J Clin Monit Comput
DOI 10.1007/s10877-015-9671-1

ORIGINAL RESEARCH

Accuracy of continuous noninvasive hemoglobin monitoring for the prediction of blood transfusions in trauma patients

Samuel M. Galvagno Jr. · Peter Hu · Shiming Yang · Cheng Gao · David Hanna · Stacy Shackelford · Colin Mackenzie

Received: 7 August 2014 / Accepted: 23 February 2015

Abstract Early detection of hemorrhagic shock is required to facilitate prompt coordination of blood component therapy delivery to the bedside and to expedite performance of lifesaving interventions. Standard physical findings and vital signs are difficult to measure during the acute resuscitation stage, and these measures are often inaccurate until patients deteriorate to a state of decompensated shock. The aim of this study is to examine a severely injured trauma patient population to determine whether a noninvasive SpHb monitor can predict the need for urgent blood transfusion (universal donor or additional urgent blood transfusion) during the first 12 h of trauma patient resuscitation. We hypothesize that trends in continuous SpHb, combined with easily derived patient-specific factors, can identify the immediate need for transfusion in trauma patients. Subjects were enrolled if directly admitted to the trauma center, >17 years of age, and with a shock index (heart rate/systolic blood pressure) >0.62. Upon admission, a Masimo Radical-7 co-oximeter sensor (Masimo Corporation, Irvine, CA) was applied, providing measurement of continuous non-invasive hemoglobin (SpHb) levels. Blood was drawn and hemoglobin concentration analyzed and conventional pulse oximetry photopletysmograph signals were continuously recorded. Demographic information and both prehospital and admission vital signs were collected. The primary outcome was transfusion of at least one unit of packed red blood cells within 24 h of admission. Eight regression models (C1–C8) were evaluated for the prediction of blood use by comparing area under receiver operating curve (AUROC) at different time intervals after admission. 711 subjects had continuous vital signs waveforms available, to include heart rate (HR), SpHb and SpO_2 trends. When SpHb was monitored for 15 min, SpHb did not increase AUROC for prediction of transfusion. The highest ROC was recorded for model C8 (age, sex, prehospital shock index, admission HR, SpHb and SpO_2) for the prediction of blood products within the first 3 h of admission. When data from 15 min of continuous monitoring were analyzed, significant improvement in AUROC occurred as more variables were added to the model; however, the addition of SpHb to any of the models did not improve AUROC significantly for prediction of blood use within the first 3 h of admission in comparison to analysis of conventional oximetry features. The results demonstrate that SpHb monitoring, accompanied by continuous vital signs data and adjusted for age and sex, has good accuracy for the prediction of need for

S. M. Galvagno Jr. (✉) · P. Hu · C. Mackenzie
Department of Anesthesiology, University of Maryland School of Medicine, 22 South Greene Street, T1R83, Baltimore, MD 21201, USA
e-mail: sgalvagno@anes.umm.edu

S. M. Galvagno Jr. · P. Hu · C. Gao · C. Mackenzie
Program in Trauma, R Adams Cowley Shock Trauma Center, University of Maryland School of Medicine, Baltimore, MD, USA

S. Yang
Department of Biomedical Engineering, University of Maryland, Baltimore County (UMBC), Baltimore, MD, USA

D. Hanna
University of Maryland School of Medicine, Baltimore, USA

S. Shackelford
Department of Surgery, University of Maryland School of Medicine, Baltimore, MD, USA

S. Shackelford
Center for Sustainment in Trauma and Readiness Skills (Baltimore-CSTARS), United States Air Force, Baltimore, MD, USA

Published online: 10 March 2015

transfusion; however, as an independent variable, SpHb did not enhance predictive models in comparison to use of features extracted from conventional pulse oximetry. Nor was shock index better than conventional oximetry at discriminating hemorrhaging and prediction of casualties receiving blood. In this population of trauma patients, noninvasive SpHb monitoring, including both trends and absolute values, did not enhance the ability to predict the need for blood transfusion.

