

Conference Abstracts

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Rapid Diagnosis of Fever Etiology in Bone Marrow Transplant Recipients Using Wearable Temperature Monitoring and Machine Learning

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Abstract

Background

Febrile neutropenia after hematopoietic cell transplantation (HCT) is routinely treated with empiric broad-spectrum antibiotics because infectious and non-infectious etiologies are difficult to distinguish early in the clinical course. While wearable sensors enable high-frequency temperature monitoring (HFTM), the diagnostic value of these high-resolution temperature data for differentiating fever etiology has not been established. We hypothesized that machine learning analysis of continuous temperature data could distinguish infectious from non-infectious fever in HCT recipients.

Methods

We analyzed 68 clinically independent fever episodes recorded in HCT patients (n=90) outfitted with an FDA-cleared wireless temperature sensor (TempTraq®, BlueSpark Technologies) that measured axillary temperature every 2 minutes throughout hospitalization. Time-series features were extracted from temperature

traces spanning 1 hour before to 3 hours after fever onset and used to train a suite of machine-learning models to distinguish engraftment fevers from other fever etiologies. Model training and evaluation were performed using repeated stratified 5-fold patient-level cross-validation, yielding 100 train-test evaluations.

Results

Among all classification models, the logistic regression classifier provided the best overall performance and interpretability, achieving 94% specificity (95% CI, 0.84–1.0) for distinguishing non-infectious (engraftment) fever from infectious fever, with a mean AUROC of 0.88 ± 0.10 . Feature importance analysis demonstrated that both clinical variables and HFTM-derived temperature dynamics contributed to model performance, with a strong reliance on time-series features captured within the first 4 hours of fever onset.

Conclusion

Continuous temperature data collected from wearable sensors contain clinically meaningful physiologic information that can be leveraged for

machine learning-based differentiation of infectious and non-infectious fever after HCT. These findings support further prospective validation of wearable-derived diagnostic tools to enable real-time clinical decision-making and guide risk-adapted antibiotic de-escalation during

febrile neutropenia. More broadly, this approach may provide a framework for leveraging continuous physiologic monitoring to detect and characterize treatment-related toxicities across hematologic malignancies.

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