome (with $p < 0.157$[13]) or improved (reduced) the model's information criteria ("consistent" Akaike and Bayesian information criteria[14]) or improved the statistical significance of a more dominant covariate. Of note, we did not use automated (forward or backward) step-wise selection methods since they may discard significant covariates.[13]

All selected admission diagnosis CDGs were ranked and categorised according to the strength of their association with outcome (death within 90 days of hospital admission), as indicated by their multivariable OR. For example, category 1 = any CDG with an OR >3; category 2: OR = 2.3–2.9; category 3: OR = 1.8–2.2; category 4: OR = 1.5–1.7; category 5: OR = 1.2–1.4; category 6: OR = 1.0–1.1; category 7: OR = 0.8–0.9; category 8: OR = 0.6–0.7; category 9: OR = 0.5–0.6; and category 10: OR < 0.5. Thus, each category contained up to several hundred separate ICD10-AM codes. The optimal number of categories and the OR range for each category were determined iteratively by assessing their effect on model information criteria[14] facilitated by the Stata command "*xtile*". The ranking and categorisation procedure was repeated for all CGDs that described chronic conditions and a third time for CGDs representing clinical signs and abnormal laboratory results. Thus, phases 1–3 reduced over 14,000 ICD10-AM diagnosis codes to fewer than 30 ranked categories (the final covariates). The ORs generated in phase 3 were only used for the purpose of stratification and aggregation to deliver parsimony and avoid high dimensionality in the final (phase 4) model.

2.5. Phase 4: Final model

The final COPE model was similar to the phase 3 model with the exclusion of all hospital descriptors (size, activity, and peer group), year of separation, and the coefficients derived from the phase 3 model. Thus, in the final model, all ICD10-AM codes and their allocated CDGs were replaced by the ranked categories generated in phase 3. The form of the estimator used for this analysis was as follows:

logit death (demographic variables) (acute-1 acute-2 … acute-i) (chronic-1 chronic-2 … chronic-j) (clinsign-1 clinsign-2 … clinsign-k), vce(cluster campus)

where *logit* is the Stata command for the estimator fitted to the binary outcome with a logistic cumulative distribution; *death* is the binary outcome of death within 90 days of hospital admission; *demographic variables* (age, male sex, etc.)*; acute1* for category 1 acute conditions and so on to category 10; *chronic-1* for category 1 chronic conditions and so on to category 7; *clinsign-1* for category 1 clinical and laboratory signs and so on to category 7, with errors adjusted for *clustering* at the hospital level. The rationale was to create a parsimonious model restricted to patient-related factors present on admission, excluding hospital characteristics and clinical management decisions (such as mechanical ventilation or vasopressor use), access and treatment delays, and complications.

2.6. Phase 5: Model validation

Validation of the COPE7 model incorporated metrics to describe calibration, discrimination, classification, and dispersion. The dataset was randomly (80:20) split into training and validation cohorts. Coefficients were generated in the former and applied to the latter for assessment of model fit. The Brier score and Hosmer−Lemeshow goodness-of-fit statistic (with equal-sized deciles, H_{10}) for each fiscal year were used to assess calibration,[15,16] while the user-written command *calibrationbelt*[17] furnished additional visual and statistical assessment. Discrimination was assessed by the area under the receiver operator characteristic curve (AUCROC) and the area under the precision-recall curve (AUCPRC[16]) since the dataset was imbalanced (more survivors than deaths). An ideal model will produce a Brier score approximating 0, an H_{10}-associated p value >0.05, AUCROC >0.80, and AUCPRC well in excess of the outcome (risk-adjusted mortality) rate.

Since the primary application of the COPE7 model is assessment of patient outcomes at the provider level, we tested model classification, reclassification, and dispersion characteristics in the following manner. The COPE7 model was recalibrated to each fiscal year and the standardised mortality ratio (SMR = [observed deaths]/[predicted deaths]) was calculated for each ICU-year. Classification of inlier/outlier status was tested using a funnel plot, with control limit set to ± 3 standard deviation (SD) of the grand mean (benchmark) and precision determined by the number of predicted deaths, without adjustment for dispersion.