Keywords Blood transfusion · Detection of hemorrhage · Hemorrhagic shock · Noninvasive monitoring · Continuous hemoglobin · Transfusion prediction

1 Introduction

Traumatic injuries remain a major public health threat, accounting for over 10 % of the world's deaths each year [1, 2]. In particular, hemorrhage after injury is the most common cause of preventable death in both military and civilian settings [3–5]. Standard physical findings and vital signs are difficult to measure during the initial stage of trauma resuscitation, and these measures are often inaccurate until patients deteriorate to a state of decompensated shock [6, 7]. Invasive laboratory testing to detect hemorrhagic shock is time consuming and often delays treatment. Point-of-care testing measurements can vary considerably between different laboratory devices in their ability to detect bleeding and shocked patients, and finger stick capillary blood samples are susceptible to wide differences compared to traditional laboratory measurements [8]. A non-invasive device that estimates trends in hemoglobin may offer considerable clinical benefit detecting the need for blood transfusion during hemorrhage in a trauma patient.

Early detection of hemorrhagic shock is required to facilitate prompt delivery of blood component therapy to the bedside and performance of other life-saving interventions. However, the ability to rapidly and reliably identify patients with life-threatening hemorrhage before or during initial presentation to a trauma center remains an unrealized goal in trauma patient resuscitation. Continuous monitoring of non-invasive percutaneous hemoglobin (SpHb) may allow detection of hemoglobin loss due to bleeding and may allow early detection of hemorrhaging patients without the problems inherent with single time-point laboratory testing. A recent meta-analysis by Kim et al., analyzed four studies in the emergency department and four studies in the intensive care unit [9]. SpHb was associated with wide variability when compared to laboratory Hb as a gold standard [9]. In the intensive care unit, SpHb has been shown to vary between −3.63 and 2.62 g/dL when compared to laboratory Hb, and in the emergency department setting, SpHb has been shown to vary between −3.78 and 2.99 g/dL [9]. Recent findings from a study of 46 pediatric patients undergoing major surgery with potential major blood loss also demonstrated wide variability (level of agreement, −2.0 to 3.2 g/dL) in SpHb measurements when compared to laboratory Hb [10]. However use of trends in continuous non-invasive SpHb may facilitate timely patient assessment and prompt timely interventions for stabilization during initial trauma patient resuscitation enabling discrimination of bleeding from non-bleeding patients.

The aim of this study is to examine an unstable injured trauma patient population to determine whether trends in a noninvasive SpHb monitor can predict the need for urgent blood transfusion (universal donor or additional urgent blood transfusion) up to 12 h after initial trauma patient resuscitation. We hypothesize that trends in continuous SpHb, combined with easily derived patient-specific factors such as age and sex, have high sensitivity and specificity for identifying the need for blood transfusions in unstable trauma patients.

2 Methods

2.1 Institutional review board

The study was approved by expedited review of Institutional Review Boards (IRB) from both the University of Maryland and the US Air Force without a requirement to obtain patient consent.

2.2 Enrollment site and criteria

Our Level 1 trauma center admits more than 5000 trauma patients annually directly from the scene of injury, of whom 5–8 % will require transfusion, and 2–3 % massive transfusion (MT), defined in this analysis as >4 units of packed red blood cells in <4 h. Most transfusions occur within the first few hours of admission and often occur as un-crossmatched universal donor group O blood on an emergency basis [11–13]. This study is a planned subgroup study analysis as part of the ongoing resuscitation vital signs data-gathering project titled Oximetry and Non-Invasive Predictors Of Intervention Need after Trauma (ONPOINT) at the University of Maryland School of Medicine, R Adams Cowley Shock Trauma Center. ONPOINT is a project designed to examine a wide range of non-invasive sensors, clinical indicators, and other physiological parameters to identify trauma patients in need of lifesaving interventions, including the need for an urgent blood transfusion.

