# Development of a novel computer aided risk score to predict the risk of death in hospital for acutely ill medical patients using their first blood test results and vital signs after admission.

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# Abstract (n=270/275 words)

**Background**: There are no established risk equations specifically for emergency medical patients who are cared for on general medical wards. However, following emergency admission, such patients usually have blood tests and (in the United Kingdom) vital signs monitoring using a physiologically based National Early Warning Score (NEWS) on admission. These data may be used to derive a risk of death on admission, which may be helpful to clinical teams.

**Objective**: To develop a computer aided risk score (CARS) based on combining the first recorded NEWS and blood test results and compare its performance with separate NEWS and blood test results models.

**Design:** Cross-sectional model development study.

**Setting:** Two acute hospitals (NH and YH respectively).

**Participants**: Adult (>=16 years) medical admissions discharged over a 24 month period with electronic NEWS and blood test results recorded on admission.

**Results**: The risk of dying in hospital was 5.4% (NH: 1336/24787) and 6.0% (YH: 1469/24674). The area under the receiver operator curve (discrimination c-statistics) for CARS (NH 0.89, YH 0.90) was better than NEWS alone (NH: 0.82, YH: 0.80) and blood results alone (NH: 0.86, YH: 0.84). The difference between observed and predicted number of deaths was not statistically significant for CARS but was significant for NEWS and blood tests alone.

**Limitations:** CARS does not apply to 20% to 26% patients who do not have blood tests and NEWS on admission. CARS has not yet been introduced into clinical practice in our study hospitals.

**Conclusions**: We have developed a novel, internally validated CARS which showed better performance than blood tests results and NEWS separately. CARS should now be carefully introduced and evaluated in routine clinical practice in our hospitals.

**Key words**: computer aided risk score, hospital mortality, vital signs, national early warning score, emergency admission

# Introduction

Internationally, it is estimated that about 3% to 6% of deaths in hospitals are preventable if care was optimised[[1]](#endnote-1),[[2]](#endnote-2),[[3]](#endnote-3),[[4]](#endnote-4). In a 10 hospital study in the United Kingdom (UK), 5% of deaths were deemed preventable4, of which 31% were estimated to be from poor clinical monitoring, 30% from diagnostic errors and 21% from inadequate drug or fluid management. These data suggest that clinical teams may not always be aware of the patient’s actual risk of death and if such information was made available to them this could enhance patient safety[[5]](#endnote-5). However, with the exception of the intensive care environment, most other hospital teams’ in general medical wards do not routinely have access to a statistically calculated risk of death5. There is some evidence to suggest that the results of routinely undertaken blood tests and/or vital signs data may be useful in predicting the risk of death5.

Blood tests are an integral part of clinical medicine, and are routinely undertaken during a patient’s stay in hospital. Typically, routine blood tests consist of a core list of seven biochemical and haematological tests, (albumin, creatinine, potassium, sodium, urea, haemoglobin, white blood cell count) and, in the absence of contraindications and subject to patient consent, almost all patients admitted to hospital undergo these tests on admission. Furthermore, in the UK National Health Service (NHS) creatinine blood test results are now used to identify patients at risk of Acute Kidney Injury (AKI)[[6]](#endnote-6) which is an important cause of avoidable patient harm[[7]](#endnote-7).

Likewise, in the UK NHS, the patient’s vital signs are monitored and summarised into a National Early Warning Score(s) (NEWS) that is mandated by the Royal College of Physicians (London), as part of the process of care and recorded on a clinical observation chart[[8]](#endnote-8). NEWS is derived from seven physiological variables or vital signs - respiration rate, oxygen saturations, any supplemental oxygen, temperature, systolic blood pressure, heart rate and level of consciousness (Alert, Voice, Pain, Unresponsive) – which are routinely collected by nursing staff as an integral part of the process of care, usually for all patients and then repeated thereafter depending on local hospital protocols8.

