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Correlation of vital sign centiles with in-hospital outcomes among adults encountered by emergency medical services

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Abstract

Background: Vital signs are a critical component of the prehospital assessment. Prior work has suggested that vital signs may vary in their distribution by age. These differences in vital signs may have implications on in-hospital outcomes or be utilized within prediction models. We sought to (1) identify empirically derived (unadjusted) cut points for vital signs for adult patients encountered by emergency medical services (EMS), (2) evaluate differences in age-adjusted cutoffs for vital signs in this population, and (3) evaluate unadjusted and age-adjusted vital signs measures with in-hospital outcomes.

Methods: We used two multiagency EMS data sets to derive (National EMS Information System from 2018) and assess agreement (ESO, Inc., from 2019 to 2021) of vital signs cutoffs among adult EMS encounters. We compared unadjusted to age-adjusted cutoffs. For encounters within the ESO sample that had in-hospital data, we compared the association of unadjusted cutoffs and age-adjusted cutoffs with hospitalization and in-hospital mortality.

Results: We included 13,405,858 and 18,682,684 encounters in the derivation and validation samples, respectively. Both extremely high and extremely low vital signs demonstrated stepwise increases in admission and in-hospital mortality. When evaluating age-based centiles with vital signs, a gradual decline was noted at all extremes of heart rate (HR) with increasing age. Extremes of systolic blood pressure at upper and lower margins were greater in older age groups relative to younger age groups. Respiratory rate (RR) cut points were similar for all adult age groups. Compared to unadjusted vital signs, age-adjusted vital signs had slightly increased accuracy for HR and RR but lower accuracy for SBP for outcomes of mortality and hospitalization.

Conclusions: We describe cut points for vital signs for adults in the out-of-hospital setting that are associated with both mortality and hospitalization. While we found age-based differences in vital signs cutoffs, this adjustment only slightly improved model performance for in-hospital outcomes.

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INTRODUCTION

Early hospital notification is widely used to rapidly mobilize receiving teams for trauma,[1,2] stroke,[3,4] or cardiac catheterization.[5] Yet these disease-specific notifications do not address all critically ill patients encountered in emergency care settings, where patients present with other time-sensitive or undifferentiated conditions such as nontraumatic hemorrhage, respiratory failure, and shock. Early warning scores and predictive models can help identify patients at highest risk of critical illness across emergency care settings.[6,7] Predictive models among adults have been reported to identify patients at risk of poor outcomes[8,9] and to screen for sepsis.[10,11] Similar instruments identify adults at risk of mortality or other outcomes associated with severe injury following trauma.[12–14] At the heart of many of these models is an assessment for abnormal vital signs based on a comparison with normal values derived from a healthy population. Other risk prediction models have incorporated vital signs for use more broadly and include the Rapid Acute Physiology Score,[15] Rapid Emergency Medicine Score,[16,17] Modified Early Warning Score,[18] and National Early Warning Score.[19]

The early identification of patients in the prehospital setting with structured notification mechanisms initiated prior to arrival can optimize the use of hospital-based resources, especially in high-census emergency departments (ED), where critically ill patients may not otherwise be rapidly identified. As prehospital assessments are among the first clinical assessments of patients, they could have an important role in informing ED clinicians of patients needing rapid evaluation. A number of early warning systems have been described from the EMS population, which may be used to facilitate the rapid identification of patients with critical illness or injury.[6,7,20,21] However, vital signs in the out-of-hospital setting may often be altered by pain, anxiety, or other confounding factors aside from the underlying disease, making their comparison to healthy subjects potentially flawed. For example, in an analysis of over 3.7 million pediatric patients encountered by a nationally representative sample of emergency medical services (EMS) agencies, 76% of patients had at least one abnormal vital sign based on Pediatric Advanced Life Support criteria.[20]

As an alternative approach, vital signs may be classified using centiles, in which these measures are assessed based on their relative position within the population of interest, expressed in terms of the percentage of data points that fall below it. The use of centile-based vital signs specific to the population of interest may provide more relevant data compared to what is commonly used in early warning systems.[6,7,20,21] Centile distributions may be calculated for an overall sample or may be adjusted by one or more variables. Specifically, age-based vital signs criteria have recently been incorporated into trauma triage guidelines.[22] Differences in vital signs among adult age groups, particularly for older patients, may enhance the identification of adults with critical illness. However, limited information exists on the relationship between age and vital signs as part of risk prediction models for adults cared for by EMS.[1]

In this study, we first sought to empirically derive centiles for heart rate (HR), respiratory rate (RR), and systolic blood pressure (SBP) for adults with out-of-hospital emergencies who were transported to an ED. Second, we aimed to evaluate the impact of adjusting for age in the evaluation of centile curves for vital signs to identify practical targets for adjustment of vital signs classification in adult patients based on age categories. Third, we examined the association of both unadjusted and age-adjusted vital signs with hospital admission and in-hospital mortality.