All "Priority 1" subjects are enrolled who meet the following enrollment criteria: direct admission (by

helicopter or ambulance) to the Trauma Resuscitation Unit (TRU) at the R Adams Cowley Shock Trauma Center, ≥18 years of age, and an abnormal Shock Index (heart rate/systolic blood pressure) >0.62 [10]. A Priority 1 designation, as defined by Emergency Medical Services (EMS) personnel, includes a critically ill or injured person requiring immediate attention or unstable patients with life-threatening injury or illness. Routine vital signs reported to the trauma center by EMS providers are used to calculate the Shock Index. Subjects admitted in active cardiac arrest or dying within 15 min of trauma center arrival are not enrolled.

2.3 SpHb sensors

Upon admission to the trauma resuscitation unit (TRU), a Masimo Radical-7^{TM} (Rev F) co-oximeter sensor (Masimo Corporation, Irvine, CA) is applied. The pulse-oximetry values, including HR, percutaneous oxygen saturation (SpO_2), and the photopletysmograph waveform (PPG) are collected using Bedmaster® Software (Excel Medical Electronics, Jupiter, FL, USA). The shielded SpHb sensor is routinely applied to the ring finger of the left hand since the blood pressure cuff is typically placed on the right arm; the SpO_2 pulse-oximeter sensor (GE Marquette, Milwaukie, WI) is usually placed on the index finger of the left hand. One hour of SpHb data is collected after admission to the TRU.

Research staff continuously enrolls subjects 24 h a day, 7 days a week. The primary outcome of interest is the administration of at least one unit of packed red blood cells (PRBCs) within the first 12 h after admission to the TRU.

2.4 Vital signs features selection and model development

Candidate variables are initially selected based on clinical intuition and previous work indicating predictive value for MT [14, 15]. Multiple variables are considered and standard forward and backward stepwise selection is used to construct simple models that avoid over-fitting. Models are evaluated in terms of area under the receiver operating curves (AUROC). To address the trade-off between fitting the data and the complexity of the model, cross-validation is used to evaluate each model's performance in both training and testing datasets. Models with <10 % difference in training and testing AUROC are considered as balanced models in goodness-of-fit and complexity. The AUROCs in *training* sets demonstrate how well the models fit the data, and the AUROCs in *testing* sets demonstrate how well the models will perform on unseen data.

Forty features of HR, and SpO_2 and the photopletysmographic waveforms are defined as previously described [14]. These features included a measure of the pulsatile versus non-pulsatile photopletysmographic signal. Features to quantify the changing pattern of SpHb during the initial 15 min monitoring, SpHb values were smoothed within a sequence of exclusive same size time windows, i.e., 1, 2, and 3 min. Features including percent (%) increase or decrease, 1-min maximum value, minimum value and slope variance (interquartile range) were extracted using the continuously accrued SpHb data.

2.5 Statistical analysis

Data analysis is focused on the comparison of transfusion predictions based on age- and sex-adjusted groups of vital signs pulse oximetry features and slope and trend features of SpHb. For each data group, we use multivariate logistic regression models adjusted for age and sex for prediction of transfusion. Forward and backward feature selection was enforced to build simple models with important variables. Variables included in the models are: age, sex, pre-hospital HR, SpHb, SpO_2, photopletymograph (PPG) waveforms, admission HR, and pre-hospital Shock Index.

To investigate the role of SpHb in blood product use prediction, eight classification models are selected as shown in Table 1. The base models (C1 and C5) only differ in using pre-hospital HR or pre-hospital SI. Models C2 and C3 compare SpHb with two commonly monitored vital signs, SpO_2 and HR; while model C4 intends to show their combined performance. SpHb is incorporated into the models to study the contribution of this variable for improving prediction results. The best combination of vital signs features included in each prediction model is selected by a stepwise feature selection procedure. AUROCs calculated from the prediction models are compared using DeLong's method [16]. AUROCs are calculated for vital signs alone, and a combination of vital signs, demographic, and SpHb features. Sensitivity and specificity are calculated from the optimal threshold determined by the Youden index [12]. The prediction models are cross-validated by