The use of NEWS is important and relevant because “Patients die not from their disease but from the disordered physiology caused by the disease”[[9]](#endnote-9). NEWS points are allocated according to basic clinical observations and the higher the NEWS the more likely it is that the patient is developing a critical illness (see appendix for further details of the NEWS). The clinical rationale for NEWS is that early recognition of deterioration in the vital signs of a patient can provide opportunities for earlier, more effective intervention. Whilst NEWS is known to be a good predictor of mortality in the hospital and pre-hospital setting[[10]](#endnote-10) it is not suitable for certain patient groups9 such as those with end stage renal failure or patients with acute intracranial conditions, which are characterised by abnormal physiology, or may not be suitably calibrated, say in patients with chronic obstructive airways disease. Furthermore, studies have shown that electronically collected NEWS are highly reliable and accurate when compared with paper based methods[[11]](#endnote-11),[[12]](#endnote-12),[[13]](#endnote-13),[[14]](#endnote-14).

Whilst several studies have considered the potential role of blood test results or patient physiology, few studies have combined these two data sources in to risk score that may be used in routine care5. In this paper we aim to combine blood tests results (including AKI score) and electronic NEWS into a novel computer aided risk score (CARS) which can be made available shortly after emergency medical admission in two acute hospitals. Specifically we aim to compare the performance of CARS separately against models based on NEWS and blood tests. If CARS is found to have better discrimination and calibration than models based on NEWS and blood tests, this would provide a strong justification for introducing and testing the use of CARS in routine clinical practice, especially as CARS involves no additional data collection burden and can readily be incorporated into the existing hospital computer systems.

# Methods

## Setting & data

Our cohorts of emergency medical admissions are from three acute hospitals which are approximately 100 kilometres apart in the Yorkshire & Humberside region of England– the Diana, Princess of Wales Hospital (n~400 beds) and Scunthorpe General Hospital (n~400 beds) managed by the Northern Lincolnshire and Goole NHS Foundation Trust (NLAG), and York Hospital (YH) (n~700 beds) (managed by York Teaching Hospitals NHS Foundation Trust). The data from the two acute hospitals from NLAG are combined because this reflects how the hospitals are managed and are referred to as NLAG Hospitals (NH), which essentially makes our study in two acute hospitals. Our study hospitals (NH, YH respectively) have been exclusively using electronic NEWS scoring since at least 2013 as part of their in-house electronic patient record systems. We chose these hospitals because they had electronic NEWS which are collected as part of the patient’s process of care and were agreeable to the study. We did not approach any other hospital.

We considered all adult (age≥16 years) emergency medical admissions, discharged during a 24 month period (1 January 2014 to 31 December 2015), with blood test results and NEWS. For each admission we obtained a pseudonymised patient identifier, patients age (years), gender (male/female), discharge status (alive/dead), admission and discharge date and time, and electronic NEWS. The NEWS ranges from 0 (indicating the lowest severity of illness) to 19 (the maximum NEWS value possible is 20). The admission/discharge date and NEWS are date and time stamped and the index NEWS was defined as the first score recorded within ±24 hours of the admission time. The first blood test results were defined as the first full set of blood tests results recorded within 4 days of admission.

We were unable to consider emergency admissions without blood tests results and NEWS recorded – this constituted 19.6% (7278/37100) of records in NH and 25.7% (9412/36751) of records in YH. We excluded records for the following reasons. (1) Records with a length of stay above the 95th centile (NH: 24.51 days, YH: 28.21 days) were excluded because the time interval from the index blood test results and NEWS data was deemed too excessive for the former to be reliable predictors of the risk of death in such long stay patients (where non-medical needs are more likely to dominate). (2) Records where the first NEWS was after 24 hours of admission and/or (3) where the first blood test was after 4 days of admission because these “delayed” data were considered less likely to reflect the sickness profile of patients on admission.

