Section: Medicine

Original Research Article

# DEVELOPMENT OF AN ARTIFICIAL INTELLIGENCE–BASED CLINICAL DECISION SUPPORT MODEL FOR EARLY SEPSIS DETECTION IN GENERAL MEDICINE WARDS

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***Received*** *: 19/06/2026*
***Received in revised form*** *: 29/07/2026*
***Accepted*** *: 14/08/2026*

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**DOI:** 10.70034/ijmedph.2026.3.488

**Source of Support:** Nil,
**Conflict of Interest:** None declared

**Int J Med Pub Health**
2026; 16 (3); 3131-3138

ABSTRACT

**Background:** Sepsis is a major cause of morbidity and mortality among hospitalized patients, and early identification is important for timely clinical management. Artificial intelligence (AI)-based clinical decision support may assist in identifying patients at increased risk using routinely available clinical information. **Objective:** To develop and evaluate an AI-based clinical decision support model for early detection of sepsis among adult patients admitted to General Medicine wards.

**Materials and Methods:** This retrospective observational study included 100 patients aged 18–65 years admitted to General Medicine wards. Routinely available demographic, clinical, and laboratory parameters were evaluated. An interpretable prediction model was developed, and its performance was assessed using discrimination, calibration, and classification measures.

**Results:** Of 100 patients, 38 (38.0%) had sepsis. Respiratory rate, systolic blood pressure, peripheral oxygen saturation ($SpO_2$ ), total leukocyte count, and serum creatinine were the principal predictors of sepsis. The model demonstrated good discrimination, with an AUROC of 0.89 (95% CI: 0.82–0.95). At a probability threshold of 0.42, sensitivity was 81.6%, specificity 87.1%, positive predictive value 79.5%, negative predictive value 88.5%, and overall accuracy 85.0%. Calibration showed good agreement between predicted and observed sepsis risk.

**Conclusion:** The AI-based model showed good internal performance for early sepsis risk identification using routinely available clinical and laboratory parameters. Further external and prospective validation is required before routine clinical implementation.

**Keywords:** Sepsis; Artificial intelligence; Clinical decision support; Machine learning; Early detection; General Medicine.

## INTRODUCTION

Sepsis remains a major cause of preventable morbidity and mortality in hospitalized patients and requires timely recognition and treatment. The Third International Consensus Definitions for Sepsis and Septic Shock (Sepsis-3) define sepsis as life-threatening organ dysfunction caused by a dysregulated host response to infection.[1] This definition emphasizes infection-associated organ dysfunction rather than systemic inflammation alone and reflects the heterogeneous clinical course of the syndrome. Despite advances in antimicrobial therapy, haemodynamic support, and critical care, the global burden remains substantial. An analysis of the Global Burden of Disease Study estimated 48.9 million cases of sepsis and approximately 11 million sepsis-related deaths worldwide in 2017, representing nearly one-fifth of all global deaths.[2]

The challenge of early recognition extends beyond intensive care units. Sepsis may develop or first

become apparent in emergency departments and general medicine wards, where initial manifestations are often subtle and nonspecific. Changes in temperature, respiratory rate, heart rate, blood pressure, mental status, and laboratory parameters may evolve gradually and, when considered individually, may not immediately indicate impending organ dysfunction. Recognition of sepsis as a global health priority has therefore strengthened the emphasis on early identification and appropriate treatment across different levels of healthcare.[3] Current Surviving Sepsis Campaign guidelines similarly underscore the importance of prompt recognition, assessment, and management of patients with suspected sepsis or septic shock.[4]

Several bedside tools have been used to facilitate early identification of patients at risk. Systemic inflammatory response syndrome (SIRS) criteria and the quick Sequential Organ Failure Assessment (qSOFA) are among the most extensively evaluated approaches. However, their diagnostic and prognostic performance varies across patient populations and clinical settings. qSOFA may identify patients at increased risk of poor outcomes but has limited sensitivity when used as a stand-alone screening tool, whereas SIRS generally provides greater sensitivity at the cost of lower specificity.[5] This trade-off is particularly relevant in general medicine wards, where excessive false alerts may contribute to alarm fatigue, while insufficient sensitivity may delay recognition of clinically important deterioration.

