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A clinical prediction model for safe early discharge of patients with an infection at the emergency department

Merijn C.F. Mulders [a], Sevilay Vural [a,b,*], Lisanne Boekhoud [c], Tycho J. Olgers [a], Jan C. ter Maaten [a], Hjalmar R. Bouma [a,c]

[a] Department of Internal Medicine, University of Groningen, University Medical Center Groningen, Groningen, the Netherlands
[b] Department of Emergency Medicine, Yozgat Bozok University, Yozgat, Turkey
[c] Department of Clinical Pharmacy & Pharmacology, University of Groningen, University Medical Center Groningen, Groningen, the Netherlands

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ABSTRACT

Background: Every hospital admission is associated with healthcare costs and a risk of adverse events. The need to identify patients who do not require hospitalization has emerged with the profound increase in hospitalization rates due to infectious diseases during the last decades, especially during the COVID-19 pandemic. This study aimed to identify predictors of safe early discharge (SED) in patients presenting to the emergency department (ED) with a suspected infection meeting the Systemic Inflammatory Response Syndrome (SIRS) criteria.
Methods: We conducted a prospective cohort study on adult non-trauma patients with a suspected infection and at least two SIRS criteria. We defined SED as hospital discharge within 24 h (e.g. direct ED discharge or rapid ward discharge) without disease-related readmission to our hospital or death during the first seven days. A prediction model for SED was developed using multivariate logistic regression analysis and tested with k-fold cross-validation.
Results: We included 1381 patients, of whom 1027 (74.4 %) were hospitalized for longer than 24 h or re-admitted within seven days and 354 (25.6 %) met SED criteria. Parameters associated with SED were relatively young age, absence of comorbidities, living independently, yellow or green triage urgency, lack of ambulance transport or general practitioner referral, normal clinical impression scores, and risk scores (i.e., qSOFA, PIRO, MEDS, NEWS, and SIRS), normal vital sign measurements and absence of kidney and respiratory failure. The model performance metrics showed an area under the curve of 0.824. The validation showed a minimal drop in performance and indicated a good fit.
Conclusion: We developed and validated a model to identify patients with an infection at the ED who can be safely discharged early.

1. Introduction

Infections represent one-fifth of all emergency department (ED) visits and are a common reason for hospital admission [1,2]. Between 1999 and 2019, the annual number of hospital admissions related to infections has increased more than fourfold in England and Wales [3]. As the duration of hospitalization for patients with an infection ranges between one and seven days, infectious diseases account for a relatively large and increasing burden on the health care system [1,4]. The need to identify patients who do not require hospitalization has emerged with the profound increase in hospitalization rates due to infectious diseases during the last decades, especially during the COVID-19 pandemic. It could thereby allow safe treatment of these patients outside of the hospital, but will require risk scores to identify patients who could be safely discharged from the ED. Together, the increase in the number of infection-related hospital admissions requires novel strategies to allocate healthcare resources to sustain qualified healthcare appropriately.

Hospitalization is associated with high costs and an increased chance of adverse and iatrogenic events, such as medication errors, nosocomial infections and falls [2,5,6]. Preventing unnecessary hospitalizations is therefore crucial to improve patient care and to secure the sustainability of healthcare. Currently available prediction models for ED admission aim at advancing the disposition of ED patients, with a systematic review identifying sixteen validated models showing varying discrimination values from 0.630 to 0.878 [7]. Risk scores to aid sepsis recognition,

* Corresponding author at: Department of Internal Medicine, University Medical Center Groningen, P.O. Box 30.001, 9700 RB Groningen, the Netherlands.
E-mail addresses: s.vural@umcg.nl, sevilay.vural@yobu.edu.tr (S. Vural).

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such as the quick Sequential Organ Failure Assessment (qSOFA), can predict the need for intensive care unit (ICU) admission and mortality in patients with an infection. However, whether this score can be utilized to identify patients eligible for ED discharge is doubtful since 7–79 % of patients who develop sepsis during hospital admission have a qSOFA score of less than two upon ED triage [8-10]. Evidence to support safe early discharge (SED) among patients with an infection at the ED is limited. Consequently, risk scores to identify infectious disease patients who do not require hospital admission are unavailable [11-13]. We hypothesized that combining the qSOFA score with demographic, logistic and medical parameters can increase the accurate prediction of SED. For this aim, we developed and validated a model to predict SED using a prospective cohort of patients with an infection at the ED.

2. Methods

2.1. Study design

The current study is a prospective observational cohort study carried out in the ED of a tertiary care teaching hospital with up to 34,000 ED visits annually. This study follows the protocol described in previous studies from our ED [14-16]. The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines were used to ensure the reporting of this observational study [17]. The Dutch Medical Research Involving Human Subjects Act is not applicable for this study, as ruled by the Institutional Review Board of the University Medical Center Groningen, and a waiver was granted (METc 2015/164). Written informed consent was obtained from all patients included in this study.