## Statistical analyses & modelling

We began with exploratory analyses including scatter plots and box plots that showed the relationship between covariates and risk of in-hospital death in our hospitals. We developed a logistic regression model to predict the risk of in-hospital death with the following covariates. Age (years), Gender, NEWS (including its components, plus diastolic blood pressure, as separate covariates), blood test results (albumin, creatinine, haemoglobin, potassium, sodium, urea, and white cell count), Acute Kidney Injury (AKI) score. We used the *qladder* function (STATA[[15]](#endnote-15)), which displays the quantiles of transformed variable against the quantiles of a normal distribution according to the ladder powers for each variable continious covariate and chose the following transformations:- (creatinine)-1/2, loge(potassium), loge(white cell count), loge(urea), loge (respiratory rate), loge(pulse rate), loge(systolic blood pressure), and loge(diastolic blood pressure). We used an automated approach to search for all two way interactions and incorporated those interactions which were statistically significant (p<0.0001) implemented in the MASS library[[16]](#endnote-16) in R[[17]](#endnote-17).

We set out to develop a CARS for each hospital, because previous work has raised concern about the risk of bias from case-mix adjustment which assume the relationship between the covariates and outcome is constant in different hospitals[[18]](#endnote-18),[[19]](#endnote-19). Another important rationale was that we intend CARS to be used by the local hospital, as part of their electronic heath record, to enhance quality of care – not for performance comparison between hospitals which has serious limitations17,[[20]](#endnote-20).

We assessed the performance of CARS versus models based on blood test results and NEWS separately using discrimination and calibration characteristics[[21]](#endnote-21) using an internal validation approach based on a bootstrapping method that is implemented in *rms* library[[22]](#endnote-22) in R17. Bootstrapping involved taking samples with replacement X times from original data. The range of X is suggested between 100 – 200 in each run. Each sample can be considered as repeating the data collection with the same number of patients and under identical circumstances as the original. In each of the 500 bootstrap samples a regression model was estimated, and evaluated on the original sample to estimate statistical optimism21,22.

Discrimination relates to how well a model can separate, (or discriminate between), those who died and those who did not. Calibration relates to the agreement between observed mortality and predicted risk. Overall statistical performance was assessed using the scaled Brier score which incorporates both discrimination and calibration19. The Brier score is the squared difference between actual outcomes and predicted risk of death, scaled by the maximum Brier score such that the scaled Brier score ranges from 0–100%. Higher values indicate superior models.

The concordance statistic (c-statistic) is a commonly used measure of discrimination. For a binary outcome, the c-statistic is the area under the Receiver Operating Characteristics (ROC) curve. The ROC curve is a plot of the sensitivity, (true positive rate), versus 1-specificty, (false positive rate), for consecutive predicted risks19. The area under the ROC curve is interpreted as the probability that a deceased patient has a higher risk of death than a randomly chosen non-deceased patient. A c-statistic of 0.5 is no better than tossing a coin, whilst a perfect model has a c-statistic of 1. Thus the higher the c-statistic the better the model. In general, values less than 0.7 are considered to show poor discrimination, values of 0.7–0.8 can be described as reasonable, and values above 0.8 suggest good discrimination. The 95% confidence interval for the c-statistic was derived using DeLong’s method as implemented in the pROC library[[23]](#endnote-23) in R17. Two ROC curves were formally tested using DeLong’s test for two correlated ROC curves (with a p<=0.05 set a priori for statistical significance), implemented in the pROC23 package in R17. Box plots showing the risk of death for those discharged alive and dead are a simple way to visualise the discrimination of each model. The difference in the mean predicted risk of death for those who were discharged alive and dead is a measure of the discrimination slope. The higher the slope the better the discrimination19. We used the Hosmer-Lemeshow deciles of risk goodness of fit test[[24]](#endnote-24) that compares observed versus predicted number of deaths, where a p<=0.05 indicates inadequate fit.

All analyses were carried using R17and STATA15.

## Role of the Funding Source

## The study is supported by the Health Foundation. The Health Foundation is an independent charity working to improve the quality of health care in the UK. The funding source was informed about the progress of the study but was not involved in the analysis of the data or the decision to submit the manuscript for publication.