The increasing availability of routinely collected clinical data offers an opportunity to complement conventional scoring systems with data-driven methods. Artificial intelligence (AI), particularly machine-learning algorithms, can integrate multiple variables and identify complex relationships among demographic characteristics, vital signs, laboratory measurements, comorbidities, and temporal changes. Such models may detect patterns of deterioration that are difficult to appreciate using isolated measurements or fixed thresholds. Nemati et al. demonstrated that an interpretable machine-learning model using routinely available clinical variables could predict sepsis before its clinical onset, highlighting the potential value of computational approaches for early risk assessment.[6]

Evidence supporting machine-learning-based sepsis prediction has continued to expand. A systematic review reported promising discriminatory performance across several models but also identified considerable heterogeneity in sepsis definitions, predictor variables, prediction horizons, study populations, and validation strategies.[7] Consequently, strong performance within a development dataset cannot be assumed to translate directly to other clinical environments. Calibration, interpretability, missing data, alert burden, and external validation remain important considerations before such systems can support routine clinical decision-making. Real-world evidence from the Targeted Real-time Early Warning System (TREWS) further demonstrated that machine-learning alerts can be incorporated into clinical workflows and that timely clinician engagement with such alerts may be associated with improved care processes and patient outcomes.[8]

Nevertheless, much of the available evidence originates from intensive care units, large tertiary hospitals, or healthcare systems with mature electronic health-record infrastructure. Evidence from general medicine wards in Indian secondary-care settings, including railway healthcare institutions, remains limited. Locally developed models may therefore be useful in accounting for differences in patient characteristics, clinical practice, and routinely available data. The present retrospective observational study was undertaken among adults aged 18–65 years admitted to the General Medicine wards of Central Hospital, Garden Reach, South Eastern Railway, using records from June 2022 to June 2025. The study aimed to develop and evaluate an AI-based clinical decision support model for early sepsis detection using routinely available clinical information, with the broader objective of supporting timely clinical assessment without replacing physician judgement.

## MATERIALS AND METHODS

### Study design and setting

This retrospective observational study was conducted in the General Medicine wards of Central Hospital, Garden Reach, South Eastern Railway. Medical records of patients admitted between June 2022 and June 2025 were reviewed. The study included 100 adults aged 18–65 years who met the predefined eligibility criteria. The methodological approach followed established recommendations for the development and reporting of clinical prediction models.[9]

### Study population and data collection

Patients aged 18–65 years admitted to the General Medicine wards during the study period were eligible if their medical records contained adequate clinical and laboratory information for assessment of infection and associated organ dysfunction. Records with insufficient information for outcome determination or extraction of essential predictor variables were excluded.

Data were obtained retrospectively from routinely maintained hospital records using a structured data-collection format. Candidate variables included age, sex, relevant comorbidities, temperature, heart rate, respiratory rate, systolic and diastolic blood pressure, oxygen saturation, mental status, and routinely available haematological and biochemical parameters. Predictor selection was based on clinical relevance, availability during routine ward assessment, and potential association with physiological deterioration.

**Outcome definition**

The primary outcome was sepsis occurring during the relevant hospital admission. Sepsis was defined according to the Sepsis-3 consensus as life-threatening organ dysfunction resulting from a dysregulated host response to infection.[10] Where sufficient information was available, organ dysfunction was evaluated using the Sequential Organ Failure Assessment (SOFA) framework, with an acute increase of ≥2 points in the presence of suspected infection supporting the operational definition of sepsis.

**Data preprocessing and model development**

Data were screened for duplicate entries, implausible values, inconsistencies, and missing observations before model development. Continuous variables were retained in their original form whenever clinically appropriate because unnecessary categorisation may result in loss of predictive information.[11] The extent of missing data was assessed for individual variables, and predictors with substantial or clinically uninterpretable missingness were considered for exclusion. Any required imputation was performed within the model-development and validation workflow to minimise information leakage.