Table 1 Variables included in regression models to calculate sensitivity and specificity for the need for administration of at least one unit of packed red blood cells (pRBCs)

Model	Variables
C1	Age + sex + prehospital heart rate
C2	C1 + SpHb
C3	C1 + SpO_2 + admission heart rate
C4	C1 + SpHb + SpO_2 + admission heart rate
C5	Age + sex + prehospital shock index
C6	C5 + SpHb
C7	C5 + SpO_2 + admission heart rate
C8	C 5 + SpHb + SpO_2 + admission heart rate

training and testing using leave-one-out methodology [17]. SAS Version 9.2 (SAS Institute, Cary, North Carolina) was used for statistical calculations and a P value of <0.05 was considered statistically significant.

3 Results

The ONPOINT project enrolled 1,191 subjects. SpHb data was available in 711 (59.7 %) of these patients. Demographic data are presented in Table 2. Among these 711 patients, 5.2 % received a blood transfusion within 12 h. All patients were transported directly to the scene, and none received blood products before admission to the TRU.

Eight regression models (C1–C8) are evaluated to determine the sensitivity and specificity for the prediction of blood use by using data collected for different time intervals after admission to the trauma center (15, 30, and 60 min). When SpHb is monitored for 15 min, SpHb does not contribute additional sensitivity and specificity for the prediction of blood transfusion. The highest AUROC is from model C8 (age, sex, prehospital SI, admission HR, SpHb and SpO_2) for the prediction of blood transfusion within the first 3 h of admission.

Fifteen minutes of SpHb monitoring does not add significant predictive power to the other variables (model C7 AUROC: 0.86 vs. model C8 AUROC: 0.87; $P = 0.63$) (Fig. 1). When data from 30 min of continuous monitoring are analyzed (Fig. 2), significant improvement in AUROC occurs as more variables are added to the model; however, the addition of SpHb to the model does not improve AUROC significantly for prediction of blood use within the first 3 h of admission (model C3 AUROC 0.87 vs. model C4 AUROC 0.93, $P = 0.06$; model C7 AUROC 0.84 vs. model C8 AUROC 0.89, $P = 0.12$). AUROC is highest in all models for predicting blood transfusion within the 1–3 h time interval and progressively lower for the remaining time intervals up to 12 h.

Sixty-minute data demonstrate significant improvement in AUROC (Fig. 3). The highest AUROC is calculated in model C4 for the 1–3 h time interval (AUROC = 0.93; $P = 0.007$). Addition of SpHb statistically significantly improves AUROC for the 1–3 min time interval for models C1–C4 ($P \leq 0.05$ for all models); however, when Shock Index is used instead of HR, the addition of SpHb data does not improve AUROC (model C7 AUROC 0.89 vs. model C8 AUROC 0.89, $P = 0.74$).

Training and testing is performed using leave-one-out methodology to validate all models [13]. For models using 60 min of data collection, balanced models are observed with the majority of percent differences between training and testing less than 15 %.

Model balance improves when pre-hospital SI (models C5–C8) rather than pre-hospital HR (models C1–C4) is used.

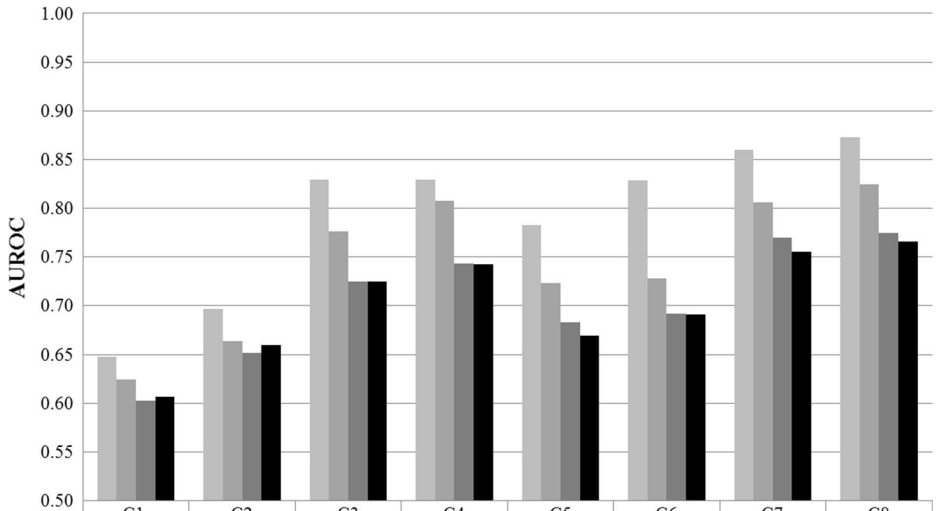
Table 2 Demographic characteristics (N = 711)