2.2. Population

Adult non-trauma patients visiting the ED from March 2016 to April 2019 between 8 a.m. and 11 p.m. with suspected infection and at least two Systemic Inflammatory Response Syndrome criteria (SIRS) were screened for inclusion. Patients who were admitted to the ICU and those who were transferred to another hospital were excluded.

2.3. Data collection

The vital signs and triage scores according to the Emergency Severity Index (ESI) were measured upon arrival at the ED. ESI levels were represented with colors (red = level 1, orange = level 2, yellow = 3, green = level 4 and blue = level 5). Subsequently, patients' vital signs were measured every 30 min by a trained member of our research staff until ED discharge or hospital admission.

After the primary assessment of the patient, the attending physician and nurse were separately asked for their clinical impression score (CIS) of the patient, which ranges from 1 (not ill) to 10 (extreme illness). The qSOFA and the National Early Warning Score (NEWS) scores were determined upon admission to the ED and using the last known vital signs at the ED. Kidney failure, or Acute Kidney Injury (AKI), was defined using the Kidney Disease Improving Global Outcomes criteria [18]. Respiratory failure was defined as the need for mechanical ventilation, either hypercapnia ($PaCO2 > 6.5$ kPa) or hypoxemia ($PaO2 < 8.0$ kPa) in the arterial blood gas analysis or either a $SpO2 < 90$ % when breathing room air or < 95 % with at least 2 L/min of oxygen supplementation. The Predisposition Infection Response Organ dysfunction (PIRO), Mortality in Emergency Department Sepsis (MEDS) and Sequential Organ Failure Assessment (SOFA) scores were calculated using vital parameters at admission, results from blood analysis, sociodemographic information gathered during admission and information from electronic medical records. We included infectious source as variable for our multivariate logistic regression model. However, based on the univariate association between source of infection and the outcome of safe early discharge that did not reach significance, we did not include it in the multivariate model.

2.4. Missing data

To calculate the SOFA scoring without a known PaO_2/FiO_2 (P/F) ratio, we estimated the PaO_2 using the peripheral oxygen saturation (SpO_2). Since arterial blood gas analyses (ABGs) were not performed in all patients meeting the inclusion criteria, the P/F ratio was the most frequent missing value. We chose the non-linear equation to calculate the P/F ratio in patients with absent PaO_2 and a $SpO_2 \leq 97$ % [19]. A missing value for lactate, as well as other missing values to calculate the clinical scoring systems used in this study, were deemed normal if missing, based on the assumption that the treating physician did not consider the measurement indicated. As depicted in Table 1, the amount of missing data is very minimal, ranging from 0 to 6.6 % for all parameters except lactate, liver and kidney failure. These latter parameters are mostly measured if a patient is severely ill and usually not measured if a patient is deemed "not very ill." Hence, excluding patients with missing values for these variables would bias our population towards being more ill, limiting the generalizability of our model that predicts SED.

2.5. Endpoints and definitions

The primary endpoint of the study was SED, defined as hospital discharge within 24 h (e.g., direct ED discharge or rapid ward discharge) without disease-related re-admission to our hospital or death during

Table 1
The main characteristics of the study population.

Variable (% missing)	SED	No SED	*p* value
Number of patients	354 (25.6)	1027 (74.4)	–
Demographics			
Age (0), [median (IQR)]	57 (45–69)	64 (54–74)	<0.001*
Male (0)	200 (56.5)	591 (57.5)	0.731
Living independently (2.3)	329 (92.9)	906 (88.6)	0.005*
Educated[1] (6.7)	291 (82.2)	831 (80.9)	0.248
Smoker[2] (3.3)	45 (12.7)	144 (14)	0.286
Alcohol user[3] (3.6)	116 (32.8)	275 (26.8)	0.034*
Arrival mode			
Referred by GP (2.2)	171 (48.3)	562 (54.7)	0.041*
Ambulance transport to ED (2.2)	63 (17.8)	505 (49.2)	<0.001*
GP + ambulance (2.9)	37 (10.5)	345 (33.6)	<0.001*
Triage color (0.9)			
Red	0 (0)	1 (0.1)	0.557
Orange	25 (7.1)	207 (20.2)	<0.001*
Yellow	293 (82.8)	774 (75.4)	0.003*
Green	32 (9)	36 (3.5)	<0.001*
Blue	0 (0)	0 (0)	–
Comorbidity			
Cardiac disease (1.5)	44 (12.4)	207 (20.2)	0.001*
COPD (1.4)	18 (5.1)	101 (9.8)	0.007*
Diabetes (1.6)	45 (12.7)	233 (22.7)	<0.001*
Chronic kidney disease (1.7)	37 (10.5)	160 (15.6)	0.015*
Chronic liver disease (1.7)	21 (5.9)	90 (8.8)	0.102
Organ transplant (1.8)	45 (12.7)	202 (19.7)	0.004*
Malignancy (1.7)	123 (34.7)	353 (34.4)	0.708
None of the above (2.3)	120 (33.9)	239 (23.3)	<0.001*
Number of comorbidities, [median (IQR)]	1 (0.5–1.5)	1 (0.5–1.5)	<0.001*
Lactate > 4 mmol/L (63.6)	1 (0.3)	16 (1.6)	0.348
Kidney failure[4] (26.1)	10 (2.8)	144 (14)	<0.001*
Respiratory failure[4] (2.2)	15 (4.2)	129 (12.6)	<0.001*
Liver failure[4] (20.5)	21 (5.9)	75 (7.3)	0.378
LOS in hospital (days) (0), [median (IQR)]	0.1 (0.1–0.2)	5.7 (2.4–9.1)	<0.001*