METHODS

Study design and setting

We derived centiles of vital signs for adults with out-of-hospital emergencies using a nationally representative cross-sectional database of EMS encounters within the United States. We evaluated the association of age with vital signs in this setting based on research demonstrating the potential benefits of using age-adjusted vital signs in other contexts[20,22] and based on research demonstrating changes in vital signs over the adult lifespan.[23] We assessed agreement for these data and correlated them to in-hospital outcomes using a separate national EMS data set. Finally, we evaluated the predictive value of vital signs among adults with out-of-hospital emergencies. The performance of this study was approved by our institutional review board. This study adhered to the STrengthening the Reporting of OBservational studies in Epidemiology reporting guidelines.[24]

Cut point derivation was performed using a sampling of data from the 2018 National Emergency Medical Services Information System (NEMSIS; v.3.4.0). NEMSIS is a national retrospective EMS registry that includes standardized patient care records submitted by U.S. EMS agencies. The 2018 data set includes 22,532,890 EMS activations submitted by 9599 EMS agencies servicing 43 states and territories. Most of these encounters (94%) are for adults. We used this year of NEMSIS data for derivation to avoid potential overlap with encounters for the ESO data set that were used to assess agreement and to evaluate for in-hospital outcomes.

The second data set we used was composed of out-of-hospital patient care records from 2019 to 2021 within the ESO Data Collaborative (ESO, Austin, TX). ESO is a widely used EMS electronic patient care reporting system that includes patient care record data from approximately 1300 (in 2019) to 2000 EMS (in 2021) agencies in all 50 states. Annually, a standard data set for research purposes is available at no cost following a research proposal process. The ESO data set pulls data directly from the electronic reports without relying on the aggregation and reporting of specific data elements through state EMS agencies.[25] A subset of EMS agencies use a health data exchange software that bidirectionally links EMS and hospital outcome data, including ED and inpatient dispositions, using standard Health Level Seven messaging (HL7), a global messaging standard for the exchange of administrative and clinical data. We used 3 years of data from ESO to maximize the number of encounters with in-hospital data available.

Selection of participants

From both data sources, we included all EMS encounters for patients, excluding (1) encounters with no documented age and (2) children (<18 years). To place greater focus on undifferentiated patients evaluated from the scene in typical scenarios, we only included encounters for 9-1-1 responses treated by a Basic Life Support (BLS) or Advanced Life Support (ALS) clinician, but not a critical care service.

Measures

From each of the study samples, we extracted the vital signs of HR, RR, and SBP. We used the first vital sign documented by EMS per encounter, on the basis that these would be prior to any interventions performed by that EMS service and because initial vital signs likely have greater use in predictive modeling or may be embedded into clinical decision support systems. We selected these variables based on their association with critical illness,[15–19] their correlation with in-hospital measures,[6–8] their potential association with age,[23] and their availability within the data set.

In encounters where time stamps were not provided (representing <3% of all vital signs), we used the first listed vital sign for that encounter in the NEMSIS data set. We additionally acquired the following descriptive data: age, sex, level of service (as ALS or BLS), census region, timing of the encounter (during the weekend and during three 8-h daytime periods), disposition, and the availability of the three vital signs.

Outcomes

Our primary outcome was the classification of vital signs using centile-based criteria. Our secondary outcomes were in-hospital mortality and hospitalization.

Data analysis

We evaluated the distribution of our data using histograms and boxplots by age. We excluded vital signs that had a high likelihood of being erroneous or were consistent with a moribund state: HR of <30 or >300 beats/min, RR of ≥120 or <1 breaths/min, and SBP of ≤30 or ≥250 mm Hg. These cutoffs have been previously used in vital signs modeling research[20,26] and have face validity as being potentially erroneous or associated with a perimortem state. We identified the proportion of all vital signs (both initial and any subsequent vital signs) among included encounters identified in the NEMSIS data set that were excluded because of these criteria. We derived centiles in two ways: as an absolute cutoff and as an age-based centile. In keeping with our prior methods, we applied ± 3 and ± 2 of gaussian noise to individual HR and RR measurements, respectively.[20] We evaluated the distribution of the three vital signs using a cumulative distribution function. We identified cut points corresponding to the 1st, 5th, 10th, 90th, 95th, and 99th centiles.

We developed age-based centiles for vital signs using a randomly selected sample of 2.5 million encounters from the NEMSIS data set, on the basis of computational burden and our prior work demonstrating the adequacy of this sample size.[20] Centile curves for each vital sign using the Generalized Additive Models for Location, Scale, and Shape (GAMLSS, v 5.4-1) modeling package. The GAMLSS package uses a distributional regression approach where all the parameters of the conditional distributions of the response variable are modeled using explanatory variables and has been used in prior research modeling vital signs.[20,26,27] As GAMLSS requires a distribution to be specified, we evaluated the Box-Cox Power Exponential, skew exponential power types 1 and 2 for HR and SBP. For RR, we trialed the Box–Cox *t* and the power exponential distributions. We used the Bayesian Information Criterion as our criteria for optimal model selection. We additionally trialed log, Box–Cox, and square root transformations of the data to identify the one with the best fit. We summarized the median cut points for these vitals within the age groups of early adulthood (18–34 years), early middle age (35–44 years), late middle age (45–64 years), and late adulthood (≥65 years).[28] To externally validate both the unadjusted and age-adjusted vital signs cutoffs, we compared the proportions between the derivation and validation data sets that were below the 1st, 5th, and 10th centiles and above the 90th, 95th, and 99th centiles.