The degree of overdispersion[18] of SMR values was quantified by the dispersion value (ϕ) and the random-effect SD (τ) with the user-written command *funnelinst*[19]. The standard metrics represent the degree to which observed variability in the dataset is greater than what would be expected for the chosen statistical model. In the ideal scenario, where an ideal model is applied to providers delivering a uniform high standard of care, ϕ approximates unity, τ approximates zero, and less than 1% of SMR values (ICU-years) exceed the ±3-SD control limit. Sensitivity analyses of calibration, discrimination, and dispersion were undertaken for each hospital peer group, and sensitivity analysis for unmeasured confounding was quantified by the E value[20] for each covariate.

3. Results

In 2023, the population of Victoria was approximately 6.81 million with a population over 17 years of age of approximately 5.28 million.[21] During the 5-year study, 13.3 million adult hospital separations were reported, including 215,148 (1.6%) adult ICU separations from 28 public and 19 private-sector hospitals. Exclusions are summarised in Fig. 1, and demographic and disease burden data are provided in Table 1 and in the online Supplement (Tables E1 and E2) and aggregate outcomes in Table 2.

The in-hospital case fatality rate (CFR) for adult ICU admissions was 8.2 (95% confidence interval [CI] = 8.1−8.3) per 100 admissions (separations) and 9.7 (95% CI = 9.4−10.0) per 100 persons; whereas 90-day fatality rates were 12.0 (95% CI = 11.8−12.1) and 16.1 (95% CI = 15.7−16.4), respectively. The unconditional ICC (residual variance in mortality) between the 47 ICU services was 0.11 (95% CI = 0.08−0.16), while the conditional variance (adjusted for patient-related factors) was 0.04 (95% CI = 0.03−0.06).

From 14,470 possible diagnosis codes in the 12th edition of ICD-10-AM,[8] hospital clinical coders used 7771 (53.7%) unique admission diagnoses over the 5 years, with 94.8% (n = 7366) included in one of the 406 CDG sets (candidate variables).[11] Each hospital record contained an average (SD) of 8.5 (±5.4) admission diagnosis codes. After phase 1 and phase 2, these diagnoses were collapsed into 24 ranked categories: 10 acute condition categories, seven clinical symptom categories, and seven chronic condition categories. Eight demographic variables (age, sex, emergency status, transfer source, relationship, and ethnicity, see Table E1 in the Supplement22−24) were retained in the final model.

For the validation process, the study population was randomly divided into training (n = 170,898) and validation (n = 42,725) cohorts. The Brier score was 0.08, and the mean annual H_{10} statistic was 15.95 (p = 0.051). A polynomial calibration plot is displayed in Figure E1 (online Supplement). The AUCROC was 0.85 (95% CI = 0.84−0.86; Figure E2), and the AUCPRC was 0.43 (Figure E3), and the sensitivity analysis for each hospital peer group is reported in Table E3 (online Supplement). Sensitivity analysis for confounding revealed a mean E value of 2.98 (Table E5, online Supplement) and a low risk from unmeasured confounders.

For the assessment of classification, 47 ICUs provided data for 232 ICU-years. The unadjusted CFR in 126 (54.1%) ICU-years exceeded ±3 SD of the mean (Fig. 2). After application of the COPE7 model, 105 (45.3%) were reclassified as SMR inliers (Fig. 3) and no CFR inliers were reclassified as SMR outliers. Moreover, 220 (94.4%) SMR values were within ±3 SD of the benchmark (Fig. 3). Dispersion metrics (Table E4) suggested the presence of over-dispersion but (the differential effects of additive, multiplicative, and Winsorised regression options [18,19; Figure E5] support) the possibility of unmeasured confounding. Model coefficients (Table E5) and worked examples (Table E6) are also available in the online supplement.

4. Discussion

4.1. Findings

We applied version 7 of the COPE model to a contemporary 5-year administrative dataset to test its validity. Despite a highly

