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IMPLEMENTATION OF AN APPLICATION-BASED ALERTING SYSTEM FOR CRITICAL BIOCHEMICAL, MICROBIOLOGICAL AND CYTOLOGICAL LABORATORY VALUES IN RESPIRATORY MEDICINE PATIENTS: A PROSPECTIVE OBSERVATIONAL STUDY

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ABSTRACT

Background: Timely identification and communication of critical laboratory values are essential for patient safety in respiratory medicine, where rapid clinical deterioration is common. Conventional manual reporting systems are often associated with delay and inefficiency, and mobile-based alert systems have emerged as a potential solution to improve real-time communication and clinical response.

Aim: To evaluate the effectiveness of a mobile-based clinical alert system (CritiCall) in improving the detection and communication of critical laboratory values in patients admitted under respiratory medicine.

Methods: This prospective observational study was conducted over 12 months and included 144 patients admitted under respiratory medicine. Conventional Electronic Medical Record (EMR)-based communication was compared with an integrated EMR + application-based alert system. Data were collected on demographic characteristics, comorbidities, alert type (biochemical, microbiological, arterial blood gas [ABG], cytological), alert timing, and patient outcome. The chi-square test, Pearson's correlation, ANOVA, and logistic regression were used for statistical analysis; $p<0.05$ was considered significant.

Results: The cohort was predominantly elderly with a high burden of comorbidities. Notification within 15 minutes was achieved in 82.0% of patients in the EMR + App group compared with 43.4% in the EMR group. Disease-specific alert patterns were observed, with ABG abnormalities predominating in COPD and interstitial lung disease and microbiological alerts predominating in pneumonia and bronchiectasis. Discharge rates were higher and deaths fewer in the application group. Alert burden correlated significantly with ICU admission in the EMR + App group ($r=0.278$, $p=0.013$) but not in the EMR-only group ($r=0.028$, $p=0.832$); however, logistic regression did not show an independent effect of the alert system on ICU admission (adjusted OR 1.879, 95% CI 0.758–4.658, $p=0.173$).

Conclusion: The mobile-based clinical alert system significantly improved the timeliness of critical-value notification and increased the number of critical alerts recorded across several clinical categories in respiratory medicine patients. Its integration into clinical practice may enhance patient safety by facilitating more timely communication of critical laboratory values.

KEYWORDS: Critical values; Respiratory medicine; Mobile health; Clinical alert system; Patient safety

INTRODUCTION

Critical values, also referred to as panic values, are laboratory or diagnostic findings that indicate life-threatening abnormalities requiring immediate medical attention. 1 The concept of critical-value reporting was introduced to improve patient safety by ensuring prompt communication between laboratory personnel and clinicians, 2 and delays in such communication have been consistently associated with increased diagnostic error and morbidity in acutely ill patients. 3

With the growing complexity of healthcare delivery and the exponential increase in diagnostic data, reliance on conventional manual reporting has become increasingly inadequate. International bodies such as the Clinical and Laboratory Standards Institute have accordingly established standardized protocols for critical-value communication to safeguard patient outcomes. 4

Respiratory medicine is a specialty in which critical-value reporting is of particular importance, as patients frequently present with rapidly evolving conditions such as chronic obstructive pulmonary disease (COPD) exacerbation, community-acquired pneumonia, and pulmonary tuberculosis. 5 These conditions are commonly accompanied by disturbances of serum electrolytes, arterial blood gas (ABG) parameters, and microbiological status that can progress swiftly to respiratory failure if not identified and managed promptly. Electrolyte derangements impair respiratory muscle function and worsen clinical outcomes, 6 microbiological findings are central to guiding targeted antimicrobial therapy in

pulmonary and bloodstream infection, 7 and ABG analysis remains the cornerstone of assessing gas exchange and acid–base status. 8

Conventional communication pathways, which remain largely dependent on manual verbal or telephonic reporting, are prone to delay, miscommunication, and inconsistent documentation, whereas secure digital notification platforms have been shown to shorten the interval between result availability and clinician acknowledgement. 9 Clinical decision-support systems and, more recently, artificial-intelligence-assisted monitoring tools have been proposed to enable real-time detection of clinical deterioration and to support timely intervention. 10,11 However, the disease-specific performance of such alerting tools within respiratory medicine, where multiple laboratory domains contribute jointly to clinical decision-making, remains incompletely characterised. The present study was therefore undertaken to evaluate the effectiveness of a purpose-built mobile-based clinical alert system, CritiCall, in improving the identification, communication, and clinical response to critical laboratory values among patients admitted under respiratory medicine.