Within the ESO sample of patients who had in-hospital data available, we removed those who were still admitted at the time of data acquisition (classified as "still a patient" in the data set) or who had a secondary transfer to another facility, where the ultimate hospital outcome was not available. We performed univariable analysis for each vital sign using a linear tail-restricted cubic spline function, with five knots selected using maximum likelihood estimation with the first and last knot set at the fifth and 95th percentiles for our secondary outcomes. We compared the measures of accuracy, sensitivity, and specificity for the in-hospital outcomes of mortality and admission by age when using unadjusted and age-adjusted vital signs, considering vital signs as abnormal when they occurred below the 10th centile or above the 90th centile.[20] We constructed calibration curves to visually inspect the model across the range of predicted probabilities. To better differentiate the performance of the extremes of individual vital signs, we reported the diagnostic accuracy of each vital sign for each outcome at the <1st, <5th, <10th, >90th, 95th, and 99th centiles. When measuring the performance of a low cut point for vital signs, we only used the subset of encounters for which that measure was recorded as being less than the 50th centile. We performed the opposite when evaluating the performance of a high value for each vital sign. Finally, as an exploratory analysis, we evaluated the association of vital signs occurring below the 10th or above the 90th centile with in-hospital outcomes stratified by the presence or absence of traumatic injury. Analyses were performed using the *gamlss* (v5.4-1) and *rms* (v6.2-0)[29] packages in R, version 4.1.2 (R Foundation for Statistical Computing).

RESULTS

Inclusion and demographics

A total of 22,532,890 EMS encounters were present within the 2018 NEMSIS data set. After encounters with a missing age (n = 3,661,912), children (n = 1,204,760), responses not from the scene (n = 4,032,865), and responses served by critical care transport teams (n = 227,495) were removed, 13,405,858 encounters were included. The ESO data set for the years 2019–2021 had 29,269,188 EMS encounters. After encounters with a missing age (n = 3,780,867), children (n = 1,369,451), responses not from the scene (n = 4,350,088), and responses served by critical care transport teams (n = 1,086,098) were removed, 18,682,684 remained. The ESO samples had generally similar characteristics with respect to age, sex, level of service, disposition, and availability of vital signs, but the ESO data set had a lower proportion of patients with trauma (Table S1). Extreme vital signs, which were removed for this analysis, were identified in 1.5% of HRs (among 30,514,652 of all [initial and subsequent] documented HRs), 0.8% of RRs (among 26,685,919 of all documented RRs), and 0.5% of SBPs (among 27,255,955 of all documented SBPs).

Distribution of vital signs and model selection

The cumulative distribution plots of all three vital signs had a middle component with a rapidly increasing slope (Figure 1). The proportion of patients above and below each cut point defined by the derivation set was similar in the ESO data set (Table S2), with all differences <1.5%, except for the ≤10% cut point for RR, where the deviation was 1.7%.

Age-based centiles for vital signs

Boxplots by age are provided in Figure S1. In age-based models for vital signs, a Box–Cox transformation with a Box–Cox power exponential distribution for HR and SBP, and a square root transformation with Box–Cox t distribution for RR provided the best fits for modeling. The proportion of patients above and below each age-based cut point defined in the derivation set was again similar in the ESO data set (Table S3).

Cut points for each age group are provided in Table 1. A gradual decline was noted at all extremes of HR with increasing age. For example, a HR of 134 beats/min marked the upper 95th percentile during early adulthood, but this declined to 123 beats/min during