## Ethical approval

## This study received ethical approval from The Yorkshire & Humberside Leeds West Research Ethics Committee on 17 September 2015 (ref. 173753)

# Results

## Cohort description

Table 1 shows the number (NH:37100, YH: 36751) of emergency medical admissions in each hospital over the 24 month period. Of these 19.6% (7278/37100) in NH and 25.6% (9412/36751) in YH were not eligible for our study because they did not have blood test results or NEWS recorded. Further exclusions are shown in Table 1.

|  |  |  |
| --- | --- | --- |
| **Characteristic** | **NLAG Hospitals**  **N (%)** | **York Hospital**  **N (%)** |
| Total emergency medical admissions | 37100 | 36751 |
| Excluded: No blood test results or NEWS recorded (%) | 7278 (19.6) | 9412 (25.6) |
| Excluded: Long length of stay >95th centile (%) | 1856 (5.0) | 1840 (5.0) |
| Excluded: First NEWS after 24 hours of admission (%) | 2036 (5.5) | 825 (2.2) |
| Excluded: First blood test results after 4 days of admission (%) | 1143 (3.1) | 0 (0) |
| Total excluded (%) | 12313 (33.2) | 12102 (32.9) |
| Total included (%) | 24787 (66.8) | 24674 (67.1) |

Table 1 Number of emergency medical admissions included/excluded in our study (%)

The in-hospital mortality was 5.4% (1336/24787) in NH and 6.0% (1469/24674) in YH. The age, sex, NEWS and blood test results profile is shown Table 2. Admissions in YH were older, with higher NEWS, higher AKI scores but higher albumin blood test results than NH.

|  |  |  |
| --- | --- | --- |
| **Characteristic** | **NLAG Hospitals** | **York Hospital** |
| N | 24787 | 24674 |
| Died in hospital (%) | 1336 (5.4) | 1469 (6.0) |
| Male (%) | 12465 (50.3) | 11771 (47.7) |
| Mean NEWS (SD) | 2.16 (2.29) | 2.58 (2.6) |
| Alertness |  |  |
| Alert (%) | 24333 (98.2) | 23968 (98.1) |
| Pain (%) | 83 (0.4) | 1197 (0.7) |
| Voice (%) | 308 (1.2) | 413 (1.7) |
| Unconscious (%) | 63 (0.3) | 126 (0.5) |
| AKI Score |  |  |
| 0 (%) | 22835 (92.1) | 22048 (89.4) |
| 1 (%) | 1197 (4.8) | 1565 (6.3) |
| 2 (%) | 390 (1.6) | 464 (1.9) |
| 3 (%) | 365 (1.5) | 597 (2.4) |
| Oxygen supplementation (%) | 4814 (19.4) | 2980 (12.1) |
| Mean Age [years] (SD) | 66.43 (19.47) | 67.7 (19.41) |
| Mean Albumin [g/L] (SD) | 33.4 (6.1) | 38.07 (5.78) |
| Mean Creatinine [umol/L] (SD) | 104.65 (81.75) | 102.08 (91.65) |
| Mean Haemoglobin [g/dL] (SD) | 127.06 (22.42) | 125.11 (22.16) |
| Mean Potassium [mmol/L] (SD) | 4.11 (0.59) | 4.27 (0.57) |
| Mean Sodium [mmol/L] (SD) | 137.06 (5.1) | 136.6 (4.68) |
| Mean White cell count [10^9 cells/L] (SD) | 9.79 (6.36) | 10.38 (11.9) |
| Mean Urea [mmol/L] (SD) | 7.7 (6.02) | 8.06 (5.97) |
| Mean Respiratory rate [breaths per minute] (SD) | 18.08 (3.63) | 18.63 (4.71) |
| Mean Temperature [oC] (SD) | 36.49 (0.67) | 36.3 (0.84) |
| Mean Systolic pressure [mmHg] (SD) | 128.92 (22.89) | 134.93 (27.23) |
| Mean Diastolic pressure [mmHg] (SD) | 74.65 (14.88) | 74.79 (15.47) |
| Mean Pulse rate [beats per minute] (SD) | 81.57 (17.88) | 86.04 (20.91) |
| Mean % Oxygen saturation (SD) | 95.91 (3.03) | 96.32 (2.9) |

Table 2 Number of emergency medical admissions included/excluded in our study (%)

Figures 1 to 4 show boxplots and scatter plots for each continuous (untransformed) covariate that was included in the CARS model for NH and YH respectively. The box plots (figures 1 & 2) show that in each hospital each covariate, to a lesser or greater extent, appears to change with discharge status – alive/died. The scatter plots in figures 3 & 4 show that there is a similar relationship between a given continuous covariate and the risk of death in each hospital.