Aims and Objectives

The primary aim of this study was to evaluate the effectiveness of CritiCall in improving the timeliness of detection and notification of critical laboratory values compared with conventional EMR-based communication, and to assess its performance in identifying critical abnormalities across biochemical, microbiological, cytological, ABG, and radiological domains. Secondary objectives were to analyse disease-specific alert patterns, to evaluate the association between patient characteristics and alert occurrence, to assess the relationship between alert burden and ICU admission, and to determine the effect of the mode of notification on patient outcome (discharge versus death).

MATERIALS AND METHODS

Study Design and Setting

This prospective observational study was conducted in the Department of Respiratory Medicine, Saveetha Medical College and Hospital, Chennai – a tertiary-care teaching institution with dedicated respiratory wards, intensive care units, and in-house laboratory services – over a total study period of 12 months, comprising application development and troubleshooting (2 months), data collection (6 months), and data analysis (2 months), with the remaining duration allocated to system implementation, user training, and validation.

The CritiCall Alerting System

CritiCall was developed as an integrated mobile-based clinical decision-support application to identify and communicate critical laboratory values in real time. The user interface was designed in Figma and implemented natively in Java (Android Studio), with role-based secure login for physicians and laboratory technicians. Laboratory values entered into structured, category-specific modules (haematology, biochemistry, microbiology, coagulation, cytology, ABG, and radiology) were automatically validated against predefined institutional critical thresholds using Firebase Cloud Functions; values breaching these thresholds triggered timestamped, severity-prioritised push notifications to the assigned clinician, with all events logged and synchronised through a Firebase Realtime Database. The application underwent iterative usability and functional testing, including verification of alert generation and real-time notification delivery, prior to deployment within routine clinical workflow.

Ethical Considerations

Ethical approval was obtained from the Institutional Ethics Committee, Saveetha Medical College and Hospital (IEC Reference Number: 015/08/2025/IEC/SMCH) prior to study initiation. The study involved no direct intervention and posed no risk to participants. Written informed consent was obtained from all participants or their legally authorised representatives; participation was voluntary, with the right to withdraw at any stage, and confidentiality of patient data was maintained throughout in accordance with Good Clinical Practice standards.

Study Population

Patients aged ≥18 years admitted under respiratory medicine (ward, ICU, or respiratory unit) with a diagnosis of COPD, asthma, pneumonia, tuberculosis, interstitial lung disease, bronchiectasis, pneumothorax, empyema, or lung malignancy, who had at least one abnormal or critical biochemical, microbiological, cytological, Arterial Blood Gas (ABG), or radiological finding, were included using consecutive sampling until the required sample size was achieved. Patients aged <18 years, those without a primary respiratory diagnosis, those with incomplete laboratory data or without a critical/abnormal value, patients under palliative or end-of-life care, and those (or their treating team) who did not provide consent were excluded. A total of 144 patients were enrolled.

Comparator Groups and Study Procedure

Two sequential notification strategies were compared during the six-month data-collection phase: conventional EMR-based communication with manual telephone notification of critical results from the laboratory to the treating physician for the first three months, and an integrated EMR + CritiCall application-based alert system for the subsequent three months. For each patient, data were prospectively recorded on demographic characteristics, comorbidities, alert category and timing, and clinical outcome, and were anonymised prior to analysis.

Outcome Measures

The primary outcome was the timeliness of detection and notification of critical laboratory values, dichotomised as ≤15 minutes or >15 minutes. Secondary outcomes included the distribution and pattern of alerts across respiratory disease

categories, the association between patient characteristics and alert occurrence, the relationship between alert burden and ICU admission, and patient outcome (discharge versus death) in relation to the mode of notification.