Percentage of missing values per variable are shown in parentheses. Variables are expressed with *n* (%) unless otherwise stated. SED = safe early discharge (hospital-discharge ≤24 h, without disease-related readmission or death ≤7 days); GP = general practitioner; ED = Emergency Department; COPD = Chronic Obstructive Pulmonary Disease; LOS = Length of stay. [1]educated past the age of 14[2];≥1 cigarette per day[3];≥1 unit of alcohol per week; [4]at ED admission. *Significant *p*-value.

the first seven days. We arbitrarily chose a seven-day interval to monitor re-admission and death, as this is commonly used to analyze the safety of hospital discharges [20-23]. Normalization of vital signs was defined as the transition of the individual vital sign from abnormal to within normal range (Supplemental Table 1). Staying normal of vital signs was described as both the first and last vital sign measurement being normal.

2.6. Statistical analysis

Continuous data were expressed as median and interquartile ranges (IQR) and analyzed with the Mann-Whitney *U* test. Categorical variables were expressed as frequency with percentages and analyzed with the Chi-square test. To determine the relationship between risk scores and SED, receiver operator characteristic (ROC) curves and the area under the ROC curve (AUC) were calculated. The Wilcoxon rank test with continuity correction was used to test the AUCs against the null hypothesis (AUC = 0.5). Cut-off point, sensitivity, specificity and positive/negative predictive values were calculated for each combination of clinical score and outcome parameter with a significant AUC. Cut-off points were selected based on a Youden index with maximum sensitivity and specificity, closest to the upper-left corner of the ROC curve. To identify parameters associated with clinical improvement, the secondary outcome measures were analyzed using multivariate logistic regression analysis. Since this is the first study analyzing parameters associated with safe, early discharge in this population, a Forward: LR method was selected. Stratified K-fold cross-validation (k = 6) was utilized for model selection and internal validation.

MedCalc Version 19.1.3 was used to compare AUCs. All other statistical analyses were performed using IBM SPSS Statistics for Windows, version 23.0. A p-value of <0.05 was considered significant.

3. Results

3.1. Patient characteristics

During the study period, 1381 patients were included (Fig. 1). Of these patients, 958 were hospitalized and 423 were discharged within 24 h of ED presentation. Within 7 days, however, 28 of the discharged patients died, and 41 of these patients revisited our hospital due to the same diagnosis, resulting in 69 (16.3 %) 'unsafe' discharges. 354 patients (83.7 %) met the SED criteria among the discharged group. Hence, 1027 were either hospitalized more than 24 h after ED admission (n = 958) or suffered a complication after early discharge (n = 69) (i.e. re-admission or death <7 days).

We first compared demographic, logistic and medical features between patients meeting SED criteria and those requiring prolonged hospitalization and unsafe discharges to identify characteristics predictive

