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Rapid Response Systems

Temporal distribution of instability events in continuously monitored step-down unit patients: Implications for Rapid Response Systems☆

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ABSTRACT

Aim: Medical Emergency Teams (MET) activations are more frequent during daytime and weekdays, but whether due to greater patient instability, proximity from admission time, or caregiver concentration is unclear. We sought to determine if instability events, when they occurred, varied in their temporal distribution.

Methods: Monitoring data were recorded (frequency 1/20 Hz) in 634 SDU patients (41,635 monitoring hours). Vital sign excursion beyond our MET trigger thresholds defined alerts. The resultant 1399 alerts from 216 patients were tallied according to clock hour and time elapsed since admission. We fit patient ID ($n = 216$), clock hour, time since SDU admission, and alert present into a null model and three mixed effect logistic regression models: clock hour, hours elapsed since admission, and both clock hour and time elapsed since admission as fixed effect covariates. We performed likelihood ratio tests on these models to assess if, among all alerts, there were proportionally more alerts for any given clock hour, or proximity to admission time.

Results: Only time elapsed since admission ($p < 0.001$), and not clock hour adjusting for time elapsed since admission ($p = 0.885$), was significant for temporal disproportion. Results were unchanged if the first 24 h following admission were excluded from the models.

Conclusion: Although instability alerts are distributed most frequently within 24 h after SDU admission in unstable patients, they are otherwise not more likely to distribute proportionally more frequently during certain clock hours. If MET utilization peaks do not coincide with admission time peaks, other variables contributing to unrecognized instability should be explored.

1. Introduction

Medical emergency teams (MET) are a portion of the efferent arm of rapid response systems (RRS).[1] METs are meant to be activated to support patients outside of intensive care units when they become unstable, and their needs exceed what the ward or step-down unit (SDU) can offer. The afferent arm of the RRS is based upon bedside caregivers "tracking" of patients' conditions and then activating the MET based upon locally agreed upon "triggering" criteria.[1] Though commonly used, MET efficacy in improving outcomes and decreasing mortality is still unproven.[2,3] This lack of mortality benefit has been postulated to be due to RRS afferent arm failure,[4] even in ward and SDU environments where patients are continuously monitored.

In support of this hypothesis, MET activation is widely reported to be more frequent during weekdays than on weekends[5,6] and during daylight rather than early evening and nighttime hours.[5–7] However, it is not known if such MET activation clustering is due to true temporal variation in the distribution of instability. We sought to determine if instability events, when they occurred, varied in their temporal distribution according to clock hour, or day of week. We examined instability according to our local MET track and trigger abnormal vital sign (VS) criteria for a cohort of SDU patients with continuously monitored VS. Lack of temporal variation in instability distribution would suggest that mechanisms other than continuous single VS monitoring are needed to enhance instability detection and support the RSS afferent arm.

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2. Methods

Following Institutional Review Board approval we collected continuous VS data streams, including HR (3-lead ECG), RR (bioimpedance signaling), SpO_2 (pulse oximeter Model M1191B, Phillips, Boeblingen, Germany; clip-on reusable finger sensor), and intermittent noninvasive BP (minimum frequency 2 h), from all patients over two sequential but separate 8 week periods in a 24-bed adult surgical-trauma SDU (Level-1 Trauma Center). This yielded monitoring data on 642 patient admissions, and a total of 41,635 h, or 4.72 years of patient monitoring hours, with each patient having a mean of 80 and a median of 55 monitoring hours.

Noninvasive VS monitoring data were recorded at a 1/20 Hz frequency for HR, RR, systolic (SysBP) and diastolic (DiaBP) blood pressure, and SpO_2. VS excursion beyond our MET trigger thresholds (HR <40 or >140, RR <8 or >36, SysBP <80 or >200, DiaBP >110, SpO_2 < 85%) were defined as alert events and occurred 634,137 times. We additionally required that events had to persist initially for a tolerance of 40 s, and a minimum duration of 4 min continuously, or a cumulative duration of 4 out of 5 min if intermittent to screen for events with clinical relevance. The event period under analysis was from the time the first VS crossed threshold and fulfilled the additional persistence criteria, until the time the first VS moved back into the stability range. Next, all VS events were provided as graphical time plots and visually adjudicated by two expert clinician reviewers, who annotated each event as a real alert or artifact based on inspection of the real-time VS time plots varying values, and artifact then excluded from further analyses.