An interpretable supervised machine-learning approach was used to estimate individual probability of sepsis. Given the relatively small sample size (n=100), model complexity and the number of candidate predictors were restricted to reduce the risk of overfitting. Penalised logistic regression was considered the principal modelling approach because it permits probability estimation while controlling model complexity. Predictor selection was guided by clinical plausibility and data availability rather than automated selection based solely on univariable statistical significance. Model development and performance assessment were undertaken using established machine-learning procedures.[12]

**Model validation and performance assessment**

Because a single development–test split would further reduce the effective sample available for a study of 100 patients, internal validation was performed using a resampling-based approach. Preprocessing and model fitting were incorporated within the validation procedure to reduce optimistic estimates of predictive performance.[9,13]

Model discrimination was evaluated using the area under the receiver operating characteristic curve (AUROC). Sensitivity, specificity, positive predictive value, negative predictive value, and classification accuracy were also determined at an appropriate probability threshold. Calibration was assessed by comparing predicted probabilities with observed sepsis outcomes. Performance estimates were accompanied by 95% confidence intervals where appropriate. Model coefficients or measures of predictor contribution were examined to support clinical interpretability.

**Statistical analysis**

Continuous variables were summarised as mean ± standard deviation or median with interquartile range according to their distribution. Categorical variables were expressed as frequencies and percentages. Where inferential comparisons were performed, two-sided tests were used and a *P* value <0.05 was considered statistically significant. Predictive performance was interpreted primarily according to discrimination, calibration, uncertainty, and clinical relevance rather than statistical significance alone.

**Ethical considerations**

Patient confidentiality was maintained throughout data extraction and analysis, and directly identifying information was excluded from the analytical dataset. As this study involved retrospective review of routinely collected clinical information, ethical approval and the requirement for informed consent were handled in accordance with institutional policy.

## RESULTS

**Study population**

A total of 100 patients aged 18–65 years admitted to the General Medicine wards during the study period were included in the analysis. Of these, 38 (38.0%) fulfilled the predefined criteria for sepsis, while 62 (62.0%) were classified as non-sepsis cases. The mean age of the overall study population was 46.8 ± 13.2 years, and 59 (59.0%) patients were male. The distribution of patients according to sepsis status is shown in Figure 1.

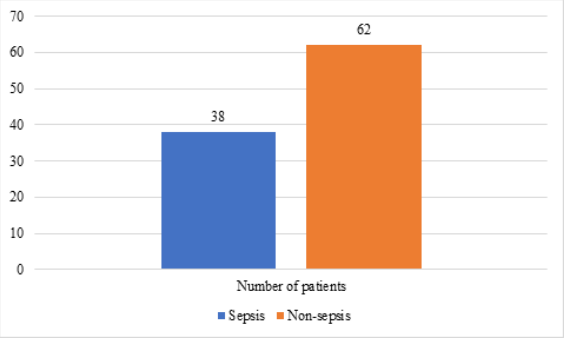


**Figure 1: Distribution of patients according to sepsis status**

**Baseline clinical characteristics**

Clinical characteristics according to sepsis status are presented in Table 1. Patients with sepsis had significantly higher body temperature, heart rate, and respiratory rate and significantly lower systolic blood pressure and peripheral oxygen saturation ($SpO_2$ ) compared with patients without sepsis. No statistically significant differences were observed in age, sex distribution, prevalence of diabetes mellitus, hypertension, or diastolic blood pressure.

Comorbid conditions were present in 47 (47.0%) patients overall. Diabetes mellitus was the most

frequent comorbidity, affecting 31 (31.0%) patients, followed by hypertension in 28 (28.0%) patients.