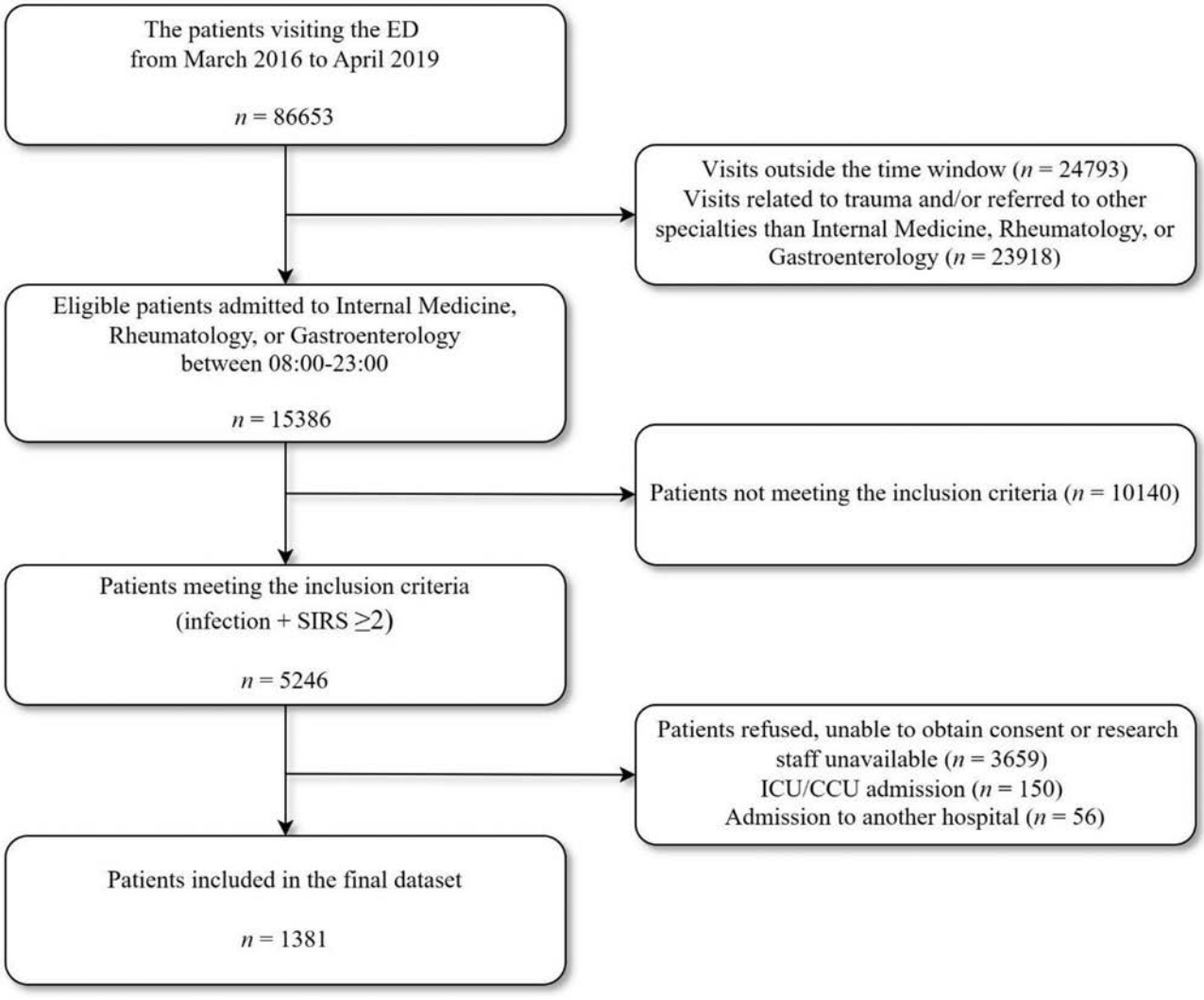

Fig. 1. The flowchart of patient selection.

of SED. Patients in the SED group were younger ($p < 0.001$), less frequently lived in their own homes ($p = 0.005$), were less often referred by their General Practitioner (GP) ($p = 0.041$) and were less often transported by ambulance to the ED ($p < 0.001$). Further, SED patients had a lower triage urgency ($p < 0.001$), a lower incidence of comorbidities and - kidney/respiratory failure ($p < 0.001$). The median hospital length of stay (LOS) was shorter in the SED group when compared to patients requiring prolonged hospitalization (0.1 vs. 5.7 days) (Table 1).

3.2. Trends in vital signs and risk scores during the ED stay

We then assessed whether trends in vital signs and risk scores during ED stay differed between the two groups. Normal vital signs and clinical scoring systems at ED admission and discharge were significantly associated with SED for the majority of the parameters ($p < 0.05$ for all except heart rate). In contrast, among patients with abnormal vital signs at ED admission, normalization of these parameters was generally not associated with SED ($p > 0.05$). Only normalization of the NEWS ($p < 0.001$) and mental status ($p = 0.033$) occurred more frequently in patients meeting the SED criteria (Table 2). Interestingly, of all patients with a negative qSOFA score at ED admission, 591 (68 %) were hospitalized for more than 24 h, re-admitted, or died within seven days (Table 2). Similarly, 414 (62.6 %) patients with NEWS ≤3 upon triage did not meet the SED criteria.