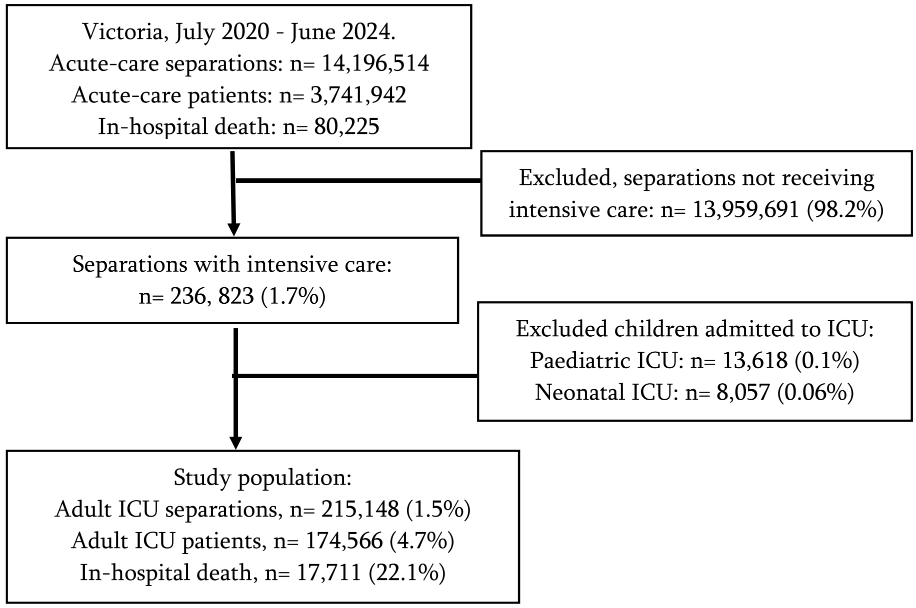

Fig. 1. Flow diagram of study population. ICU = intensive care unit.

Table 1
Study population: summary demographic data by hospital peer group.

Peer group	Tertiary public	Tertiary private	Major metropolitan	Major regional	Other private	Total
Hospitals, n (%)	7 (14.9)	13 (27.7)	11 (23.4)	10 (21.3)	6 (12.8)	47
Separations	65693 (30.5)	52615 (24.5)	46775 (21.7)	33732 (15.7)	16334 (7.6)	215148
Age, median years (IQR)	62 (48–72)	71 (61–78)	63 (47–74)	67 (53–77)	71 (60–79)	66 (52–76)
Male	41005 (62.4)	30086 (57.2)	25214 (53.9)	18372 (54.5)	8039 (49.2)	122716 (57.0)
Unplanned admission	44736 (68.1)	13612 (25.9)	35632 (76.2)	27368 (81.1)	5482 (33.6)	126830 (59.0)
Up-transfer	11271 (17.2)	2168 (4.1)	2387 (5.1)	1407 (4.2)	274 (1.7)	17507 (8.1)
Aged-care resident	281 (0.4)	5 (0.01)	266 (0.5)	391 (1.2)	9 (0.06)	952 (0.4)
Any chronic disease CDG	55941 (89.3)	46471 (88.3)	39061 (83.5)	28145 (83.4)	13893 (85.1)	183511 (85.3)

Frequency (percentage) displayed unless otherwise noted; CDG = clinical diagnosis group; IQR = interquartile range; up-transfer = interhospital transfer to hospital with greater range of services.[11]

Table 2
Study population outcomes by hospital peer group.

Peer group	Tertiary public	Tertiary private	Major metropolitan	Major regional	Other private	Total
Hospitals, n (%)	7 (14.9)	13 (27.7)	11 (23.4)	10 (21.3)	6 (12.8)	47 (100)
Separations	65693 (30.5)	52615 (24.5)	46775 (21.7)	33732 (15.7)	16334 (7.6)	215148
ICU aLOS, days (SD)	4.3 (7.6)	2.1 (3.0)	3.1 (4.4)	2.6 (3.2)	2.2 (3.1)	3.1 (5.2)
Hospital aLOS, days (SD)	15.1 (24.5)	11.2 (12.8)	12.1 (19.8)	8.9 (18.4)	10.2 (12.8)	12.2 (19.5)
Transfer to residential aged-care	225 (0.3)	146 (0.3)	192 (0.4)	229 (0.7)	107 (0.7)	899 (0.4)
Death in hospital	7709 (11.7)	1904 (3.6)	4837 (10.3)	2607 (7.7)	654 (4.0)	17711 (8.2)
Death at 90 days	10002 (15.2)	3118 (5.9)	7054 (15.1)	4479 (13.3)	1073 (6.6)	25726 (12.0)

Frequency (percentage) displayed unless otherwise noted; aLOS = average length of stay; ICU = intensive care unit; SD = standard deviation.

dimensional dataset of over 7000 candidate variables in a large population of over 200,000 records, the COPE7 methodology produced a parsimonious model with 31 covariates and acceptable calibration, discrimination, classification, and stability. Source data were extracted from an established administrative dataset common to all Australian and New Zealand jurisdictions.[6,8] Model covariates were restricted to patient-related factors independent of clinical management and the provision of care. Worked examples are provided in the online Supplement (Table E6).