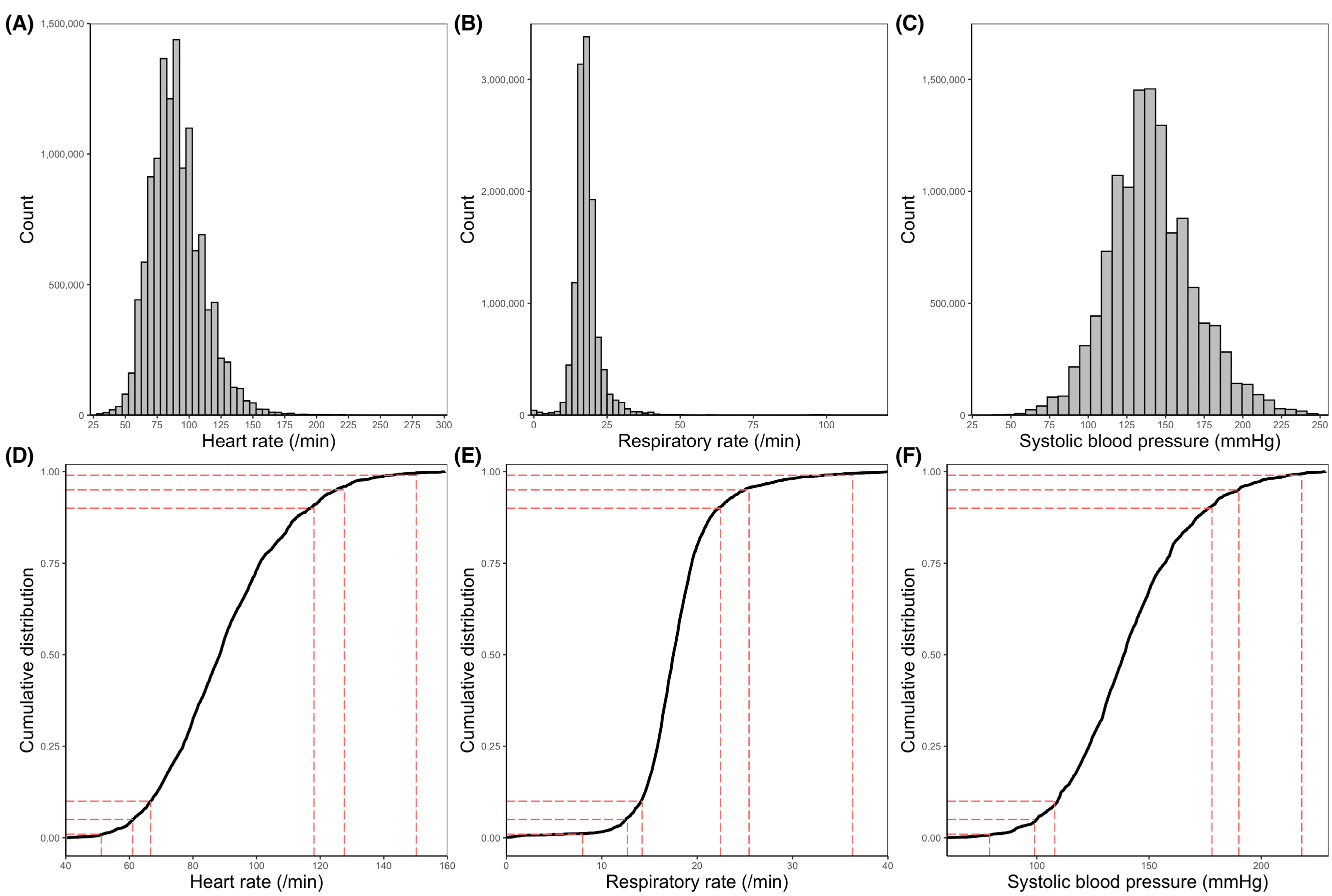

FIGURE 1 Histograms (A–C) and cumulative distribution plots (D–F) for vital signs. These graphs describe the probability of a vital sign having a value less than or equal to that value. For example, 75% of initial heart rates assessed by EMS are <100 beats/min. Red dashed lines indicate the selected cut points for each vital sign at 1%, 5%, 10%, 90%, 95%, and 99%.

TABLE 1 Summary of cutoffs of vital signs by age group.

Vital sign and centile	Early adulthood (18–34)	Early middle age (35–44)	Late middle age (45–64)	Late adulthood (65+)
HR (beats/min)				
99	154	153	151	149
95	134	132	128	123
90	124	122	118	111
10	72	72	69	63
5	67	66	64	57
1	56	55	53	48
RR (breaths/min)				
99	35	34	36	38
95	24	24	25	25
90	22	22	22	22
10	14	14	14	14
5	12	12	12	12
1	8	8	8	8
SBP (mm Hg)				
99	188	207	219	220
95	168	182	192	195
90	159	170	179	183
10	110	110	108	105
5	103	102	98	94
1	89	86	79	75

Abbreviations: HR, heart rate; RR, respiratory rate; SBP, systolic blood pressure.

late adulthood. The extremes of SBP at upper and lower margins were greater in older age groups relative to younger age groups. A SBP of 168 mm Hg marked the 95th centile for young adults, compared to 195 mm Hg for older adults. A SBP of 89 mm Hg represented the first centile for young adults, compared to 75 mm Hg for older adults. RR cut points were similar for all adult age groups.

In-hospital outcomes

Within the ESO data set, in-hospital data were available for 2,510,261 transports. This sample more frequently involved responses with ALS clinicians and more frequently had vital signs reported (Table S4).

In-hospital mortality

Among encounters within the ESO data set, in-hospital mortality occurred in 67,035 (2.7%). Using unadjusted vital sign cutoffs, in-hospital mortality among patients with a HR between the 10th and 90th percentiles was 2.0% (Table 2). This rose in both the upper and the lower extremes and was highest (11.4%) among patients below the first centile. Mortality among patients with a RR between the 10th and 90th centiles was 1.5%. This again increased in the extremes and was highest among patients below the 1st centile (17.4%). Mortality among patients with SBP in the 10th–90th centiles was 1.7%. Mortality was higher among patients with high blood pressure (3.0% among patients >99th centile) and markedly higher among patients with hypotension (14.3% among patients below the 1st centile). In spline-based models, a U-shaped curve was demonstrated for HR and RR when using both unadjusted values and age-adjusted values (Figure 2). When inspecting calibration, all parameters demonstrated a tendency to overestimate mortality at higher ranges of predicted probability (Figure S2). Compared to unadjusted vital signs, adjusted vital signs had slightly higher accuracy for RR, equal accuracy of HR, and lower accuracy for SBP (Table 3). The specificity of individual vital signs to predict mortality was greater at the extremes, but these cutoffs were generally associated with lower sensitivity (Table S5).