3.3. Risk scores to predict SED

Next, we calculated the sensitivity and specificity of the different risk scores to assess the accuracy of the currently used risk scores in predicting SED, optimal cut-off points were based on Youden's index (Supplemental Table 2). All studied risk scores were associated with SED ($p < 0.001$) (Table 3). The discriminative performance was highest for the CIS of the attending physician (AUC:0.739) and lowest for the qSOFA and SIRS criteria (AUC:0.576 and 0.593, respectively). There was no difference in performance between the rest of risk scores (i.e., NEWS, SOFA, PIRO, and MEDS scores), with AUCs ranging from 0.631 to 0.651. The CIS, NEWS, SIRS, qSOFA, PIRO, and MEDS score all had a good negative predictive value (NPV) between 78 and 85 % with a relatively low positive predictive value (PPV) between 30 and 45 %.

3.4. SED prediction model development

Finally, we performed a multivariate logistic regression analysis to develop a model with optimal accuracy for predicting SED. Fifty-five parameters, including individual features of the risk scores, were selected for the initial univariate analysis. Patients meeting Sepsis-3 criteria at the ED were all hospitalized, which resulted in a complete separation of data [$n = 196$ (14.2 %)]. Therefore, we gave these patients a SED probability of 0 and excluded them from further analysis. Using a Forward:LR method with stratified k-fold cross-validation, 9 out of 54 initially selected parameters were included in the final model (Table 4). The excluded parameters, including PIRO infection focus, were shown in Supplemental Table 3. Factors predictive of SED were younger age, no history of organ transplantation, arrival by own transport if referred by GP, not appearing ill according to the CIS, absence of liver and kidney failure at the ED, normal body temperature, and a negative, stable qSOFA. The model correctly predicted 75.5 % of the SED cases and explained 24.7 % of its variance (Table 5). Analysis of the ROC curve yielded an AUC of 0.824, indicating a significantly better prediction of SED than the currently available risk scores ($p < 0.002$ for all analyses) (Fig. 2).

3.5. Model validation

Stratified k-fold cross-validation of the created model resulted in a mean AUC of 0.824 and 0.804 for the training and test sets, respectively. This minimal drop in model performance indicates that our model fit the test data well. To minimize false positives, we propose a cut-off point of 0.58, which has a near-maximum specificity of 97 % (Fig. 2, Supplemental Table 4) and yielded a PPV of 73.4 % with an accuracy of 78.3 %. When we applied the SED prediction model using the cut-off of 0.58 to our dataset, we predicted SED in 115 (8.3 %) of 1381 patients.

Table 2
Vital sign and clinical score progression during ED stay both in the groups with values within and outside the normal range at triage.

Variable [n (%)]	SED		No SED		*p* value
Number of patients	354 (25.6)		1027 (74.4)		
	Within normal range at triage	Stayed normal	Within normal range at triage	Stayed normal	
Vital signs					
Heart rate	339 (95.8)	336 (94.9)	934 (90.9)	915 (89.1)	0.164
Systolic blood pressure	336 (94.9)	323 (91.2)	909 (88.5)	816 (79.5)	<0.001*
Diastolic blood pressure	322 (91)	298 (84.2)	852 (82)	702 (68.4)	<0.001*
Mean arterial pressure	343 (96.9)	335 (94.6)	951 (93)	877 (85.4)	<0.001*
Respiratory rate	292 (82.5)	268 (75.7)	689 (67.1)	562 (54.7)	<0.001*
Oxygen saturation	348 (98.3)	347 (98)	970 (94.5)	941 (91.6)	0.004*
Body temperature	278 (78.5)	244 (65.9)	630 (61.3)	512 (49.9)	0.016*
Mental status	350 (98.9)	350 (98.9)	954 (92.9)	934 (90.9)	0.006*
Sepsis scores					
qSOFA[1]	274 (77.4)	243 (68.6)	591 (57.6)	433 (42.2)	<0.001*
NEWS[2]	247 (69.8)	211 (59.6)	414 (40.3)	311 (30.3)	0.002*
	Outside normal range at triage	Normalized	Outside normal range at triage	Normalized	
Vital signs					
Heart rate	15 (4.2)	11 (3.1)	93 (9.1)	66 (6.4)	0.851
Systolic blood pressure	18 (5.1)	9 (2.5)	118 (11.5)	49 (4.8)	0.498
Diastolic blood pressure	32 (9.4)	16 (4.5)	175 (17)	81 (7.9)	0.699
Mean arterial pressure	11 (3.1)	9 (2.5)	76 (7.4)	43 (4.2)	0.111
Respiratory rate	62 (17.5)	21 (5.9)	338 (32.9)	132 (12.9)	0.440
Oxygen saturation	6 (1.7)	3 (0.8)	57 (5.6)	45 (4.4)	0.113
Body temperature	76 (21.5)	32 (9)	397 (38.7)	195 (19)	0.262
Mental status	4 (1.1)	4 (1.1)	73 (7.1)	33 (3.2)	0.033*
Score normalization					
qSOFA[1]	80 (22.6)	29 (8.2)	436 (42.5)	127 (12.4)	0.202
NEWS[2]	107 (30.2)	37 (10.5)	613 (59.7)	117 (11.4)	<0.001*

SED, safe early discharge (hospital-discharge ≤24 h, without disease-related readmission or death ≤7 days). [1]normal if score is 0, [2]normal if score is ≤3. *Significant p-value.