Statistical Analysis

Continuous variables were expressed as mean ± standard deviation and categorical variables as frequencies and percentages. The chi-square test was used to compare categorical variables, Pearson's correlation coefficient to assess relationships between continuous variables, and analysis of variance (ANOVA) for comparison of means across multiple groups. Unadjusted and adjusted (for age, gender, and comorbidities) logistic regression analyses were performed to evaluate the independent effect of the notification method on ICU admission. A p-value <0.05 was considered statistically significant for all analyses.

RESULTS

Demographic and Clinical Characteristics

A total of 144 patients were included in the study. The majority of patients were aged >60 years (52.78%), followed by 51–60 years (38.89%), 41–50 years (6.94%), and <41 years (1.39%) (Table 1). Males constituted 53.5% (n=77) and females 46.5% (n=67) of the cohort. There was no significant difference in mean age (t=0.9345, p=0.3744) or gender distribution (χ^2=14.67, p=0.7380) between the EMR-only and EMR + App groups. Non-smokers formed the largest group (50.7%), followed by former smokers (27.8%) and current smokers (21.5%); smoking status showed a statistically significant association with notification group (χ^2=71.41, p=0.0008). Most patients (75.7%) were managed in the ward, while 24.3% required ICU admission, with no significant difference in admission location between the two notification groups (χ^2=22.30, p=0.2695).

Table 1. Age Distribution of the Study Participants (n=144)

Age Group (years)	Mean ± SD	n	Percentage (%)
<41	35.00 ± 1.414	2	1.39
41–50	46.10 ± 1.912	10	6.94
51–60	57.14 ± 2.178	56	38.89
>60	66.28 ± 4.088	76	52.78
Total	–	144	100

Comorbidities

Comorbidities were common in the study population (Table 2). Hypertension was present in 68.05% of patients, diabetes mellitus in 31.95%, chronic kidney disease in 33.34%, and coronary artery disease in 23.61%. Diabetes mellitus, hypertension, and coronary artery disease each showed a statistically significant association with notification group (p<0.05 for all), whereas chronic kidney disease did not (p=0.1209).

Table 2. Prevalence of Major Comorbidities in the Study Population (n=144)

Comorbidity	Present, n (%)	Absent, n (%)
Hypertension	98 (68.05)	46 (31.95)
Diabetes mellitus	46 (31.95)	98 (68.05)
Chronic kidney disease	48 (33.34)	96 (66.66)
Coronary artery disease	34 (23.61)	110 (76.39)

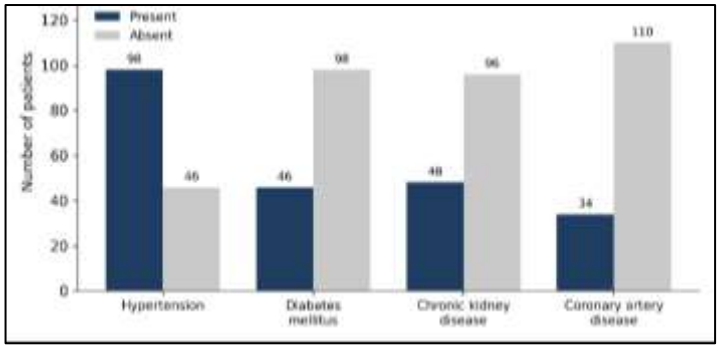

Figure 1. Prevalence of Major Comorbidities in the Study Population (n=144)

Disease-Specific Alert Patterns

The overall distribution of alerts by disease category and notification method is shown in Table 3. COPD exacerbation and community-acquired pneumonia generated the largest alert burden, followed by pulmonary tuberculosis and bronchiectasis. ABG abnormalities predominated in COPD, asthma, pneumothorax, and interstitial lung disease, reflecting acute derangement of ventilation and gas exchange; microbiological alerts (sputum, blood, bronchoalveolar-lavage, urine, and pleural-fluid cultures) predominated in pneumonia, bronchiectasis, and empyema; biochemical and microbiological

alerts, including CBNAAT and AFB positivity, were most frequent in pulmonary tuberculosis; and cytological alerts were most informative in lung malignancy. The EMR + App group demonstrated a numerically higher alert yield across most categories, most notably in COPD exacerbation (78 versus 40 alerts).