Figure 1 Boxplot without outliers for continuous covariates with respect to patient’s discharge status (Alive/Died) for NLAG hospitals

## **Figure 2 Boxplot without outliers for continuous covariates with respect to patient’s discharge status (Alive/Died) for York hospital**

Figure 3 Scatter plots showing the observed risk of death with continuous covariates for NLAG hospitals.

NB: y-axis range changes in each plot.



Figure 4 Scatter plots showing the observed risk of death with continuous covariates for York hospital.

NB: y-axis range changes in each plot.

## Statistical Modelling of CARS

We compared the performance of three logistic regression models (see appendix) – CARS vs NEWS and blood test results. In each model we retained the patients age and gender. The CARS model included two way interaction effects but the NEWS and blood test results models did not. The model coefficients (log scale) are shown in the appendix with accompanying internal validation plots.

We compared the calibration and discrimination of CARS vs NEWS and blood test results alone. In each hospital CARS was found to have superior calibration and discrimination characteristics which is readily seen in ROC curves in figure 5 and discrimination box plots in figure 6. The difference in AUC for CARS was statistically significant in both hospitals (p<0.0001 CARS vs NEWS and CARS vs blood).

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Hospital and Model** | **Chi-square**† | **p-value**† | **Mean predicted risk: Alive** | **Mean predicted risk: Died** | **Discrimination** | **Scaled Brier Score** | **AUC**  **[95% CI]** |
| NLAG: NEWS | 32.8 | 0.000 | 0.047 | 0.167 | 0.120 | 0.114 | 0.824  [0.813 - 0.834] |
| NLAG: Bloods | 12.5 | 0.131 | 0.046 | 0.199 | 0.153 | 0.148 | 0.858  [0.849 - 0.867] |
| NLAG: CARS | 11.6 | 0.171 | 0.042 | 0.255 | 0.212 | 0.207 | 0.891  [0.883 - 0.899] |
| York: NEWS | 20.8 | 0.008 | 0.053 | 0.158 | 0.105 | 0.100 | 0.804  [0.794 - 0.815] |
| York: Bloods | 20.4 | 0.009 | 0.052 | 0.184 | 0.133 | 0.127 | 0.838  [0.829 - 0.848] |
| York: CARS | 11.4 | 0.180 | 0.045 | 0.287 | 0.242 | 0.236 | 0.897  [0.890 - 0.905] |

Table 3 Comparing calibration and discrimination of CARS vs NEWS and blood results based models to predict in-hospital mortality.

NB: † is based on the Hosmer-Lemeshow deciles of risk goodness of fit test with 8 degrees of freedom.

**Figure 5 Area under the Receiver Operating Characteristic (AUROC) curve for each hospital**

Grey line is for NEWS model, and grey dashed line is for Blood model. Black line is for CARS model.

**Figure 6 Discrimination of predicted risks from (A) NEWS model (B) Blood model (C) CARS model for NLAG Hospitals and (D) NEWS model (E) Blood model (F) CARS model for York hospital.**

# Discussion

We have used a simple set of routinely collected clinical variables based on the index routine blood test results and NEWS to develop an internally validated CARS for in-hospital mortality following emergency admission of adults. CARS exhibits superior discrimination and calibration than separate models based on blood test results or NEWS in each hospital. Whilst this may be somewhat unsurprising, it is perhaps the first time this has been demonstrated5. Indeed several previous studies5 have used blood test results[[25]](#endnote-25),[[26]](#endnote-26),[[27]](#endnote-27),[[28]](#endnote-28),[[29]](#endnote-29),[[30]](#endnote-30),[[31]](#endnote-31),[[32]](#endnote-32) or patient physiology[[33]](#endnote-33),[[34]](#endnote-34) but few studies have combined these two data sources[[35]](#endnote-35),[[36]](#endnote-36),[[37]](#endnote-37),[[38]](#endnote-38).