Table 3
The discriminative performance of individual clinical scoring systems.

Clinical scoring system[1] (range)	AUC (95 % CI)	Cut-off point[2] (≤)	Sens (%)	Spec (%)	PPV (%)	NPV (%)	*p* value
CIS physician (1−10)	0.739 (0.707; 0.771)	3	62	74	45	85	<0.001*
CIS nurse (1–10)	0.699 (0.663; 0.735)	3	47	80	45	81	<0.001*
NEWS (0−20)	0.631 (0.599; 0.663)	3	76	44	32	84	<0.001*
SIRS (0–4)	0.593 (0.559; 0.627)	1	40	74	35	78	<0.001*
qSOFA (0–3)	0.576 (0.543; 0.609)	0	73	41	30	82	<0.001*
SOFA (0–24)	0.637 (0.604; 0.669)	3	57	63	35	81	<0.001*
PIRO (0−33)	0.651 (0.620; 0.683)	6	67	55	34	83	<0.001*
MEDS (0–27)	0.631 (0.598; 0.664)	3	75	47	33	85	<0.001*

The range of the individual scoring systems are shown in parentheses. Abbreviations: *AUC* Area Under the Curve, *CI* Confidence interval, *Sens* Sensitivity, *Spec* Specificity, *PPV* Positive Predictive Value, *NPV* Negative predictive value.[1]Measured at ED admission[2];Point in the receiver operator characteristics curve with the maximum sensitivity and specificity. * $p < 0.05$.

To verify the accuracy of our model, we compared the predicted SED with the clinical decision made to admit or discharge the patient by the treating physician at the ED. By this approach, we identified 31 (27 %) cases that had a positive score (SED prediction) but were hospitalized and could be considered as false positives (Supplemental Table 5). When analyzing these 31 cases specifically, we found out that: i) 6 patients (19.4 %) were discharged and re-admitted within seven days, ii) 26 patients (83.9 %) were hospitalized >24 h and iii) importantly, none of these patients died within seven days (Supplemental Table 6). Remarkably, however, 16 patients (51.6 %) with a potentially false positive score were admitted on either a Thursday or a Friday, which is associated with prolonged hospital admission because patients are less frequently discharged on weekend days [24]. Together, based on this retrospective analysis, we speculate that most of the false positive cases are potential patients who could have been discharged home earlier.

4. Discussion

Despite the availability of risk scores that can predict deterioration, evidence regarding the characteristics of patients with an infection at the ED who can be safely discharged early is scarce. Here, we identified demographic, logistic, and medical factors associated with SED among 1381 patients who presented with an infection at our ED. Nine of these parameters were utilized to create and internally validate a prediction model to discriminate these patients from those requiring prolonged hospitalization and unsafe discharges. Remarkably, 68 % of patients with a qSOFA of 0 upon triage and 63 % with a NEWS ≤3 were hospitalized for more than 24 h, re-admitted, or died within seven days.

To the best of our knowledge, this is the first study that analyzes predictors of *safe and early* discharge among patients presenting to the ED with an infection and potential sepsis. Multiple studies focused on predicting *early* discharge among specific patient populations and proposed prediction models without taking safety into account [25-30]. Only two studies based their prediction model on ED patients [29-30]. The first included 894 general ED patients and showed an AUC of 0.84 for the prediction of discharge within 48 h [29]. The second included 297 general ED patients and demonstrated an AUC of 0.68 for discharge prediction within 72 h [30]. On the other hand, three studies proposed a model for predicting *safe* discharge, with AUCs ranging from 0.68 to 0.83 and taking readmission, ICU admission and mortality into account [13,21,22]. In summary, currently available studies have analyzed predictors for *early* discharge or predictors for *safe* discharge, with AUCs up to 0.83, similar to our model, which predicts *early and safe* discharge.