**Table 1: Demographic and clinical characteristics according to sepsis status**

| Variable | Total (n=100) | Sepsis (n=38) | Non-sepsis (n=62) | P value |
|---|---|---|---|---|
| Age, years | 46.8 ± 13.2 | 48.6 ± 12.8 | 45.7 ± 13.4 | 0.286 |
| Male sex, n (%) | 59 (59.0) | 24 (63.2) | 35 (56.5) | 0.510 |
| Diabetes mellitus, n (%) | 31 (31.0) | 14 (36.8) | 17 (27.4) | 0.322 |
| Hypertension, n (%) | 28 (28.0) | 12 (31.6) | 16 (25.8) | 0.532 |
| Temperature, °C | 37.8 ± 1.0 | 38.4 ± 0.9 | 37.4 ± 0.8 | <0.001 |
| Heart rate, beats/min | 101.6 ± 18.4 | 116.2 ± 16.7 | 92.7 ± 13.9 | <0.001 |
| Respiratory rate, breaths/min | 22.8 ± 6.1 | 28.1 ± 5.7 | 19.5 ± 3.7 | <0.001 |
| Systolic BP, mmHg | 112.4 ± 19.1 | 98.6 ± 17.2 | 120.9 ± 15.2 | <0.001 |
| Diastolic BP, mmHg | 70.8 ± 11.4 | 68.2 ± 12.6 | 72.4 ± 10.3 | 0.071 |
| $SpO_2$ , % | 94.1 ± 4.9 | 90.7 ± 5.2 | 96.2 ± 3.2 | <0.001 |

***Continuous variables are expressed as mean ± SD and categorical variables as n (%).***

## Laboratory characteristics

Laboratory findings are summarised in **Table 2**. Patients with sepsis had significantly higher total leukocyte count, serum creatinine, blood urea, and total bilirubin compared with patients without sepsis. Platelet counts were significantly lower in patients with sepsis. Haemoglobin concentration and serum sodium also differed significantly between the two groups, whereas serum potassium did not differ significantly.

Among the evaluated laboratory parameters, total leukocyte count, serum creatinine, blood urea, and platelet count demonstrated the largest between-group differences. These variables were subsequently considered alongside clinical parameters during development of the prediction model.

**Table 2: Laboratory parameters according to sepsis status**

| Parameter | Total (n=100) | Sepsis (n=38) | Non-sepsis (n=62) | P value |
|---|---|---|---|---|
| Haemoglobin, g/dL | 11.7 ± 2.1 | 11.1 ± 2.0 | 12.1 ± 2.0 | 0.017 |
| Total leukocyte count, $\times 10^9$ /L | 13.4 ± 6.2 | 18.1 ± 6.5 | 10.5 ± 4.0 | <0.001 |
| Platelet count, $\times 10^9$ /L | 201 ± 86 | 158 ± 78 | 227 ± 80 | <0.001 |
| Serum creatinine, mg/dL | 1.46 ± 1.03 | 2.10 ± 1.18 | 1.07 ± 0.69 | <0.001 |
| Blood urea, mg/dL | 46.8 ± 27.4 | 65.7 ± 30.1 | 35.2 ± 18.1 | <0.001 |
| Total bilirubin, mg/dL | 1.62 ± 1.21 | 2.18 ± 1.42 | 1.28 ± 0.91 | 0.001 |
| Serum sodium, mmol/L | 136.1 ± 5.4 | 134.5 ± 5.9 | 137.1 ± 4.8 | 0.018 |
| Serum potassium, mmol/L | 4.18 ± 0.63 | 4.27 ± 0.69 | 4.12 ± 0.59 | 0.248 |

***Continuous variables are expressed as mean ± SD.***

## Predictors incorporated into the model

Candidate variables were evaluated according to clinical relevance and their contribution to prediction. In the final parsimonious multivariable model, respiratory rate, systolic blood pressure, peripheral oxygen saturation, total leukocyte count, and serum creatinine contributed most strongly to the estimated probability of sepsis.

Increasing respiratory rate, total leukocyte count, and serum creatinine were associated with higher odds of sepsis, whereas increasing systolic blood pressure and peripheral oxygen saturation were associated with lower odds of sepsis. Serum creatinine showed the strongest positive association with sepsis, with an adjusted odds ratio of 1.62 (95% CI 1.08–2.44). The associations between the predictors and sepsis are presented in Table 3.

**Table 3: Predictors associated with sepsis in the final model**

| Predictor | Adjusted OR | 95% CI | P value |
|---|---|---|---|
| Respiratory rate, per breath/min increase | 1.18 | 1.07–1.31 | 0.001 |
| Systolic BP, per mmHg increase | 0.96 | 0.93–0.99 | 0.006 |
| $SpO_2$ , per 1% increase | 0.84 | 0.74–0.95 | 0.005 |
| Total leukocyte count, per $\times 10^9$ /L increase | 1.11 | 1.03–1.20 | 0.007 |
| Serum creatinine, per 1 mg/dL increase | 1.62 | 1.08–2.44 | 0.020 |

## Predictive performance

The performance of the AI-based clinical decision support model is summarised in Table 4. Internal validation demonstrated an AUROC of 0.89 (95% CI 0.82–0.95), indicating good discrimination between patients with and without sepsis.