Table 3. Distribution of Alerts by Respiratory Disease Category and Notification Method

Condition	EMR (No. of Alerts)	EMR + App (No. of Alerts)
Asthma exacerbation	3	5
Bronchiectasis	25	22
Community-acquired pneumonia	45	49
COPD exacerbation	40	78
Empyema	2	6
Interstitial lung disease	14	18
Lung malignancy	18	19
Pneumothorax	3	4
Pulmonary tuberculosis	30	22
Tuberculous pleural effusion	14	13

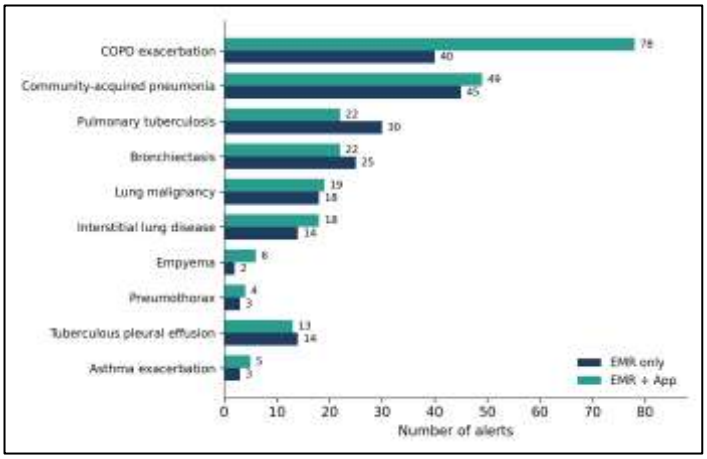

Figure 2. Distribution of Alerts by Respiratory Disease Category and Notification Method

Alerting Time Distribution

Notification within 15 minutes was achieved in 82.0% of patients in the EMR + App group compared with 43.4% in the EMR group.

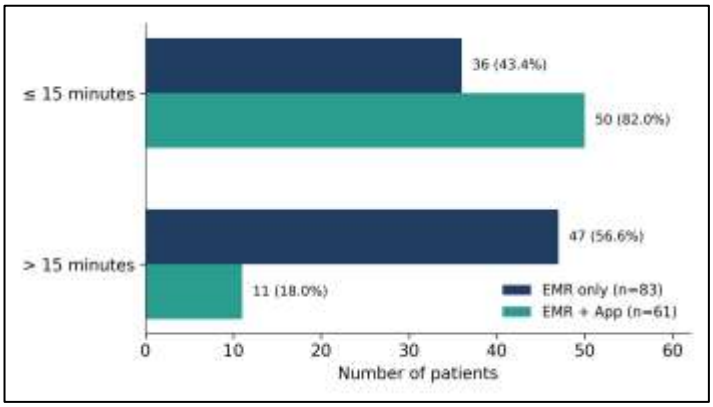

Figure 3. Alerting Time Distribution – EMR versus EMR + App

Patient Outcomes

A higher proportion of patients were discharged, and fewer deaths were recorded, in the EMR + App group (53 discharged, 8 deaths; 86.9% survival) compared with the EMR-only group (66 discharged, 17 deaths; 79.5% survival).