Mean age in years (SD)	38.6 (16.7)
Sex (N, %)	
Male	495 (69.6)
Female	216 (30.4)
Injury type (N, %)	
Blunt	615 (86.5)
Penetrating	86 (12.1)
Other	10 (1.41)
Mechanism of injury (N, %)	
Motor-vehicle-associated	373 (52.5)
Falls	157 (22.1)
Interpersonal violence	133 (18.7)
Other	48 (6.7)
Disposition at discharge (N, %)	
Home or institutional care	700 (98.5)
Died in hospital	11 (1.5)

4 Discussion

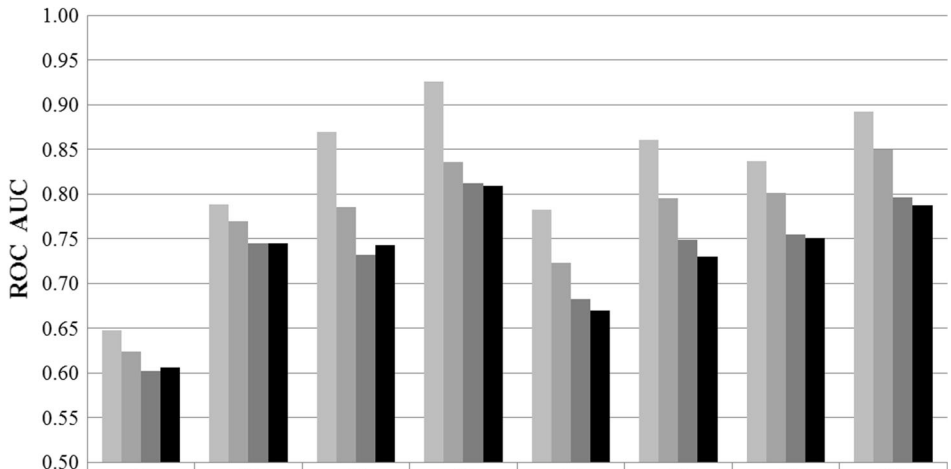
Considering both the high mortality associated with hemorrhagic shock and the risks of blood component therapy, rapid, robust, and reliable methods for assessing the likely need for transfusion and other life-saving interventions are urgently needed to ensure optimal patient outcomes. The results from this study demonstrate that a model using age, sex pre-hospital HR, and continuous vital signs data obtained from features of PPG (model C3), has good accuracy for predicting the need for transfusion. When SpHb is added to the model, sensitivity and specificity do not significantly improve AUROC beyond data derived from age, sex, and conventional continuous vital signs. The best current pre-hospital data for predicting blood transfusion includes pre-hospital Shock Index, SaO_2, and HR [15]. When Shock Index is included (model C5), there is no improvement in transfusion prediction, even when monitoring is extended for a period of at least 60 min. Shock Index is accurate for correctly classifying those patients in need of a blood transfusion within the first 3 h of admission to a trauma center; however, Shock Index adds no benefit as a predictor of early transfusion in comparison to PPG derived features. Shock Index gives only intermittent rather than continuous updates, and requires the addition of a non-invasive blood pressure monitor to calculate [18].

