

## **Advantage of Vital Sign Monitoring Using a Wireless Wearable Device for Predicting Septic Shock in Febrile Patients in the Emergency Department: A Machine Learning-Based Analysis**

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### **Background.**

Sepsis is a critical complication in patients visiting emergency department (ED) with fever. Detecting changes in vital signs is crucial for early intervention and treatment, but it's practically impossible for physicians to monitor every patient closely in the ED due to restricted resources. Recently, wearable devices for continuous monitoring of vital signs have been introduced but their reliability in clinical environments is not fully validated. Moreover, the size of data obtained using a continuous monitoring device is much larger than that obtained using the manual method in which the measurements are obtained intermittently. With the growing number of patients presenting to EDs and the enormous amount of data related to patient monitoring, conventional techniques are considered inadequate to process these data. Machine learning-based analysis is being used to manage large-scale datasets promptly. Therefore, the efficiency of emergency medical practice can be maximised if a large amount of data generated during the emergency department stay can be immediately processed using a machine learning algorithm. Therefore, in the present study, we aimed to evaluate the predictive performance of a wireless monitoring device for the continuous measurement of heart rate (HR) and respiratory rate (RR) in febrile but stable patients in the ED using machine learning-based analysis.

### **Methods.**

We aimed to evaluate the predictive performance of a wireless monitoring device that continuously measures HR and RR and a machine learning analysis in febrile but stable patients in the ED. We analysed 468 patients (age,  $\geq 18$  years; training set,  $n = 277$ ; validation set,  $n = 93$ ; test set,  $n = 98$ ) having fever (temperature  $>38$  °C) and admitted to the isolation care unit of the ED. The primary outcome was clinically identified septic shock requiring treatment with vasopressors to maintain a mean arterial pressure of 65 mm Hg or more in the absence of hypovolemia after adequate fluid administration within 24 h. Electrocardiogram rhythm and respiratory signals were continuously monitored using the wearable wireless device and manually measured intermittently. Measurement of vital signs, such as systolic blood pressure, diastolic blood pressure, HR, RR, and mental status, was performed manually and recorded every hour, from baseline to 6 h later, while the wearable device was attached to the patient. We created a data fragment to build two different models—a simple computed model that predicted outcomes using only one data fragment in a specific time unit, and the accumulated model that predicted outcomes by considering all previous data fragments comprehensively. For data fragmentation, data units of the 14 values (five static values, four dynamic values, and four time-difference values), measured every hour, were used as manual data, whereas data units of the same 14 values, with HR and RR replaced with signal data from the wearable device, measured every 5 min, were used as device data. For the development of the model, we used a convolutional neural network and a long-short term memory network for time-sensitive analysis. Regarding the estimation of the time to predict deterioration, it was assumed and recorded that it took over 6 h to predict septic shock if the model failed to predict it within the first 6 h.

### **Results.**

The area under receiver operating characteristic (AUROC) of the fragmented model with device data was 0.858 (95% confidence interval [CI], 0.809–0.908), and that with manual data was 0.841 (95% CI, 0.789–0.893). The AUROC of the accumulated model with device data was 0.861 (95% CI, 0.811–0.910), and that with manual data was 0.853 (95% CI, 0.803–0.903). In the test set, both fragmented and accumulated models developed using device data accurately predicted septic shock within 6 h in one more patient than those developed using manual data. Regarding the time to predict septic shock when the threshold was set at maximum sensitivity with specificity over 0.9, compared with the model with manual data, the fragmented model with device data predicted septic shock at least 9 h earlier in total, and the accumulated model with device data predicted septic shock 5 h 30 min earlier at the minimum. Systolic and diastolic blood pressure, both the value of the current time point and the difference value between the present and the time of the visit, showed high feature importance scores in all four models. Additionally, accumulating the latest HR value was important for prediction since the current HR ranked higher in the model using the device data. On the other hand, in the model using manual data, the HR difference value ranked higher.

### **Conclusion.**

The present study is a pilot trial in which a wearable device continuously captured patients' vital signs that occurred in the clinical field but could not be detected and converted into a useful data source for clinical practice. It showed that continuous monitoring of vital signs using a wearable device and machine-learning based analysis could predict clinical deterioration accurately and reduce the time to recognise potential clinical deterioration in stable ED patients with fever. Our results support the application of a novel approach in clinical settings to decrease safety risks due to limited ED resources. Similar studies are needed to secure the use of these digital technologies in various clinical settings in the future.