More importantly perhaps, CARS has employed covariates that are routinely measured, electronically recorded, routinely quality assured/audited, are an integral part of the process of care, are not susceptible to gaming, have clinical face-validity and are an established clinical currency in hospitals. These features lend themselves to the careful introduction of CARS into routine care (see later).

Our study is based on data from two different hospitals and our findings are similar. This suggests that our approach is likely to be generalisable to other UK NHS hospitals with electronically recorded blood test results and NEWS, especially as the use of NEWS in the UK NHS is mandated and that our approach does not rely in reference ranges from blood tests which can vary between hospitals. We excluded 20% and 26% of emergency admissions because they did not have blood test results and NEWS recorded. It is likely that such patients were very low risk (typically with short hospital stays) and/or very high risk requiring admission to, say, intensive care. Clearly CARS is not intended to apply to these patients. CARS does not consider the clinical history of the patient and diagnoses and comorbidity labels. These clinical data remain crucial to the clinical decision making process and serve to highlight that CARS, like other risk scores, can only be an aid to clinical teams5,21. We did not seek to undertake external validation of the CARS model because our aim was to produce, internally validated, hospital specific models. Nonetheless our approach lends itself to replication in hospitals with electronic blood test results and NEWS.

CARS is developed and designed for computerised real-time use. Whilst this offers a number of advantages (stated above), it is clear that CARS is not engineered for a paper based hospital systems. Quite aside from the complexity of CARS, the paper based calculations of NEWS is unreliable13,14 and this would undermine the performance of CARS in routine care. Nonetheless whilst NEWS data, and to a lesser extent blood test results, are repeated for a patient during hospitalisation, CARS is based on the first set of blood tests results and NEWS, yet the updating of CARS in real-time when new data becomes available is likely to be important to clinical teams and so warrants further study.

Further studies are also required to determine how best to incorporate CARS into the routine process of care and to evaluate the use of CARS in routine care. Such implementation issues are important but often overlooked in the development of risk equations5. In our study we have an ongoing work package dedicated to co-design (eg to consider real time updating of CARS) with staff to ensure careful introduction of CARS, a patient and public engagement theme to ensure their voice is heard. Finally we plan to carefully introduce CARS into routine clinical practice, evaluate its acceptance by staff and its impact on care including unintended consequences and threats to patient safety, especially as the role of risk scores to support clinical decision making for individual patients’ remains less clear5.

# Conclusion

We have developed a novel, internally validated CARS which showed better performance than blood tests results and NEWS separately. CARS should now be carefully introduced and evaluated in routine clinical practice in our hospitals.

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# Contributorship

MAM & DR had the original idea for this work. NJ was study coordinator. MF, AS and MAM undertook the statistical analyses. JD, CM & NJ are leads for qualitative studies. RH and KB extracted the necessary data frames. DR, JW and KS gave a clinical perspective. MAM and MF wrote the first draft of this paper and all authors subsequently assisted in redrafting and have approved the final version. MAM will act as guarantor.

# Competing Interests

The authors declare no conflicts of interest.