Several studies have examined variables that are associated with moderate to good sensitivity and specificity



	C1	C2	C3	C4	C5	C6	C7	C8
pRBC 1-3	0.65	0.70	0.83	0.83	0.78	0.83	0.86	0.87
pRBC 1-6	0.62	0.66	0.78	0.81	0.72	0.73	0.81	0.82
pRBC 1-12	0.60	0.65	0.73	0.74	0.68	0.69	0.77	0.77
pRBC 1-24	0.61	0.66	0.73	0.74	0.67	0.69	0.76	0.77

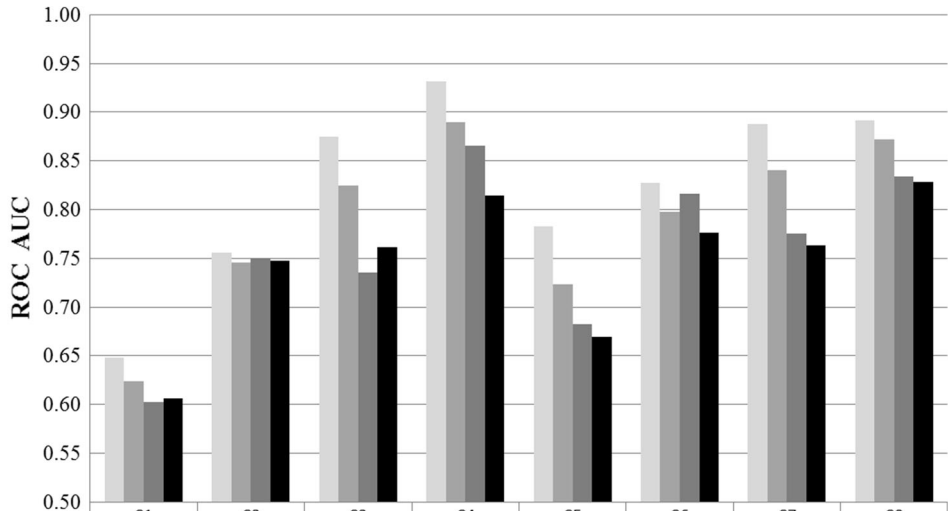
Fig. 1 AUROCs for the various models when monitoring was continued for up to 15 min (example: pRBC 1–3 refers to administration of at least one unit of packed red blood cells within 1–3 h; 1–6 refers administration of at least one unit of packed red blood cells within 1–6 h, etc.)



	C1	C2	C3	C4	C5	C6	C7	C8
pRBC 1-3	0.65	0.79	0.87	0.93	0.78	0.86	0.84	0.89
pRBC 1-6	0.62	0.77	0.79	0.84	0.72	0.80	0.80	0.85
pRBC 1-12	0.60	0.75	0.73	0.81	0.68	0.75	0.76	0.80
pRBC 1-24	0.61	0.75	0.74	0.81	0.67	0.73	0.75	0.79

Fig. 2 AUROCs for the various models when monitoring was continued for up to 30 min (example: pRBC 1–3 refers to administration of at least one unit of packed red blood cells within 1–3 h; 1–6 refers administration of at least one unit of packed red blood cells within 1–6 h, etc.)

for the prediction of MT [14, 15]. In these studies, calculations of a score to predict MT are based not only on physiological but the addition of laboratory data collected after a patient is admitted to the emergency department or trauma center [14]. The most sensitive and specific prediction scores rely on ultrasound [15] or blood draws for laboratory tests [14]. Point of care laboratory tests such as lactate and base excess have been shown to be helpful for predicting transfusion requirements [9, 18, 19], but these tests require an invasive blood draw that may be difficult to obtain in austere or pre-hospital settings. While algorithms have become greatly simplified and validated for the prediction of MT, efforts to formulate more accurate prediction algorithms are still needed. These algorithms should incorporate easily derived data so predictions may be made before or shortly after the patient arrives at the medical treatment facility. Even the recently developed Traumatic Bleeding Severity Score (TBSS), while sensitive and specific (AUROC of 0.98 with a score of 15 or greater), requires an abdominal ultrasound exam, a pelvic radiograph, and measurement of lactate [19].