The use of 90-day mortality, rather than in-hospital mortality, captured a greater proportion of early deaths which may have been related to provision of hospital care. The observed CFR at 90 days (12.0 per 100 separations) was 45% higher than the observed in-hospital CFR (8.2 per 100 separations). Three-quarters of hospital ICUs with outlier CFR values were reclassified as SMR inliers.

4.2. Implications

The results provide useful clinical insights. Despite the wide range of observed CFR between hospitals and between peer groups, most of this variance was attributable to patient-related factors that were present on arrival and were therefore outside the influence of the treating hospital; this is supported by the low ICC (probabilities). Over-dispersion of the COPE7 model may have played a small role in the residual variance.[18]

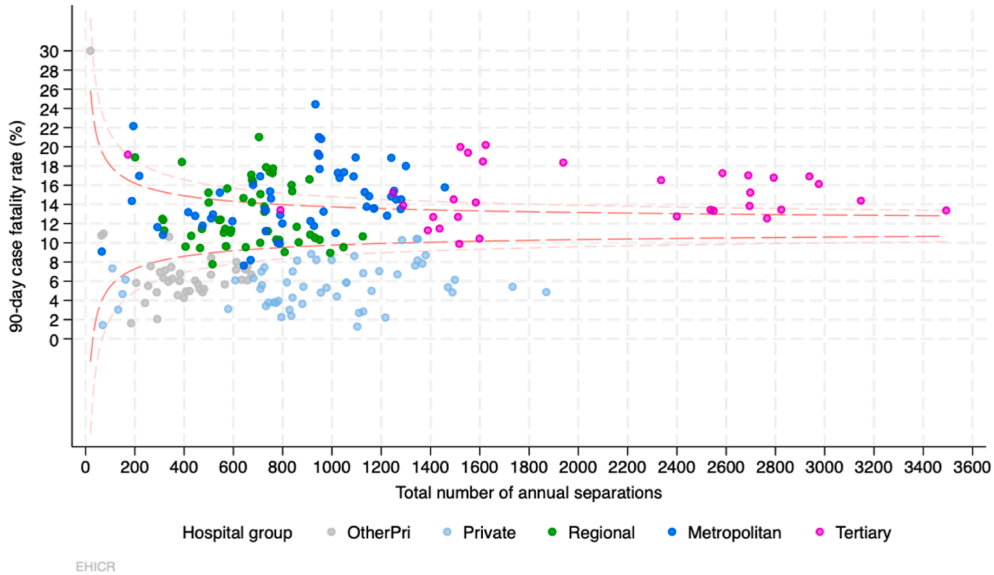

Fig. 2. Funnel plot of 90-day case fatality rates for all intensive care units from July 2020 to June 2024; the red dashed lines show ±2 SD and ±3 SD of the overall mean, with colour coding by the hospital peer groups. Precision is determined by the total number of adult intensive care separations (ordinate axis). SD = standard deviation.

The study period traversed the recent COVID-19 pandemic (2019–2022), and three of the five hospitals with higher than expected SMR values were designated pandemic referral centres. Of note, COVID-19 was not selected as a significant covariate in the final model. On the other hand, several COVID-19 complications (viral pneumonia, acute respiratory failure, and pulmonary thrombosis; see Table E5) were selected. It is clinically plausible that the mortality risk of COVID-19 was linked with a severe disease subgroup and not simply a confirmed serologic diagnosis. Under the current model of Australian intensive care, there appears to be a high degree of uniformity in patient outcomes despite the diverse cohorts, high-acuity patients, and the large distances between populations and health services.

COPE7 is complementary with other outcome prediction models, including the Australian and New Zealand Risk of Death (ANZROD[4]) model. While a detailed review of mortality prediction models and a direct comparison with ANZROD were beyond the scope of this report, a brief comparison is noteworthy. Both assess the outcome of adult intensive care admissions but have important differences in data collection, covariates, and structure. The ANZROD hospital SMR is generated from eight separate models fitted to hospital outcome based on the primary reason for admission to the ICU, seven chronic conditions, clinical measures of illness severity, and management decisions (treatment limitation, mechanical ventilation, and operative therapy) within the first 24 h of ICU admission. In contrast, COPE7 is a single parsimonious model fitted to 90-day outcome and permits multiple (admission) diagnoses and a wider range of chronic conditions. While it lacks the clinical granularity of the ANZROD model, it excludes management decisions[5] and is derived from administrative data extracted from the medical records based on international and national coding standards.[7,8]