# Appendix

Model covariates and coefficients for CARS vs bloods vs NEWS in each hospital

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **NLAG Hospitals** | | | **York Hospital** | | |
|  | **CARS** | **Bloods** | **NEWS** | **CARS** | **Bloods** | **NEWS** |
| (Intercept) | 2.68  (2.832) | -6.855 (0.879) | -8.032 (0.215) | 6.147 (2.579) | -7.177 (0.912) | -7.765 (0.201) |
| Male | 0.082 (0.068) | 0.054 (0.065) | 0.124 (0.061) | 0.285 (0.066) | 0.123 (0.061) | 0.207 (0.057) |
| Age | -0.023 (0.012) | 0.038 (0.003) | 0.055 (0.003) | -0.026 (0.014) | 0.032 (0.002) | 0.052 (0.002) |
| Albumin | -0.328 (0.041) | -0.139 (0.006) | – | -0.376 (0.039) | -0.135 (0.006) | – |
| 1/sqrt(Creatinine) | 15.49 (2.791) | 17.095 (1.925) | – | 24.973 (2.492) | 15.874 (1.728) | – |
| Haemoglobin | 0.002 (0.003) | 0.009 (0.002) | – | -0.001 (0.002) | 0.009 (0.001) | – |
| Log(Potassium) | 0.125 (0.204) | 0.183 (0.198) | – | -0.251 (0.216) | 0.113 (0.205) | – |
| Sodium | -0.018 (0.007) | -0.013 (0.005) | – | 0.007 (0.007) | -0.005 (0.005) | – |
| Log(White Blood Count) | -0.268 (0.267) | 0.423 (0.062) | – | -1.07 (0.302) | 0.523 (0.055) | – |
| Log(Urea) | 1.254 (0.087) | 1.501 (0.081) | – | 1.196 (0.083) | 1.543 (0.079) | – |
| **AKI=0** |  |  |  |  |  |  |
| AKI1 | 0.247 (0.507) | – | – | 1.101 (0.468) | – | – |
| AKI2 | 0.577 (0.158) | – | – | 2.143 (0.128) | – | – |
| AKI3 | 0.419 (0.185) | – | – | 1.255 (0.158) | – | – |
| NEWS | 0.15  (0.07) | – | 0.332  (0.01) | 0.034  (0.06) | – | 0.274 (0.008) |
| Log(Respiratory) | 0.771 (0.214) | – | – | 0.816 (0.179) | – | – |
| Temperature | -0.156 (0.047) | – | – | -0.238 (0.037) | – | – |
| Log(Systolic) | -0.738 (0.265) | – | – | -0.599 (0.212) | – | – |
| Log(Diastolic) | 0.718 (0.221) | – | – | 0.398 (0.198) | – | – |
| Log(Pulse) | 0.748 (0.223) | – | – | 0.853 (0.183) | – | – |
| Oxygen Saturation | -0.021 (0.009) | – | – | -0.033 (0.01) | – | – |
| Oxygen sup | 4.66  (1.867) | – | – | 12.155 (1.965) | – | – |
| **Alert** |  |  |  |  |  |  |
| Pain | 0.377 (1.582) | – | – | -3.273 (1.36) | – | – |
| Voice | 0.315 (0.193) | – | – | 0.645 (0.171) | – | – |
| Unconscious | 2.436 (3.211) | – | – | 7.861 (2.041) | – | – |
| Log(pulse) \*  Oxygen sup | -0.729 (0.289) | – | – | -1.358 (0.269) | – | – |
| Age \* Albumin | 0.002  (<0.001) | – | – | 0.002  (<0.001) | – | – |
| NEWS \* 1/sqrt( Creatinine) | -0.21  (0.44) | – | – | -1.01 (0.354) | – | – |
| NEWS \* AKI1 | -0.037 (0.035) | – | – | -0.087 (0.024) | – | – |
| Pain \* Albumin | 0.011 (0.053) | – | – | 0.138 (0.038) | – | – |
| Oxygen sup \* Sodium | -0.006 (0.01) | – | – | -0.041 (0.011) | – | – |
| AKI1\*Albumin | 0.004 (0.017) | – | – | 0.021 (0.013) | – | – |
| Albumin \* Log(White Cell Count) | 0.018  (0.01) | – | – | 0.043 (0.009) | – | – |
| NEWS \* Haemoglobin | 0.0001  (<0.001) | – | – | 0.001  (<0.001) | – | – |
| Unconscious \* Log (Respiratory) | -0.16 (1.058) | – | – | -1.953 (0.673) | – | – |

Figure: Internal validation plots

(A) NEWS model for NLAG (B) Blood model for NLAG (C) CARS model for NLAG

(D) NEWS model for York (E) Blood model for York (F) CARS model for York

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