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| **APPENDIX 1: EXPANDED DESCRIPTION OF VARIABLES INCLUDED IN THE PREDICTIVE MODEL** | | |
| **CATEGORY** | **ELEMENTS INCLUDED** | **COMMENT** |
| Demographics | Age, sex | --- |
| Location | Specific hospital unit indicators | No standard nomenclature exists in our hospital systems; specific identification had to be obtained for each unit (e.g., ward, telemetry unit), whether for inclusion or exclusion of a patient. |
| Health services | Admission venue (emergency department or not) | Admission venue is employed as a predictor in main equation as well as in one of the two algorithms that generate the LAPS2 |
| Elapsed length of stay (LOS) in the hospital | Refers to cumulative time in the hospital at the time a patient’s EMR is scanned. Since inter-hospital transport is common in KPNC, this means a summation of LOS across both units *within* a hospital stay (e.g., ward, ICU, TCU) as well as hospital stays prior to discharge home or death. T0 is time of rooming in at the first eligible hospital unit. Very difficult variable to calculate in real time environment |

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| **APPENDIX 1: EXPANDED DESCRIPTION OF VARIABLES INCLUDED IN THE PREDICTIVE MODEL (continued)** | | |
| **CATEGORY** | **ELEMENTS INCLUDED** | **COMMENT** |
| Status | Care directive orders | Our electronic record permits 4 categories: full code, partial code, “do not resuscitate,” and comfort care only. Patients with a “comfort care order” are not eligible for an alert |
| Admission status | In order for algorithms to be executed, patients must have been admitted to an eligible unit (ward, TCU, telemetry). Both inpatient and observation admissions are eligible. |
| Physiologic | Vital signs (temperature, heart rate, respiratory rate, systolic blood pressure, diastolic blood pressure) | Obtained from nursing documentation flowsheets. Simple data processing employed (no complex data cleaning, just dropping certain out of range values) prior to secondary statistical processing. |
| Pulse oximetry |
| Neurologic status |
| Neurological status | Free text entries from nursing documentation flowsheets collapsed into 5 categories | See citation \_ for a description of how we collapsed all possible text entries into a simple scoring schema |

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| **APPENDIX 2: PREDICTOR VARIABLES – EXPANDED DESCRIPTION** | | |
| **CATEGORY** | **ELEMENTS INCLUDED** | **COMMENT** |
| Pulse oximetry | Obtained from nursing documentation flowsheets | Standardized to mean 0 std 1  We need to specify truncation rules |
| Laboratory test results | Anion Gap  Bicarbonate  Bicarbonate squared  Glucose  Hematocrit  Hematocrit squared  Hematocrit cubed  Lactate  Log Blood Urea Nitrogen  Log Creatinine  Log Creatinine squared  Sodium  Troponin  White Blood Cell Count | Standardized to mean 0 std 1 |
| Laboratory test results (transformed) | Poor Man’s Lactate  Shock Index  This refers to things like the poor man’s lactate | Standardized to mean 0 std 1 |
| Composite severity of illness score (LAPS2) | Includes all laboratory test results listed above | See citations 11 and 18 for details on how this score is calculated |
| Composite comorbidity score (COPS2) | All International Classification of Diseases diagnosis codes incurred by a patient in preceding 12 months | See citation 18 for details on how this score is calculated |

**APPENDIX 3: INSTANTIATION APPROACHES WE CONSIDERED**

Currently, three broad strategies for instantiating predictive models in the EMR are being explored in several Kaiser Permanente regions. One approach consists of creating a real time copy of EMR data in a data repository that (with a small time delay) mirrors the “front end.” It is then possible to perform calculations using these data; results from these calculations can then be reported in an external viewer or via a web link in the EMR. A second approach involves embedding a predictive model directly into the EMR such that calculations are executed using the native code used by the system (in this case, Caché, www.intersystems.com). As “proof of concept” that one could embed equations in Epic, our team worked with the Kaiser Permanente EMR team on a project that applies the American Academy of Pediatrics’ bilirubin guideline nomogram to neonatal bilirubin results1, 2.This automated system has now been running in KPNC for several years. Lastly, it is possible to employ a technology known as a web service, which extracts (“pulls”) data from the EMR, transmits it to a second application where calculations are performed. It is then possible to “push” these results back into the EMR so they can be displayed for clinicians. We excluded the first option because displaying results outside the EMR was not an option given the need to have clinician acceptance. In theory, the second option was attractive. However, the bilirubin algorithm only uses 4 variables (chronological age, gestational age, direct antibody test, and bilirubin test result), whereas the current equations have many more variables. Given the complexity of the calculations involving many variables we elected to employ web services to extract data for processing using a Java application outside the EMR, which then “pushed” results into the EMR “front end.”

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1. American Academy of Pediatrics. Management of hyperbilirubinemia in the newborn infant 35 or more weeks of gestation. Pediatrics. Jul 2004;114(1):297-316.

2. American Academy of Pediatrics. Management of hyperbilirubinemia in the newborn infant 35 or more weeks of gestation. Pediatrics. 2004;114(4):1138.