Supplementary Online Content


**eFigure.** Theoretical Framework of the Predictor Constructs We Hypothesized Contributed to Alarm Response Time and the Variables in Our Dataset That We Mapped to the Predictor Constructs.

**eMethods.** Description of Model Building and Evaluation.

**eTable.** Characteristics of Actionable Alarm Subtypes.

This supplementary material has been provided by the authors to give readers additional information about their work.
Faster response time to monitor alarms that occur when not in room

**Response Construct Variable**
- Faster response time to monitor alarms that occur when not in room
- RN's concern that patient is at increased risk of a life-threatening condition
- RN intervened during a prior alarm for this patient
- RN's physical and mental alertness
- RN has a light patient load
- Lack of safety net to get help if there is a true emergency
- Alarm is a "crisis alarm" indicating life-threatening arrhythmia
- RN early in career
- RN's lack of chronic alarm fatigue
- RN's lack of acute alarm fatigue
- RN unfamiliar with patient
- RN has a light patient load
- [on complex care service]
- [nasogastric or nasojejunal feeding tube]
- [central venous line present]
- [age group]
- [prior observed alarm with intervention]
- [each successive hour in shift]
- [1:1 nurse:patient assignment]
- [no family at bedside]
- [crisis alarm level]
- [<1 year of experience working as a nurse]
- [nonactionable alarm exposure for this patient]
The goal of our study was to explain the relationships between the variables in the conceptual model and response time. For that reason we did not aggressively pursue formal variable selection methods to fit the best possible model in terms of variable combinations. We did examine correlation between variables; we examined a correlation matrix of all possible pairs of variables used in the model. The average absolute value of all the correlation coefficients was 0.09, suggesting that overall there was little correlation between variables. There were 5 variable pairs with correlation coefficients with absolute values greater than 0.20: naso-enteral tube + patient service (0.56), patient age + patient service (0.34), prior nurse intervention + hour number in shift (0.32), naso-enteral tube + patient age (0.28), and naso-enteral tube + in room family (0.24). The remaining 40 pairs of variables had correlation coefficients with absolute values less than or equal to 0.20. We also examined all possible 2x2 tables arising from different variable combinations; none of the tables were aliased (meaning that there were no 2x2 tables with 2 of the 4 cells with zero observations.) This analysis reassured us that it was unlikely that the model would produce spurious results.

We carefully considered which distribution to use before deciding to use Weibull, and aimed to optimize fit in that regard. We compared AICs of models using the Weibull, exponential, lognormal, and loglogistic distributions. Weibull models had the lowest AIC and thus this distribution was the most suitable fit for the data. We also directly compared the Weibull and exponential models using the likelihood-ratio test and demonstrated that the Weibull model had better fit than the exponential model (P<0.0001). We graphically confirmed the appropriateness of the Weibull distribution by examining smoothed hazard and log-hazard plots stratified by each level of each categorical variable in the model.

We examined a Cox-Snell residual plot to evaluate the overall fit of the final model. We verified that the model had reasonably good fit as evidenced by the plot varying only minimally about the 45 degree reference line, deviating slightly in the right hand tail, as is often seen due to the reduced effective sample in the tail.

We examined unadjusted point estimates prior to building the multivariable model, but did not use formal criteria (such as P values) to decide what to include in the multivariable model. Comparing unadjusted and adjusted point estimates formally would be relevant to confounding. Examination of confounding would be most appropriate if we were developing a model examining the role of one important pre-specified exposure and its relationship to the outcome adjusted for confounding, such as the relationship between a drug and a clinical outcome. We were interested in looking at the adjusted relationships of each potential risk factor rather than designing an explanatory model to evaluate a single exposure-outcome relationship. For that reason we did not present the unadjusted point estimates in the manuscript.
We intended to evaluate model stability using bootstrapping. However, Stata does not allow bootstrapping of stratified parametric regression survival-time models with clustering if there are “singletons.” In our model, singletons were instances when one nurse took care of only one patient who was a subject in our study. This represented approximately one-third of the nurses in our study. Thus dropping the singletons to bootstrap was not a viable option. We also considered using delete-one jackknife to identify overly influential observations, however, this is not possible to do using Stata with stratified parametric regression survival-time models. Therefore, we took a conservative approach to building the stratified model and estimating the standard errors using clustering by patient.
## eTable. Characteristics of Actionable Alarm Subtypes.

<table>
<thead>
<tr>
<th></th>
<th>Actionable-intervention&lt;sup&gt;a&lt;/sup&gt;</th>
<th>Actionable-consultation&lt;sup&gt;b&lt;/sup&gt;</th>
<th>Actionable-warranted action&lt;sup&gt;c&lt;/sup&gt;</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total alarms, n</td>
<td>24</td>
<td>10</td>
<td>16</td>
<td>50</td>
</tr>
<tr>
<td>Alarms occurring while no clinicians were in patient’s room or were viewing the central monitoring station, n (%)</td>
<td>10 (42)</td>
<td>3 (30)</td>
<td>16 (100)</td>
<td>29 (58)</td>
</tr>
<tr>
<td>Median response time to alarms occurring while no clinicians were in the patient’s room or were viewing the central monitoring station, time in minutes (range)</td>
<td>0.3 (0.02-1.6)</td>
<td>0.3 (0.3-1.1)</td>
<td>1.7 (0.3-13.5)</td>
<td>0.7 (0.02-13.5)</td>
</tr>
<tr>
<td>Alarm type</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SPO$_2$ low, n (%)</td>
<td>24 (100)</td>
<td>8 (80)</td>
<td>11 (69)</td>
<td>43 (86)</td>
</tr>
<tr>
<td>Apnea, n (%)</td>
<td>0 (0)</td>
<td>0 (0)</td>
<td>2 (12)</td>
<td>2 (4)</td>
</tr>
<tr>
<td>RR high, n (%)</td>
<td>0 (0)</td>
<td>1 (10)</td>
<td>0 (0)</td>
<td>1 (2)</td>
</tr>
<tr>
<td>Brady/HR low, n (%)</td>
<td>0 (0)</td>
<td>0 (0)</td>
<td>3 (19)</td>
<td>3 (6)</td>
</tr>
<tr>
<td>Tachy/HR high, n (%)</td>
<td>0 (0)</td>
<td>1 (10)</td>
<td>0 (0)</td>
<td>1 (2)</td>
</tr>
<tr>
<td>Interventions observed</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reposition / stimulate, n (%)</td>
<td>20 (83)</td>
<td>NA</td>
<td>NA</td>
<td>20 (40)</td>
</tr>
<tr>
<td>Initiate or increase supplemental oxygen, n (%)</td>
<td>3 (13)</td>
<td>NA</td>
<td>NA</td>
<td>3 (6)</td>
</tr>
<tr>
<td>Suction, n (%)</td>
<td>1 (4)</td>
<td>NA</td>
<td>NA</td>
<td>1 (2)</td>
</tr>
</tbody>
</table>

Abbreviations: HR, heart rate; NA, not applicable; RR, respiratory rate; SPO$_2$, blood oxygen saturation

**Actionable definitions:** A valid clinical alarm that either (a) leads to an observed clinical intervention (such as initiating supplemental oxygen) or (b) leads to an observed consultation with another clinician (such as discussing the patient’s tachycardia with a resident) at the bedside or (c) warrants intervention or consultation for a clinical condition (such as a prolonged desaturation) but the condition was unwitnessed: occurring while no clinicians are present and resolving before any clinicians entered the room or visualized the central monitoring station.