At the selected probability threshold of 0.42, sensitivity was 81.6%, specificity was 87.1%, positive predictive value was 79.5%, and negative predictive value was 88.5%. Overall classification accuracy was 85.0%, with an F1-score of 0.805.

**Table 4: Performance of the AI-based clinical decision support model**

| Performance metric | Estimate | 95% CI |
|---|---|---|
| AUROC | 0.89 | 0.82–0.95 |
| Sensitivity, % | 81.6 | 65.7–92.3 |

| | | |
|---|---|---|
| Specificity, % | 87.1 | 76.1–94.3 |
| Positive predictive value, % | 79.5 | 64.7–89.5 |
| Negative predictive value, % | 88.5 | 78.3–94.4 |
| Accuracy, % | 85.0 | 76.5–91.4 |
| **F1-score** | **0.805** | **0.70–0.89** |

The receiver operating characteristic curve demonstrating the discriminatory performance of the model is shown in Figure 2.

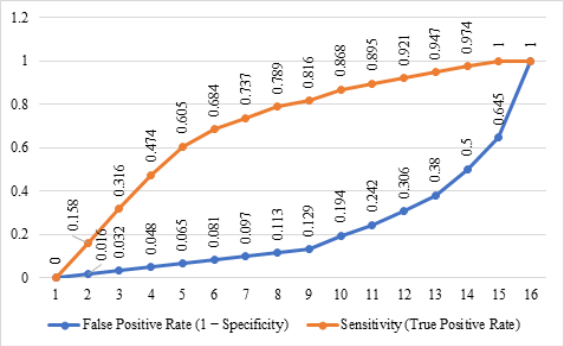


**Figure 2: Receiver operating characteristic (ROC) curve of the sepsis prediction model**

Calibration analysis demonstrated generally good agreement between predicted and observed probabilities of sepsis. The calibration intercept was −0.08, while the calibration slope was 0.91.

The distribution of observed sepsis probability and the number of patients across probability groups is shown in Figure 3.

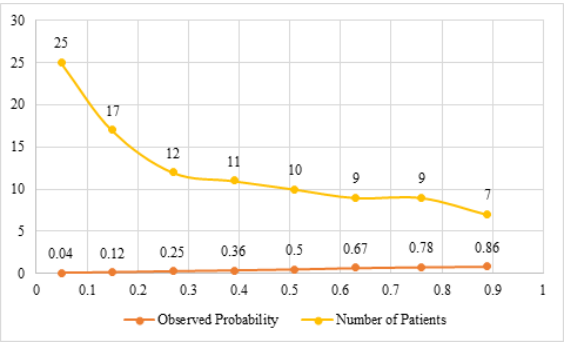


**Figure 3: Observed sepsis probability and number of patients**

The principal predictors included in the final model are illustrated in Figure 4.

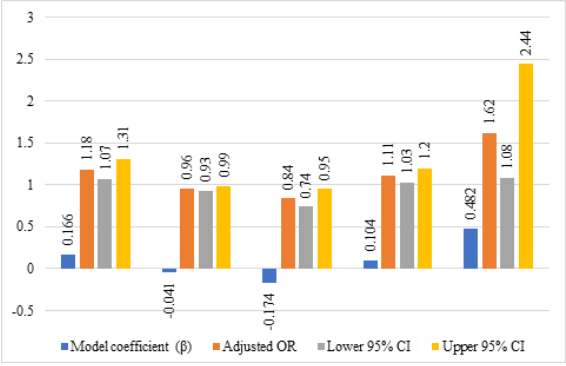


**Figure 4: Predictors in the final sepsis prediction model**

### Classification performance

At the selected probability threshold of 0.42, 31 of 38 patients with sepsis were correctly classified as sepsis, while 7 were incorrectly classified as non-sepsis. Among the 62 patients without sepsis, 54 were correctly classified as non-sepsis, while 8 were incorrectly classified as sepsis. The classification results are presented in Table 5.