Hospitalization

Hospitalization occurred in 866,690 (34.5%) patients. The proportion with hospitalization for all three vital signs was greater among the extremes of vitals relative to those in the 10th–90th centile range. In spline-based models, all demonstrated a pointed ("V"-shaped) curve,

TABLE 2 Performance of unadjusted vital signs cutoffs associated with in-hospital mortality and hospitalization among encounters in the ESO data set with available in-hospital data.

Vital sign and centile cutoff	Number meeting criteria	Mortality	Admission
HR (*n* = 2,490,543)			
≥99	34,420 (1.4)	3120 (9.1)	17,516 (50.9)
≥95	160,651 (6.5)	9126 (5.7)	75,346 (46.9)
≥90	297,847 (12.0)	14,136 (4.7)	131,105 (44.0)
10–90	1,941,501 (78.0)	39,240 (2.0)	637,699 (32.8)
≤10	251,195 (10.1)	10,214 (4.1)	93,353 (37.2)
≤5	145,145 (5.8)	7768 (5.4)	57,860 (39.9)
≤1	36,928 (1.5)	4206 (11.4)	18,605 (50.4)
RR (*n* = 2,447,808)			
≥99	34,244 (1.4)	4096 (12.0)	22,059 (64.4)
≥95	175,640 (7.2)	13,948 (7.9)	105,475 (60.1)
≥90	288,396 (11.8)	18,595 (6.4)	159,131 (55.2)
10–90	1,867,016 (76.3)	28,763 (1.5)	590,826 (31.6)
≤10	292,396 (11.9)	16,836 (5.8)	97,635 (33.4)
≤5	122,549 (5.0)	13,312 (10.9)	44,101 (36)
≤1	14,199 (0.6)	2470 (17.4)	5347 (37.7)
SBP (*n* = 2,474,132)			
≥99	31,599 (1.3)	948 (3.0)	15,133 (47.9)
≥95	153,517 (6.2)	3158 (2.1)	63,340 (41.3)
≥90	286,493 (11.6)	5205 (1.8)	111,174 (38.8)
10–90	1,911,202 (77.2)	33,050 (1.7)	608,946 (31.9)
≤10	276,437 (11.2)	18,796 (6.8)	136,584 (49.4)
≤5	151,750 (6.1)	13,636 (9.0)	83,533 (55.0)
≤1	35,755 (1.4)	5125 (14.3)	22,108 (61.8)

Note: Data are reported as *n* (%).

Abbreviations: HR, heart rate; RR, respiratory rate; SBP, systolic blood pressure.

with a higher overall probability of hospitalization at extreme input values (Figure 3). When using unadjusted RR, an additional hinge occurred at the 95th centile, following which risk of hospitalization increased less acutely. Calibration was superior for HR and RR when using age-adjusted vital signs; calibration was superior for SBP when using unadjusted values (Figure S3). Compared to unadjusted vital signs, adjusted vital signs again had slightly increased accuracy for HR and RR but lower accuracy for SBP. The specificity of individual vital signs to predict hospitalization was again greater at the extremes, with greater drop-offs in sensitivity when using the <1st and>99th centiles (Table S6).

When comparing patients with (*n* = 471,193) and without (*n* = 2,039,068) traumatic injury, age-based vital signs demonstrated improved accuracy compared to unadjusted vital signs for HR and RR among both groups (Tables S7 and S8). Among all unadjusted and age-adjusted vital signs, the accuracy was greater for predicting in-hospital outcomes for patients with trauma compared to those without trauma.

DISCUSSION

We used a large multiagency EMS data set to derive centiles for vital signs among adults encountered by EMS. We used a second multiagency data set to assess for the agreement of these centiles and evaluate their role in predicting in-hospital outcomes. Differences among vital sign ranges across adult age groups were most notable for the upper limits of HR and for the extremes of SBP. Univariable analyses suggested only small changes in performance between unadjusted and age-adjusted vital signs. Future efforts toward multivariable modeling to identify critically ill adults among those with out-of-hospital emergencies may benefit in some contexts by using age-based centiles for vital signs in addition to other assessment data.