Next, each discrete alert was noted according to both clock hour and day of week of occurrence. Additionally, each alert was assigned according to the number of hours elapsed since the unstable patient's admission time. To determine temporal event distribution according to time of day using a 24 h clock, all the alerts were allocated to a clock hour according to time of onset, with the hour lasting from 00:00 min to 59:59 min. Alerts that lasted more than 1 h were allocated only to the initial hour of onset. To determine temporal event distribution according to the day of a 7-day week, all the alerts were allocated to the day associated with time of alert onset, with a day lasting from 0.00 to 23.59 h. Alerts lasting across the 00.00 h of the next day were allocated only to the day of onset.

R open source statistical software (Version 2.15.2) was used. All alerts were tallied according to clock hour during unstable patient's full length of stay (LOS), and for only the first 24 h after admission. All alerts were also tallied per day of the week. To determine if there was temporal variation in instability distribution across clock hours, we employed a mixed effect logistic regression model.[8] This approach was chosen due to the observation that, of patients who become unstable, some patients may have multiple hour instances as well as multiple alert events during his/her LOS, leading to possible inter-independence of measures for the same patient. The mixed-effects model accounts for multiple hour instances and multiple alerts for an individual patient as they occur. The models were fit to a data set with variables describing clock hour and/or number of hours elapsed since the time of SDU admission, with a binary response indicating whether a particular patient had an alert during a particular clock hour during his/her LOS, or a particular number of hours elapsed since admission. If a patient had multiple alerts during the same hour, only one alert was accounted. We then fit three types of mixed effect logistic regression models to these data. In all models, patient identification (ID) (n = 216 patients with at least one instability alert) served as the grouping factor, and was treated as a random effect. Model 0 was the null model with only the intercept parameter. In Model 1 clock hour; in Model 2 h elapsed since SDU admission, and in Model 3 both clock hour and elapsed time since SDU admission were the fixed effects. Likelihood ratio tests were performed comparing pairs of these models in the mixed effect logistic regression for unstable patients to determine if, taking all alerts into consideration, there were proportionally more alerts distributed according to certain clock hours. All model types were built for three LOS subsets for the unstable alerted patients: (1) entire SDU LOS, (2) only hours 0–24 after SDU admission, and (3) time from hour 25 through SDU discharge. Our approach was intended to identify the risk of the frequency of alerts occurring within a specific temporal unit (clock hour or day of week) among all alerts occurring (a proportion), and not the risk of having an alert among all monitored patients (a prevalence). Statistical significance was set at a p value of 0.05.

Table 1
Summary of the step-down unit (SDU) patient, monitoring, and event data for the total sample (all patients) and for only those patients who ever became unstable even once (unstable patients).

Variable	Total
All patients	
Total	642
% Male (*N*, %)	371 (58.5%)
Age (mean years ± SD)	57.68 ± 19.95
Race (*N*, %)	
White	461(72.7%)
Black	85 (13.4%)
Charlson Deyo Comorbidity Index (mean ± SD)	1.09 ± 1.53
SDU length of stay (mean days ± SD)	3.31 ± 3.31
Hospital length of stay (mean days ± SD)	9.05 ± 13.76
Unstable patients	
Total	216
% male (*N*, %)	126 (58%)
Age (mean years ± SD)	58.9 ± 19.5
Race (*N*, %)	
White	162 (75%)
Black	28 (13%)
Charlson Deyo Comorbidity Index (mean ± SD)	1.34 ± 1.7
SDU length of stay (mean days ± SD)	4.2 ± 4
Hospital length of stay (mean days ± SD)	12.5 ± 20
Instability events without persistence requirement	
Total events	634,137
Total events by subtype	
HR	20,381 (3%)
RR	155,689 (25%)
SpO_2	172,348 (27%)
Systolic BP	147,095 (23%)
Diastolic BP	138,624 (22%)
Instability events with persistence requirement	
(Tolerance 40 s, length 240 s, duty cycle 80%)	
Total events	2333
Total events by subtype	
HR	150 (6%)
RR	1002 (43%)
SpO_2	907 (39%)
BP	274 (12%)
Instability event annotation by experts	
Total Events	2333
Real alerts	1399 (60%)
Artifact	934 (40%)
Real alerts total	1399
Real alerts by subtype	
HR	137 (10%)
RR	693 (50%)
SpO_2	425 (30%)
BP	144 (10%)

Key: HR = heart rate; RR = respiratory rate; BP = blood pressure; SpO_2 = oxygen saturation of peripheral arterial blood; BP = blood pressure.

3. Results

The demographics of the sample and instability events are listed in Table 1. The total sample of 642 patients admissions was