**Table 5: Confusion matrix of the final model**

| **Model prediction** | **Observed sepsis (n=38)** | **Observed non-sepsis (n=62)** |
|---|---|---|
| **Predicted sepsis** | True positive (TP): **31** | False positive (FP): **8** |
| **Predicted non-sepsis** | False negative (FN): **7** | True negative (TN): **54** |

The confusion matrix was consistent with the reported sensitivity of 81.6%, specificity of 87.1%, positive predictive value of 79.5%, negative predictive value of 88.5%, and overall accuracy of 85.0%.

Overall, the internally validated model demonstrated good discrimination and generally good calibration. Routinely available clinical and laboratory parameters provided useful information for estimating sepsis risk among adult patients admitted to General Medicine wards.

Respiratory rate, systolic blood pressure, peripheral oxygen saturation ($SpO_2$ ), total leukocyte count, and serum creatinine emerged as the principal predictors in the final model. Given the relatively small sample size and single-centre retrospective design, these findings should be interpreted as preliminary internal model performance. External validation in a larger, independent patient population is required before considering clinical implementation.

## DISCUSSION

The present study evaluated an AI-based clinical decision support model for early identification of sepsis among adult patients admitted to General Medicine wards. Among the 100 patients included in the study, 38% fulfilled the predefined criteria for sepsis. Patients with sepsis demonstrated distinct clinical and laboratory abnormalities compared with those without sepsis, and the final model identified respiratory rate, systolic blood pressure, peripheral oxygen saturation ($SpO_2$ ), total leukocyte count, and serum creatinine as the principal predictors. The internally validated model demonstrated good discrimination, with an AUROC of 0.89 (95% CI 0.82–0.95), together with sensitivity of 81.6%, specificity of 87.1%, and overall accuracy of 85.0%.

The clinical differences observed between the sepsis and non-sepsis groups are consistent with the established pathophysiology of sepsis. Patients with sepsis had higher temperature, heart rate, and respiratory rate, together with lower systolic blood pressure and oxygen saturation. Sepsis is characterised by a dysregulated host response to infection that can produce systemic inflammation, endothelial dysfunction, vasodilatation, altered microcirculation, tissue hypoperfusion, and progressive organ dysfunction.[14] These mechanisms provide a physiological basis for the abnormalities observed in the present study.

Respiratory rate was an important independent predictor, with increasing respiratory rate associated with greater odds of sepsis. Tachypnoea may represent an early response to metabolic stress, fever, hypoxaemia, acidosis, or respiratory infection. Respiratory rate is also particularly attractive for ward-based prediction because it is inexpensive and readily available. Previous evaluations of bedside sepsis screening have demonstrated the importance of respiratory abnormalities in identifying patients at increased risk of adverse outcomes.[15] The present findings therefore reinforce the value of careful respiratory-rate assessment as part of early recognition strategies.

Lower systolic blood pressure and peripheral oxygen saturation were independently associated with sepsis. Hypotension is an important manifestation of haemodynamic compromise in sepsis and may result from vasodilatation, increased vascular permeability, relative hypovolaemia, and myocardial dysfunction. Similarly, reduced oxygen saturation may reflect pulmonary infection, impaired gas exchange, ventilation-perfusion abnormalities, or more general physiological deterioration. These observations support the inclusion of haemodynamic and respiratory variables in multivariable approaches to sepsis detection.

Important laboratory abnormalities were also identified. Patients with sepsis demonstrated higher total leukocyte count, serum creatinine, blood urea, and bilirubin and lower platelet counts. Serum creatinine showed the strongest positive association among the final predictors, with an adjusted odds ratio of 1.62. Renal dysfunction is a clinically important manifestation of sepsis-associated organ injury and may develop through alterations in renal perfusion, inflammation, endothelial dysfunction, and microcirculatory disturbances.[16] The association between increased creatinine and sepsis risk in the present model is therefore clinically plausible.