Our findings support the use of empirically derived cutoffs for the assessment of adults with out-of-hospital emergencies, without the need to adjust for age when predicting for in-hospital outcomes. We expand upon research evaluating centile-based criteria for vital signs among adults in the acute care setting by the development and comparison of unadjusted and age-adjusted models.[6,7] For example, a HR of 110 beats/min, which corresponds to the 75th percentile in younger adults (<65 years), may be of much greater significance in older adults, where it falls at close to the 95th percentile. Despite this, the use of age only resulted in a small improvement in model performance compared to unadjusted models for predicting in-hospital outcomes. Our findings differ from recent work suggesting the use of differing age-based criteria (specifically for SBP) among adults with trauma. The majority of these studies have been limited to geriatric patients, without comparisons for younger adults.[30–33] In studies that did provide a direct comparison, the use of a higher (100–110 mm Hg) cutoff to define hypotension had greater sensitivity in both geriatric and younger adult patients, though there was a relatively greater loss of specificity among younger adults with this change.[34,35] While age adjustment of vital signs did not enhance predictive modeling for adults with out-of-hospital emergencies overall, its application may be of greater benefit within specific subpopulations of adults with out-of-hospital emergencies, such as trauma, stroke, or ST-elevation myocardial infarction.[34,35]

An appropriate next step will be to prospectively validate and correlate these centile-based vital sign criteria with stakeholder-defined in-hospital outcomes to subsequently enhance clinical care by better identifying at-risk or unstable adults across a variety of clinical complaints. If demonstrated to be associated with clinically meaningful outcomes, these findings may be incorporated into ED alert systems or point-of-care decision tools used by first responders. The use of age-based criteria may add further granularity in the interpretation of vital signs, at the cost of increased complexity. This added complexity could be mitigated through point-of-care decision support tools embedded into an electronic health record system or smartphone applications. Prior work has demonstrated the potential utility of smartphone-based decision support to assist in medical decision making in the out-of-hospital setting.[36] The use of

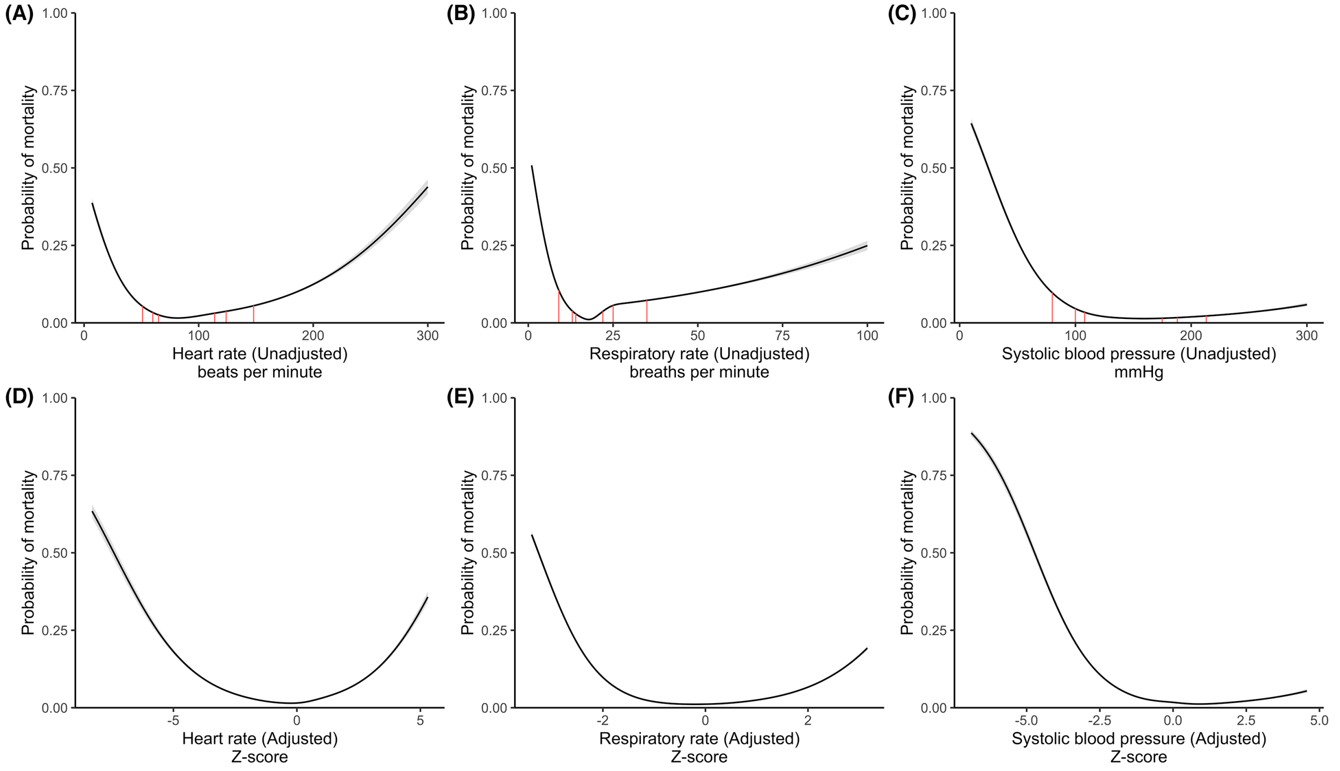

FIGURE 2 Prediction plots for *Z*-scored vital signs in univariable analyses using (A–C) unadjusted vital signs and (D–F) *Z*-scored for age vital signs for an outcome of in-hospital mortality. In plots A–C, red lines indicate (from left to right) the 1st, 5th, 10th, 90th, 95th, and 99th centiles.