	C1	C2	C3	C4	C5	C6	C7	C8
pRBC 1-3	0.65	0.76	0.88	0.93	0.78	0.83	0.89	0.89
pRBC 1-6	0.62	0.75	0.82	0.89	0.72	0.80	0.84	0.87
pRBC 1-12	0.60	0.75	0.74	0.87	0.68	0.82	0.77	0.83
pRBC 1-24	0.61	0.75	0.76	0.81	0.67	0.78	0.76	0.83

Fig. 3 AUROCs for the various models when monitoring was continued for up to 60 min (example: pRBC 1–3 refers to administration of at least one unit of packed red blood cells within 1–3 h; 1–6 refers administration of at least one unit of packed red blood cells within 1–6 h, etc.)

This is one of the initial and largest studies examining the use of SpHb in trauma patients. It is likely that subsequent iterations of SpHb technology will improve substantially. The next generation of SpHb sensors did not become available until all patient data had been collected. However, until further testing in this unstable patient population is carried out we agree with Kim et al. [9] that providers should remain cautious when using this technology for making clinical decisions about blood transfusions [9] or in making judgments about whether a patient is bleeding based on trends in SpHb. One solution for improving the use of SpHb technology may be to employ the methods used by Patino et al. [10] to use an the initial Hb laboratory value so that subsequent SpHb values are offset by the bias entered by the user.

This study has several limitations. First, only a limited number of patients received a blood transfusion (5.2 %). There are no standardized protocols to indicate when blood transfusion is indicated in unstable trauma patients. Our pulse oximetry features are significantly better that the clinical judgment of our pre hospital providers, trauma center physicians and nurses at predicting those patients that are given blood [12]. While the transfusion of at least one unit of blood is generally reserved for patients with obvious signs of imminent exsanguination or hemorrhagic shock, extremes of age, medications, and medical conditions can confound clinical decisions regarding the need for emergent blood transfusion. In previous work by our group, level of experience during trauma resuscitation is an important factor for timely selection of life-saving interventions such as transfusion of uncrossmatched blood. The optimal thresholds for sensitivity and specificity are undetermined, and a major goal in predicting life-saving interventions is to improve the accuracy for clinical decisions using the least amount of data required. Finally, patient-specific factors, such as temperature, vasoconstriction, and ambient light may have altered the accuracy of SpHb measurements in our patient population, although pre-processing with a signal quality index was employed to avoid inclusion of poor quality signals and by averaging and slope rends ample consideration was given for allowing stabilization of the SpHb reading.

Our work demonstrates that SpHb monitoring, accompanied by continuous vital signs data, and adjusted for age and sex, has good accuracy for the prediction of need for transfusion. SpHb alone does not enhance predictive models in comparison to use of features extracted from conventional pulse oximetry. Likewise, Shock Index did not perform better than conventional oximetry at discriminating the need for urgent blood transfusions in seriously injured patients. Non-invasive monitors capable of reproducing the high levels of sensitivity and specificity associated with diagnostic tests such as lactate and ultrasound [14, 19] have unrealized potential to detect the need for life saving interventions during the initial resuscitation of trauma patients. In our trauma patient population, the analysis of both SpHb trends and absolute SpHb values did not contribute significantly to models relying on age, sex, and continuous vital sign parameters does not appear to justify the cost of first generation SpHb monitors at this juncture for trauma patients. Nevertheless, with improved monitoring technology, such as improved amplitude and

signal quality analytic features, SpHb remains a promising modality. Additional trials are required to study the utility of continuous vital signs data for the prediction of life saving interventions in trauma patients.

Acknowledgments This work was funded by the Department of Defense (USAF 8650-11-6142). The views represent those of the authors not USAF or the Department of Defense. Masimo (Masimo Corporation, Irvine, CA) provided the SpHb monitors, but had no role in the design, execution, or analysis of this research.

Conflict of interest Other than the abovementioned funding, none of the authors have any conflicts of interest to report.