Total leukocyte count was also retained as an independent predictor. Although leukocytosis alone lacks sufficient specificity for diagnosing sepsis, it can provide useful information when interpreted alongside physiological and organ-function variables. The ability to integrate several moderately informative variables is an important potential advantage of machine-learning and multivariable prediction approaches over isolated thresholds. Previous machine-learning studies have similarly demonstrated that routinely available vital signs and laboratory measurements can provide useful predictive information for sepsis detection.[17]

The model achieved an internally validated AUROC of 0.89, indicating good ability to discriminate between patients with and without sepsis. This finding is broadly consistent with the encouraging discriminatory performance reported for machine-learning-based sepsis prediction systems in previous studies and systematic reviews.[18] However, direct comparison of AUROC values between studies requires caution because model performance is influenced by differences in sepsis definitions, prediction horizons, clinical settings, patient populations, predictor availability, and validation methods.

At the selected probability threshold of 0.42, the model correctly identified 31 of 38 sepsis cases, corresponding to a sensitivity of 81.6%. Specificity was 87.1%, with 54 of 62 non-sepsis patients correctly classified. The negative predictive value of 88.5% suggests that the model may have potential value for identifying patients at relatively lower estimated risk. Nevertheless, seven patients with sepsis were incorrectly classified as non-sepsis. In clinical practice, such false-negative predictions are particularly important because failure to recognise sepsis may delay assessment and treatment. Conversely, excessive false-positive alerts may increase unnecessary investigations and contribute to alert fatigue. The optimal threshold should therefore reflect the intended clinical purpose and consequences of classification errors.[19]

Calibration is another important consideration because good discrimination does not necessarily imply accurate risk estimates. In the present study, the calibration intercept was −0.08 and the calibration slope was 0.91, indicating generally close agreement between predicted and observed probabilities. The slope below one may suggest some degree of overfitting, which is plausible given

the relatively small sample. Evaluation of both discrimination and calibration is recommended when assessing clinical prediction models because clinically useful models should distinguish higher-risk patients while also providing reasonably accurate absolute risk estimates.[20]

A practical strength of the proposed model is its reliance on routinely available clinical information. Respiratory rate, systolic blood pressure, oxygen saturation, leukocyte count, and serum creatinine are commonly measured in General Medicine wards and do not require specialised biomarkers. An interpretable model based on these parameters may therefore be more feasible in settings with limited advanced diagnostic infrastructure. Importantly, AI-based prediction should complement rather than replace clinical judgement. Evidence from real-world sepsis alert systems indicates that effective clinical integration depends not only on algorithmic performance but also on timely clinician evaluation and appropriate workflow implementation.[21]

Several limitations should be acknowledged. The sample size of 100 patients was small for development of a multivariable prediction model and increases the risk of overfitting and imprecise performance estimates. The retrospective, single-centre design also limits generalisability. Data quality depended on routinely documented hospital records, and missing or inconsistently measured variables may have influenced model development. Furthermore, internal validation cannot establish performance in new clinical populations. External validation in larger, independent and preferably multicentre cohorts is therefore essential before clinical implementation.

In conclusion, the present study suggests that routinely available clinical and laboratory parameters may provide a useful signal for early sepsis risk estimation in General Medicine wards. The AI-based model demonstrated good internal discrimination and calibration, with respiratory rate, systolic blood pressure, $SpO_2$ , total leukocyte count, and serum creatinine emerging as important predictors. These findings support further investigation of interpretable AI-assisted sepsis screening; however, prospective and external validation is required before routine clinical use.

## CONCLUSION

This study evaluated an AI-based clinical decision support model for the early detection of sepsis in patients admitted to General Medicine wards. The model used routinely available clinical and laboratory parameters, including respiratory rate, systolic blood pressure, $SpO_2$ , total leukocyte count, and serum creatinine.

The model showed good performance, with an AUROC of 0.89, sensitivity of 81.6%, specificity of 87.1%, and overall accuracy of 85.0%. These findings suggest that routinely available patient information can be useful for identifying patients at increased risk of sepsis.

The proposed model may help clinicians recognise sepsis earlier and support timely clinical assessment. However, it should be used as a supportive tool and not as a replacement for clinical judgement.

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