TABLE 3 Metrics of accuracy for mortality and admission when using adjusted and unadjusted cutoffs for vital signs when classifying vital signs as abnormal when occurring at the extremes of below the 10th and above the 90th centile.

Vital sign and measure		Accuracy (%)	Sensitivity (%)	Specificity (%)
Outcome: mortality				
HR				
	Unadjusted	77.4	38.3	78.4
	Age-adjusted	77.4	40.9	78.4
RR				
	Unadjusted	76.5	55.2	77.1
	Age-adjusted	80.3	52.7	81.0
SBP				
	Unadjusted	78.3	40.4	79.2
	Age-adjusted	77.5	38.2	78.4
Outcome: admission				
HR				
	Unadjusted	61.4	26.0	80.1
	Age-adjusted	61.9	26.9	80.4
RR				
	Unadjusted	62.6	30.3	79.8
	Age-adjusted	64.1	26.9	83.9
SBP				
	Unadjusted	63.1	27.3	82.0
	Age-adjusted	61.4	26.0	80.2

Abbreviations: HR, heart rate; RR, respiratory rate; SBP, systolic blood pressure.

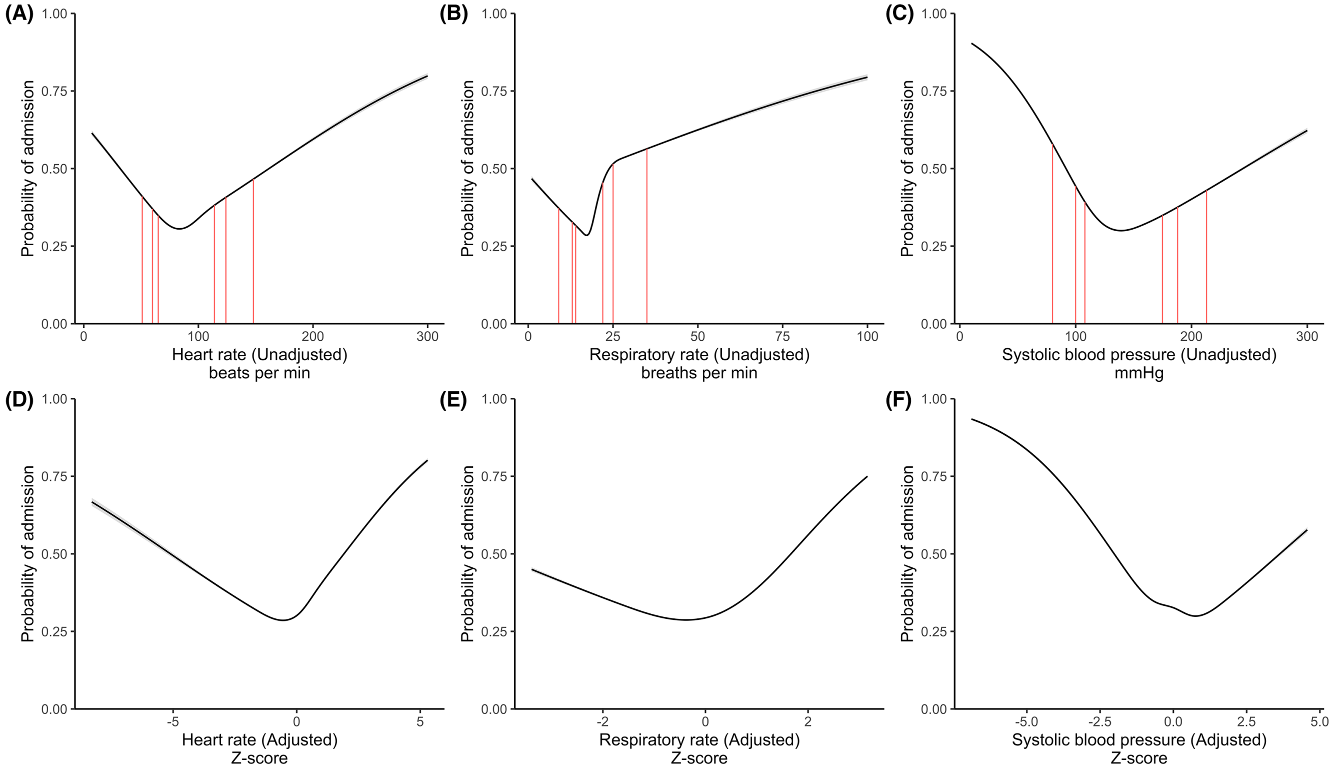

FIGURE 3 Prediction plots for *Z*-scored vital signs in univariable analyses using (A–C) unadjusted vital signs and (D–F) *Z*-scored for age vital signs for an outcome of hospitalization. In plots A–C, red lines indicate the 1st, 5th, 10th, 90th, 95th, and 99th centiles.

centile-based vital sign data may also be useful to identify patients for whom consultation with medical command is advisable outside of specific clinical syndromes (e.g., trauma, stroke, ST-elevation myocardial infarction) or based on the identified need for specific interventions prescribed by clinical EMS protocols. This consultation with a physician may help to identify the need for nonprotocolized out-of-hospital interventions on the sickest subset of patients and identify those who may benefit from emergent assessment and evaluation by in-hospital personnel upon hospital arrival.