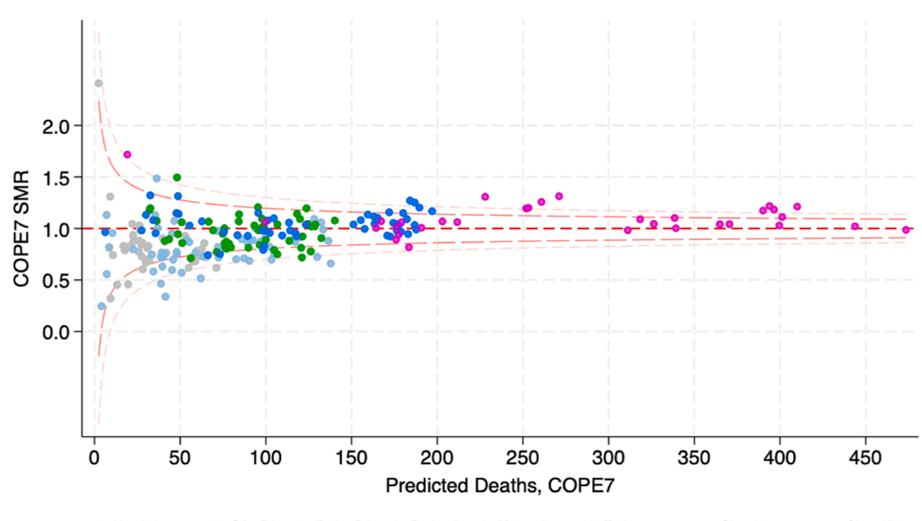

Fig. 3. Funnel plot for COPE7 standardised mortality ratio (SMR) for ICU-years (dots) compared to ±2 SD and ±3 SD (red dashed lines) of the state benchmark, colour coded for hospital peer group. Precision is determined by the total number of predicted deaths. COPE7 = critical care outcome prediction equation, version 7; ICU = intensive care unit; SD = standard deviation.

4.3. Strengths

This analysis was derived from a jurisdictional dataset of consecutive records over 5 years, including all adult ICU admissions and all hospitals in Victoria. While these data are collected primarily for activity-based funding, they are comprehensive and regularly audited. Linkage with the state's death registry enabled the 90-day survival analysis, which captures deaths that occur after hospital discharge or transfer or administrative reclassification. In addition to standard calibration and discrimination validation statistics, we found acceptable results for classification and dispersion metrics. We deliberately removed hospital factors and treatment decisions to minimise bias which may otherwise obscure important differences in patient outcome due to such factors.

4.4. Limitations

The quality of administrative data depends on the accuracy of coding and, more importantly, on the quality of the clinical documentation from which it is derived. While such datasets include some pertinent clinical information, they are binary and lack granularity. Their primary purpose is epidemiology- and activity-based funding rather than quality of care. The model was fitted to the outcome of all separations, and (hospital) readmissions were not excluded. The dimensionality and complexity of ICD10-AM required a multistage approach. The presence of over-dispersion suggests the presence of unmeasured confounders and highlights the trade-off between parsimony and calibration. Despite acceptable calibration in large groups, the model should not be used for prediction of outcome or management decisions in individuals, as evidenced by AUCPRC[16] data (Table E3). Finally, it is yet to be formally compared with existing models, including ANZROD, or tested in other jurisdictions.

In conclusion, COPE7 is a hospital mortality prediction model for all adult intensive care admissions, derived from administrative data common to all jurisdictions, and provides a pragmatic and complementary method for assessing and comparing the quality of intensive care services, epidemiology, and related research. Access to more than one metric focused on the same population augments clinical insights and allows triangulation of signals of interest such as outlier ICU with a high mortality rate.[9]

CRediT authorship contribution statement

GJD: conceptualisation, methodology, analysis, writing, editing, approval, accountability. JDS: conceptualisation, methodology, writing, editing, approval, accountability. SH: analysis, editing, approval, accountability. FS: methodology, analysis, writing, editing, approval, accountability. DP: analysis, writing, editing, approval, accountability. CK: writing, editing, approval, accountability. JM: methodology, analysis, writing, editing, approval, accountability.

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Conflict of 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 data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ccrj.2025.100131.

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