Changes in vital signs over time can provide important insights into the patient's condition and prognosis. Studies have shown that repeated measurement of vital signs is more predictive of patient outcomes than a single measurement [14,31,32]. Further, early changes in vital signs can be associated with adverse outcomes, as patients with normalized vital signs had a lower mortality risk than patients with deteriorating vital signs [13,14,31-34]. We show that vital signs normalized in more than half of the patients during the ED stay. Yet, only normalization of mental status and NEWS occurred more frequently in the group meeting SED criteria than in patients requiring hospitalization. Patients with normal vital signs and risk scores upon ED admission (triage) and discharge were more likely to be safely discharged than those with abnormal vital signs and risk scores upon triage that normalized during their ED stay. As a clinical consequence, it is essential for

Table 4
Multivariate logistic regression analysis for SED.

Variables in the equation	Regression coefficient (SE)	Odds Ratio (95 % CI)	*p* value
Constant	−0.965 (0.376)	0.381	0.010*
Demographics			
Younger age	−0.012 (0.005)	0.988 (0.977; 0.998)	0.023*
Absence of organ transplant	−0.858 (0.250	0.424 (0.260; 0.692)	0.001*
Arrival mode			
Neither ambulance nor GP referral	Reference category		
Referred by GP	0.302 (0.205	1.353 (0.905; 2.023	0.140
Arrival by ambulance	−0.228 (0.310)	0.796 (0.434; 1.461)	0.461
GP + ambulance[1]	−0.906 (0.287)	0.404 (0.230; 0.709)	0.002*
First impression			
Low CIS physician at admission	0.741 (0.188)	2.097 (1.451; 3.031)	<0.001*
Low CIS nurse at admission	0.457 (0.201)	1.578 (1.065; 2.340)	0.023*
Organ dysfunction			
Kidney failure at ED admission	−1.384 (0.546)	0.250 (0.102; 0.613)	0.002*
Liver failure at ED admission	−0.695 (347)	0.499 (0.253; 0.985)	0.045*
Vital signs and sepsis scores			
Normal qSOFA, both at triage and discharge[2]	0.430 (0.188)	1.537 (1.063; 2.223)	0.003*
Normal body temperature, both at triage and discharge[2, 3]	0.591 (0.184)	1.805 (1.259; 2.588)	0.001*
Sepsis-3 upon ED discharge, probability of safe, early discharge = 0			

Note: $R^2 = 0.247$ (Nagelkerke). Model Chi-square: 149,729, P < 0.001*. Percentage correctly predicted = 75.5 %. *GP*, General Practitioner, qSOFA is normal if score is 0.[1]Referred by GP and transported by ambulance to the ED[2];Measured at ED admission and discharge[3];Abnormal if <36 °C or > 38 °C. *significant p-value.

Table 5
The model statistics.

Method	AUC (95 % CI)	Cut-off point[1] (≥)	Sens (%)	Spec (%)	PPV (%)	NPV (%)
Forward: LR	0.824 (0.797; 0.851)	0.58	24	97	73.4	78.8

AUC Area Under the Curve, *CI* Confidence interval, *Sens* Sensitivity, *Spec* Specificity, *PPV* Positive Predictive Value, *NPV* Negative predictive value.[1]Proposed point in the receiver operator characteristics curve to facilitate safe, early discharge.

healthcare providers to closely monitor vital signs in patients with infections in the ED and to consider changes in vital signs as part of the risk assessment. However, to identify patients who could be discharged early, one should consider normal vital signs and risk scores throughout the ED stay instead of normalization of abnormal vital signs and risk scores.

Given that most patients with a low qSOFA or NEWS needed prolonged hospitalization or experienced unsafe discharge in our cohort, those frequently employed scores are likely unable to identify which patients may benefit from an early ED discharge. Clinicians should be aware that currently used scoring systems to stratify severely ill patients or identify patients with an infection who would require hospital admission are designed as rule-in tools. Therefore, their performance as rule-out tools seems limited, as our findings indicate. Remarkably, vital signs are not independent predictors of SED in our model, as opposed to the qSOFA score (i.e., altered mental status, tachypnoea, hypotension), body temperature, clinical impression, age, history of organ transplantation, arrival mode, and kidney/liver dysfunction.