Selection of the optimal cut points for vital signs as part of hospital alert systems must consider the proportion classified by specific ranges and the sensitivity and specificity of these cut points, along with the action intended to be solicited by the alert system (e.g., triage to a specific location of the ED or mobilization of specific resources). Prediction tools that prioritize greater specificity may represent the best target group for out-of-hospital alert systems that can facilitate room availability with early physician and nurse presence in the ED. In one study of hospitalized adults, for example, investigators used centile-based vital signs to provide graded responses for incorporation into early warning systems.[7] By prioritizing specificity, these centiles may mitigate alarm fatigue and overutilization of the alert system by identifying patients that are most in need of prompt attention without overclassifying a large number of patients as being critically ill. Alternately, vital sign ranges that are highly sensitive for clinically meaningful outcomes may be useful to triage low-risk patients to low-acuity areas of an ED following an initial brief evaluation, such as to the waiting room. For these systems to enhance care, improved interoperability between EMS and ED data is required. Recent advances suggest that existing limitations in data sharing between EMS and the ED can be overcome.[37]

The use of centile-based vital signs demonstrated associations with in-hospital mortality and hospitalization among our patient sample. We build on prior work evaluating early warning score systems for vital signs.[15–19] Notably, univariable models for age-adjusted HR and RR demonstrated improved model fit for mortality compared to the use of these as unadjusted values, though the gain in performance when comparing unadjusted to age-adjusted vital signs was small. The improved performance of the *Z*-score–based model for HR is likely due to its adjustment for observed age-based variations. In contrast, SBP did not demonstrate superior performance for mortality compared to the use of this as an unadjusted value, suggesting that age-related physiologic changes may be of lesser importance than the absolute value of this measure. Importantly, the use of vital signs alone demonstrates poor predictive capacity for identifying mortality overall, as demonstrated in calibration plots. This calibration may be due to several reasons, including the low prevalence of these outcomes, the limited ability to generate predictions at extreme percentiles, and extrapolations made from the linear tail of the spline prediction model. Further research will be needed to compare the potential benefits of age-adjusted vital signs with unadjusted vital signs within multivariable prediction models. Prior studies, for example, have incorporated variables such as source of presentation (e.g., nursing home), mental status, and pulse oximetry, among other variables in predicting in-hospital outcomes.[8] In addition, models may be improved upon by incorporating outcomes into a consensus-based composite measure, which may include need for operative measurement, mechanical ventilation, intensive care unit hospitalization, and need for critical lifesaving procedures.

LIMITATIONS

Our findings are subject to limitations. Both the NEMSIS and ESO data sets were built using retrospective data. Not all encounters had vital sign data. We excluded extremes of vital signs based on implausibility. While these criteria are subjective, the use of a very large data set likely limits the impact of outliers. Some values may have been rounded by EMS clinicians at the point of care and the NEMSIS data set has little information on the mode of vital sign acquisition (such as monitor-measured vs. manual ascertainment). While this type of data set lacks the standardization of a research setting, its large size likely outweighs this limitation and more pragmatically describes the broader interpretation of vital signs regardless of these specific elements. Vital signs may be modified due to reasons unrelated to presenting pathology (such as use of beta blockers to modify HR); these data were not available in our data set. In practice, however, vital signs in the out-of-hospital setting often need to be interpreted in the absence of this information. Despite these limitations, these empirically derived vital signs for out-of-hospital encounters provide a useful basis for further work prospectively validating these findings and employing them in out-of-hospital clinical decision and support algorithms.

CONCLUSIONS

We developed a distributional model for vital signs among adults in the out-of-hospital setting, both with and without age. Age-based distributional models demonstrated changes in HR and SBP across the lifespan. However, their application in predicting in-hospital outcomes had similar performance to unadjusted values. In future steps, these vital sign distributions may be combined with other routinely collected emergency medical systems data to generate meaningful prediction models to identify critically ill patients in the out-of-hospital setting. These data may be additionally useful for use in hospital-based early warning systems.

AUTHOR CONTRIBUTIONS

Sriram Ramgopal designed the study, interpreted the data, and drafted the initial manuscript. Robert J. Sepanski assisted with analysis and interpretation of results and revised the manuscript. Remle P. Crowe assisted in data acquisition and interpretation of study results and revised the manuscript. Masashi Okubo and Clifton W. Callaway assisted in interpretation of results and in revising the manuscript. Christian Martin-Gill designed the study, interpreted study results, and revised the manuscript. All authors approved the final manuscript as submitted and agree to be accountable for all aspects of the work.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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