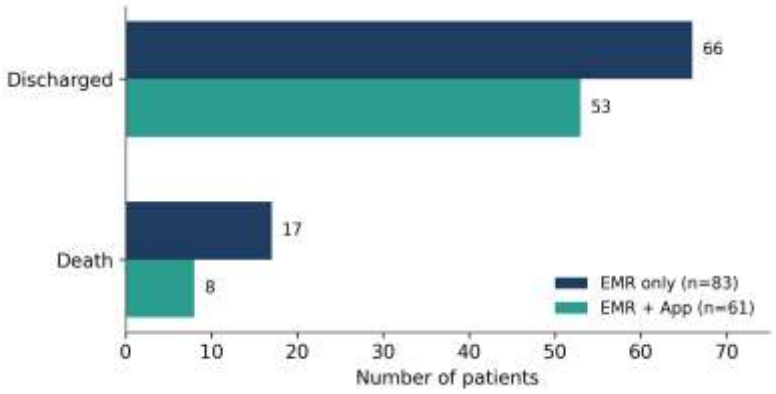

Figure 4. Impact of Notification Method on Patient Outcome

Alert Burden, ICU Admission, and Logistic Regression Analysis

A weak but statistically significant positive correlation was observed between alert burden and ICU admission in the EMR + App group (r=0.278, p=0.013), whereas no significant correlation was found in the EMR-only group (r=0.028, p=0.832). On logistic regression analysis, application-based notification was not independently associated with ICU admission in either the unadjusted model (OR 2.067, 95% CI 0.964–4.429, p=0.063) or the model adjusted for age, gender, and comorbidities (OR 1.879, 95% CI 0.758–4.658, p=0.173) (Table 4).

Table 4. Correlation Between Alert Burden and ICU Admission, and Logistic Regression Analysis of the Effect of Application-Based Notification on ICU Admission

Group / Model	r / OR	95% CI	p-value	Interpretation
EMR + App (correlation)	0.278	–	0.013	Weak positive correlation (significant)
EMR (correlation)	0.028	–	0.832	No significant correlation
Unadjusted logistic model	2.067	0.964–4.429	0.063	Not significant
Adjusted logistic model*	1.879	0.758–4.658	0.173	Not significant

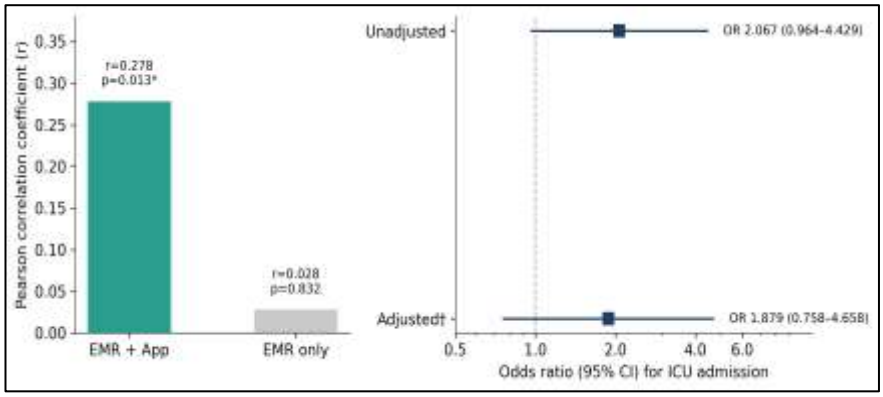

Figure 5. Alert Burden, ICU Admission, and Logistic Regression Analysis

**Adjusted for age, gender, and comorbidities. OR = odds ratio; CI = confidence interval.*

DISCUSSION

The present study demonstrates that a mobile-based clinical alert system substantially improves the timeliness of critical-value notification in respiratory medicine: the proportion of alerts delivered within 15 minutes rose from 43.4% with EMR-only communication to 82.0% when the application was used, a magnitude of improvement consistent with earlier evaluations of digital and automated critical-result notification platforms. 9,32,33

Disease-specific alert patterns observed in this study were consistent with the known pathophysiology of the respective conditions. ABG abnormalities predominated in COPD exacerbation, asthma, pneumothorax, and interstitial lung disease (ILD), reflecting acute derangement of ventilation and gas exchange. ABG abnormalities are established predictors of severity and outcome in COPD exacerbation, 12 and severe asthma exacerbations are similarly known to produce hypercapnia and acidosis indicative of impending respiratory failure. 13 In ILD, hypoxemia and respiratory acidosis were the predominant alerts, consistent with the primary effect of interstitial fibrosis on gas exchange; 14 hypoxemias a recognised predictor of disease progression and mortality in this population, 15 and structured monitoring has been shown to facilitate timely escalation of oxygen therapy and ventilatory support. 16,17