Physicians make many decisions based on their clinical judgments during routine practice, consciously or unconsciously based on clinical impression. We included the clinical impression, also known as"gestalt" or gut feeling, of the health care professional in our model to increase accuracy by capturing more subjective factors like frailty and general appearance. Although there is not a routinely used and validated standard version; it is an effective method to predict the clinical course of acute illness [35]. Another study from our research team reported that the clinical impression at the ED can predict ICU admission, in-hospital mortality, and 28-day mortality [36]. Other studies demonstrated that clinical impression predicts ICU admission and mortality [16,37-39]. By choosing a cut-off point with near maximum specificity,

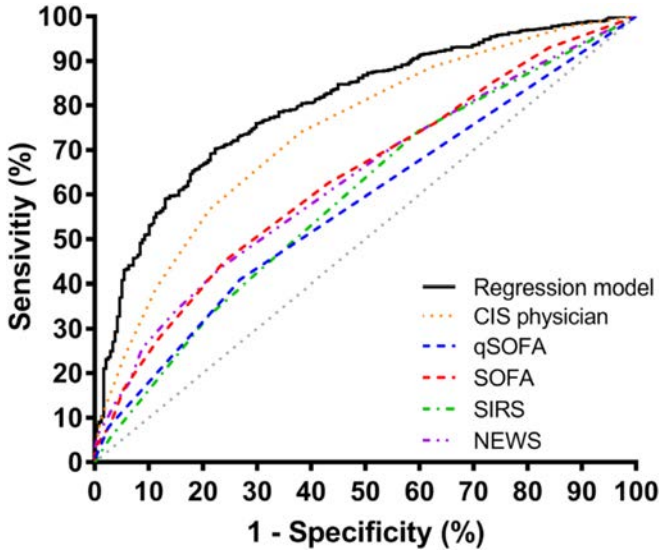

Fig. 2. Receiver operating curve analysis of the validated model to predict safe, early discharge among patients with an infection presenting to the ED. Model characteristics: AUC 0.824, 95 % CI 0.797–0.851, proposed cut-off point ≥0.58, sensitivity 24 %, specificity 97 %, PPV 73.4 %, NPV 78.8 %.

the number of false positives was minimized, and there were no unsafe discharges resulting in death. The prediction model supports the identification of low-risk patients who can benefit from SED. Our model is a promising tool that can facilitate SED in the EDs. Yet, prospective validation is warranted to evaluate its accuracy and safety.

Many factors determine the implementation success of a model in the healthcare system. One of them is model content. We selected age, history of organ transplantation, arrival mode (ambulance or own transport), CIS, liver and kidney failure at the ED, body temperature, and qSOFA parameters for model development. All those parameters, except liver and kidney failure at the ED, can be considered easily accessible or readily available during the ED patient evaluation. Liver and kidney failure can be recognized within 1–2 h upon ED arrival. Besides, physicians almost always consider those parameters during the discharge decision-making process. Therefore, this prediction model can be used practically by physicians in person or by an automated algorithm implemented into the hospital automation systems. Whether the integration is manual or system-connected, successful implementation requires strong stakeholder engagement, coordination of routine ED workflow and implementation strategies, training, and practical usability [40].

Our study has several limitations. First, the prediction model could not be validated in external patient cohorts since the clinical impression score, our strongest predictor, is not measured in other hospitals in the Netherlands. However, we did validate our model with stratified k-fold cross-validation, which many viewed as the best method for internal model validation. Second, to analyze the safety of the discharges, we chose a 7-day interval to monitor readmissions and mortality by reviewing electronic patient files. Because of this, and our patient records do not account for readmissions to other hospitals, the number of patients whosafely discharged may be overestimated. However, if a patient is known in a tertiary care center like ours, readmission to another hospital is very unlikely due to the complexity of their condition. Third, since all patients meeting Sepsis-3 criteria were hospitalized, including this feature in the model resulted in complete separation. The model should, therefore, only be applied to patients with an infection at the ED who do not meet Sepsis-3 criteria.

5. Conclusion

By combining readily available parameters, we developed and internally validated a prediction model for safe, early discharge among patients Further research, preferably in a multi-center setting, is warranted to externally validate the model and determine whether the use of this discharge prediction tool can indeed reduce the number of unnecessary hospitalizations.

Ethics approval and consent to participate

This study was carried out in accordance to the Declaration of Helsinki, the Dutch Agreement on Medical Treatment Act and the Dutch Personal Data Protection Act. The Institutional Review Board of the University Medical Center Groningen ruled that the Dutch Medical Research Involving Human Subjects Act is not applicable for this study and granted a waiver (METc 2015/164). All participants provided written informed consent.

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CRediT authorship contribution statement

Merijn C.F. Mulders: Writing – original draft, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Sevilay Vural:**

Writing – review & editing, Visualization, Data curation. **Lisanne Boekhoud:** Methodology, Formal analysis, Data curation. **Tycho J. Olgers:** Writing – review & editing, Data curation, Conceptualization. **Jan C. ter Maaten:** Writing – review & editing, Supervision, Methodology, Data curation, Conceptualization. **Hjalmar R. Bouma:** Writing – review & editing, Visualization, Supervision, Methodology, Conceptualization.

Data availability

The datasets used and analyzed during the current study are available from the corresponding author upon reasonable request.

Declaration of competing interest

The authors declare no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ajem.2024.10.014.

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