References

1. World Health Organization. Injuries and violence: the facts. Geneva, World Health Organization, 2010.
2. Corso P, Finkelstein E, Miller T, Flebelkorn I, Zaloshnja E. Incidence and lifetime costs of injuries in the United States. Inj Prev. 2006;12:212–8.
3. Holcomb J. Optimal use of blood products in severely injured trauma patients. Hematol Am Soc Hematol Educ Prog. 2010;2010:465–9. doi:10.1182/asheducation-2010.1.465.
4. Allen J. Photoplethysmography and its application in clinical physiological assessment. Physiol Meas. 2007;28:R1–39.
5. Deaths and Mortality. Centers for disease control and prevention, 2010. http://www.cdc.gov/nchs/fastats/deaths.htm. Accessed 6 Feb 2014.
6. Guyette F, Gomez H, Suffoletto B, et al. Preshospital dynamic tissue saturation response predicts in-hospital lifesaving interventions in trauma patients. J Trauma Acute Care Surg. 2012;72:930–5.
7. McGee S, Abernethy WI, Simel D. The rational clinical examination: is this patient hypovolemic. JAMA. 1999;281:1022–9.
8. Gehring H, Hornberger C, Dibbelt L, et al. Accuracy of point-of-care-testing (POCT) for determining hemoglobin concentration. Acta Anaesthesiol Scand. 2002;46:980–6.
9. Kim SH, Lilot M, Murphy LSK, et al. Accuracy of continuous noninvasive hemoglobin monitoring: a systematic review and meta-analysis. Anesth Analg. 2014;119:332–46.
10. Patino M, Schultz L, Hossain M, Moeller J, Mahmoud M, Gunter J, Kurth CD. Trending and accuracy of noninvasive hemoglobin monitoring in pediatric perioperative patients. Anesth Analg. 2014;119(4):920–5.
11. de Biasi A, Stansbury L, Dutton R, Stein D, Scalea T, Hess JR. Blood product use in trauma resuscitation: plasma deficitversus plasma ratio as predictors of mortality in trauma. Transfusion. 2011;51:1925–32.
12. Mackenzie CF, Gao C, Hu PF, Anazodo A, Chen H, Dinardo T, Imle PC, Hartsky L, Stephens C, Menaker J, Fouche Y, Murdock K, Galvagno S, Alcorta R, Shackelford S, ONPOINT Study Group. Comparison of decision-assist and clinical judgment of experts for prediction of life saving interventions. Shock. 2014. doi:10.1097/SHK.0000000000000288.
13. Como J, Dutton R, Scalea T, Edeleman B, Hess J. Blood transfusion rates in the care of acute trauma. Transfusion. 2004;44:809–13.
14. Shackelford SA, Colton K, Stansbury LG, Galvagno SM Jr, Anazodo AN, DuBose JJ, Hess JR, Mackenzie CF. Early identification of uncontrolled hemorrhage after trauma: current status and future direction. J Trauma Acute Care Surg. 2014;77(3 Suppl 2):S222–7.
15. Vandromme M, Griffin R, Kerby J, McGwin G, Rue L, Weinberg J. Identifying risk for massive transfusion in the relatively normotensive patient: utility of the prehospital shock index. J Trauma Acute Care Surg. 2011;70:384–8.
16. DeLong E, DeLong D, Clarke-Pearson D. Comparing the areas under two or more correlated receiver operating characteristic curves: a nonparametric approach. Biometrics. 1988;44:837–45.
17. Stone M. Cross-validatory choice and assessment of statistical predictions (with discussion). J R Stat Soc B. 1974;36:111–47.
18. Mackenzie C, Wang Y, Hu P, et al. Automated prediction of early blood transfusion and mortality in trauma patients. J Trauma Acute Care Surg. 2014;76:1379–85.
19. Ogura T, Nakamura Y, Nakano M, et al. Predicting the need for massive transfusion in trauma patients: the Traumatic Bleeding Severity Score. J Trauma Acute Care Surg. 2014;76:1243–50.