

Relationship between In-Hospital Sepsis Prediction Score and Prevalence of Community-Onset Sepsis: Triage for Sepsis Risk Management

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Abstract

Early diagnosis of sepsis is crucial in clinical practice. Several studies have proposed sepsis prediction models to forecast the onset of sepsis in hospitals. However, validation of prediction models for community-onset sepsis, which is sepsis developed before admission to the hospital, is insufficient. This study investigates the relationship between the in-hospital prediction model scores and community-onset sepsis. We used hierarchical logistic regression analysis to explore the relationship between sepsis prevalence and AITRICS-VC SEPS tertile categories while adjusting for potential confounders. The low-SEPS group was used as the reference group. The odds ratio (ORs) of sepsis comparing the moderate versus low SEPS group are 1.198 (95%, 1.075-3.654), and the high versus low VC-SEPS group are 8.683 (95%, 4.995-15.095). Even though the sepsis prediction model was designed to predict in-hospital sepsis, high prediction scores are related to the prevalence of community-onset sepsis. This result implies that SEPS scores can stratify sepsis risks and be considered a patient assessment tool for triage.

Keywords: Sepsis; Prediction; Deep learning; Risk stratification; Regression analysis

Introduction

Identifying sepsis early is essential in clinical settings [1]. Numerous prediction models have been developed to identify in-hospital sepsis [2]. However, research validating these models' effectiveness on patients who develop sepsis before hospital admission, known as community-onset sepsis, is insufficient. This study examined the connection between community-onset sepsis and the prediction score of AITRICS-VC SEPS, a model designed to predict in-hospital sepsis.

Materials and Methods

Study Participants and Definition of Sepsis

We collected patient data from the electronic medical records (EMR) of Keimyung University Dongsan Hospital (KUDH) from June 5th, 2023, to January 31st, 2024. Patients were identified as having sepsis using Rhee et al.'s Sepsis Clinical Surveillance Definition criteria [3]. Sepsis was classified into community-onset sepsis (COS) and hospital-onset sepsis (HOS), depending on whether it was identified within or after 48 hours of hospital admission. We excluded patients who identified as HOS in this analysis.

Sepsis Prediction Model (AITRICS-VC SEPS)

The sepsis prediction model was developed based on deep learning [4] and has been approved by the Korean Ministry of Food and Drug Safety for use in general wards as an AI-based clinical decision support system (CDSS). This model primarily aims to generate early warning scores to help medical staff screen patients before they develop septic shock. This model generates a score to identify sepsis in patients by providing an alert 4 hours before a formal diagnosis. It can handle data from clinical practice in time series and requires systolic blood pressure, diastolic blood pressure, pulse rate, respiratory rate, and body temperature to calculate scores. Additional laboratories related to sepsis can also be used to improve the model's predictive performance. It achieved the area under the receiver operating characteristic (AUROC) curves for 0.894 (95% CI, 0.832-0.937) on identifying COS in KUDH.

Statistical Analysis

We investigated whether AITRICS-VC SEPS could be used to stratify the risk of developing sepsis. Since age and gender are closely linked to sepsis prevalence [5], we grouped VC-SEPS scores into three categories based on age-specific and gender-specific percentiles: (Low-SEPS / Moderate-SEPS / High-SEPS). Additionally, we assessed if AITRICS-VC SEPS could serve as an independent biomarker for predicting sepsis. We used hierarchical logistic regression analysis to explore the relationship between sepsis prevalence and AITRICS-VC SEPS tertile categories while adjusting for potential confounders such as age, gender, body mass index (BMI), systolic blood pressure (SBP), and respiratory rate (RR). The low-SEPS group was used as the reference group.

Results

Study Populations

A total of 6455 patient data were enrolled in the study, and 325 patients were diagnosed as having sepsis. In sepsis patients, 229 patients were identified as COS, and 96 patients were identified as HOS. In this study, 6130 non-sepsis patients and 229 COS patients were used for analysis.

Hierarchical Logistic Regression Analysis

Table 1 shows the results of hierarchical regression analysis when incrementally adding variables related to sepsis. In the crude analysis, the odds ratios (ORs) of sepsis comparing the moderate versus low SEPS group are 2.516 (95% CI, 1.377-4.598), and the ORs of the high versus low SEPS group are 13.225 (95% CI, 7.779-22.484) for sepsis. After adjustments for age, gender, BMI, SBP, and RR, the ORs of sepsis comparing the moderate versus low SEPS group are 1.198 (95% CI, 1.075-3.654), and the high versus low VC-SEPS group are 8.683 (95% CI, 4.995-15.095).

Table 1. Results of the hierarchical regression analysis when incrementally adding variables related to sepsis. All values in each cell are reported in the form of Odds Ratio (Confidence Interval)

Variable		Regression 1	Regression 2	Regression 3	Regression 4
SEPS	Low	ref	ref	ref	ref
	Moderate	2.516 (1.377-4.598)	1.973 (1.070-3.637)	1.971 (1.069-3.633)	1.982 (1.075-3.654)
	High	13.225 (7.779-22.484)	10.212 (5.923-17.609)	10.127 (5.850-17.532)	8.683 (4.995-15.095)
Age			1.060 (1.049-1.072)	1.060 (1.049-1.072)	1.059 (1.048-1.071)
Gender	Male		ref	ref	ref
	Female		0.323 (0.240-0.433)	0.324 (0.241-0.435)	0.341 (0.253-0.459)
BMI			0.963 (0.926-1.000)	0.963 (0.927-1.001)	0.967 (0.930-1.005)
SBP				0.999 (0.994-1.005)	0.997 (0.992-1.003)
RR					1.125 (1.076-1.175)

Discussion

In this study, we investigated that SEPS score can be used as independent predictors to assess COS. ORs were exponentially increased when the SEPS score increased even after adjustment for confounding factors. The SEPS high group was highly related to the prevalence of COS compared to the SEPS low group. However, the limitation of our study is that we focused only on COS, which is identified near admission. The relationship between SEPS scores and HOS could be different compared to COS. So, further analysis is necessary to make guidance for interpreting SEPS scores.

Conclusions

Even though AITRICS-VC SEPS were designed to predict HOS, SEPS scores are highly related to the prevalence of COS. This result implies that SEPS scores can stratify sepsis risks and be considered a patient assessment tool for triage.

List of Abbreviations: Odds Ratio (ORs), Body Mass Index (BMI), Systolic Blood Pressure (SBP), Respiratory Rate (RR), Electronic Medical Records (EMR), Confidence Interval (CI), Clinical Decision Support System (CDSS), Community-onset Sepsis (COS), Hospital-onset Sepsis (HOS), Keimyung University Dongsan Hospital (KUDH), area under the receiver operating characteristic (AUROC).

Author Contributions: KHL and KBL defined the research's aim and the experiment's design. KHL, SSJ, HWC, SSH, KBL, and HCC participated in the study's design. KHL carried out the experiments and performed the statistical analysis. KHL made a table. KHL wrote the manuscript. KHL and HCC collected the data and cleaned them. HWC, SJH, KBL, and HCC critically reviewed the draft and helped complete the manuscript.

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Ethics Statement: The Institutional Review Board (IRB) of KUDH approved this study, and a waiver of consent was obtained (IRB No. 2020-08-045).

Data Availability Statement: The data utilized in this study were obtained under the supervision and grant support of Keimyung University Dongsan Hospital. Individual contact with the hospital is required for access to the data.

Conflict of Interest: HWC, SSH, KBL, and KHL are AITRICS employees.

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