Biochemical alerts, particularly hyponatraemia and hypokalaemia, were the most frequent abnormality in pulmonary tuberculosis, followed by microbiological alerts including CBNAAT and AFB positivity. Hyponatraemia in tuberculosis has been attributed to the syndrome of inappropriate antidiuretic hormone secretion and adrenal involvement, 18,19 while CBNAAT remains the diagnostic cornerstone for rapid confirmation and treatment initiation. 20,21 Given that delayed microbiological confirmation in tuberculosis can increase both morbidity and transmission risk, automated alerting of positive results, as demonstrated in this study, may support earlier initiation of anti-tubercular therapy. 22

In bronchiectasis, both biochemical and microbiological alerts – particularly sputum- and bronchoalveolar-lavage-culture positivity for Pseudomonas aeruginosa – were prominent, consistent with the chronic infective and inflammatory nature of the disease and its association with more frequent exacerbation and hospitalisation. 23,24 Digital monitoring systems that enable earlier recognition of exacerbation have similarly been shown to reduce hospital admission and improve quality of life in bronchiectasis. 25 In empyema, pleural-fluid culture positivity was the predominant alert, consistent with the established role of microbiological evaluation in guiding antibiotic selection in pleural infection, 26 while cytological alerts were most informative in lung malignancy, underscoring the importance of rapid reporting of malignant cytology for timely oncological intervention. 27

The application-based system also demonstrated a weak but statistically significant positive correlation between alert burden and ICU admission ($r=0.278$, $p=0.013$), consistent with evidence that an accumulation of physiological and laboratory derangements is predictive of subsequent deterioration and ICU-level care. 28,29 In contrast, no significant correlation was observed in the EMR-only group. This difference may reflect variations in patient characteristics, alert burden, or the sequential study design and should not be interpreted as evidence of under-detection by conventional reporting. Nevertheless, logistic regression analysis did not demonstrate a statistically significant independent effect of application-based notification on ICU admission, either before or after adjustment for age, gender, and comorbidities. This pattern – in which digital alerting improves process measures such as detection and timeliness without a statistically demonstrable effect on hard clinical outcomes – has been reported previously and likely reflects the multifactorial determinants of ICU admission, including disease severity, comorbidity burden, and clinical decision-making that lie outside the scope of an alerting system alone. 30,31

Overall, these findings support the growing evidence base for real-time, application-based alerting as an adjunct to, rather than a replacement for, clinical judgement in the management of acutely unwell respiratory patients. 32,33

Limitations

This study has several limitations. It was conducted at a single tertiary-care centre, which may limit the generalisability of the findings, and the sample size and study duration, while adequate to demonstrate improvements in process measures, may have been insufficient to detect smaller effects on hard clinical outcomes such as ICU admission or mortality. The sequential, rather than randomised or concurrent, comparison of notification strategies may have introduced temporal confounding, and user compliance and satisfaction with the application were not formally evaluated. Larger, multicentric, and ideally randomised studies are warranted to confirm these findings and to establish their impact on long-term clinical outcomes.

CONCLUSION

This prospective observational study demonstrated that a mobile-based clinical alert system significantly improved the timeliness of critical-value notification and increased the number of critical alerts recorded across several clinical categories in patients admitted under respiratory medicine. Although its independent effect on ICU admission was not statistically demonstrable on regression analysis, the application-based system was associated with a favourable trend in patient outcomes and a significant correlation between alert burden and ICU admission. These findings support further evaluation of real-time, application-based alerting systems as an adjunct to routine clinical communication in respiratory medicine, particularly in larger multicentre studies

Conflict of Interest

The authors declare that they have no conflict of interest.

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This study received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Ethical Approval

The study was approved by the Institutional Ethics Committee, Saveetha Medical College and Hospital (IEC Reference Number: 015/08/2025/IEC/SMCH).

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