MAYO CLINIC

MAYO CLINIC PROCEEDINGS:
INNOVATIONS, QUALITY & OUTCOMES

ORIGINAL ARTICLE

An Artificial Intelligence-Enabled Electrocardiogram to Evaluate Patients With Dyspnea in the Emergency Department

Hee Tae Yu, MD, PhD; Laura E. Walker, MD; Eunjung Lee, PhD; Muhannad Abbasi, MBBCh; Samuel Wopperer, MD; Gal Tsaban, MD, PhD; Kathleen Kopecky, MD; Francisco Lopez-Jimenez, MD; Paul Friedman, MD; Zachi Attia, PhD; and Jae K. Oh, MD

Abstract

Objective: To evaluate whether an Artificial Intelligence-Enabled Electrocardiogram (AI-ECG) for diastolic function/filling pressure can determine whether dyspnea in emergency department (ED) patients is cardiac in origin.

Patients and Methods: We identified 2412 patients aged 18 years or older presented with dyspnea/shortness of breath to the ED who had an ECG performed at the time of evaluation from January 2020 to December 2022. The AI-ECG for determining left ventricular diastolic function to identify the patients with cardiac cause of dyspnea was assessed, using the final diagnosis based on subsequent evaluation.

Results: Of the 2412 patients, 966 (40%) were found to have cardiac dyspnea, and the remaining 1446 (60%) were noncardiac. The AI-ECG-estimated diastolic function was divided into 4 groups: 922 (38.2%) were normal, 245 (10.2%) grade 1, 1192 (49.4%) grade 2, and 53 (2.2%) grade 3. The probability of cardiac dyspnea was considerably higher in patients with grade 2 (62.2%±48.5%) and 3 (83%±37.9%) diastolic function compared with normal (14.1%±34.8%) and grade 1 (20.8%±40.7%). The incidence of cardiac dyspnea increased as the probability of increasing filling pressure increased on AI-ECG.

Conclusion: Patients often present to the ED with undifferentiated dyspnea. It is important to promptly determine whether the symptoms have cardiac origin. Cardiac dyspnea often reflects elevated left ventricular filling pressures. Artificial intelligence-enhanced 12-lead electrocardiograms can precisely assess diastolic function and filling pressures. Among patients who presented to the ED with dyspnea/shortness of breath, AI-ECG assessing diastolic function strongly distinguished whether the cause was cardiac.

 ■ Mayo Clin Proc Inn Qual Out 2025;9(5):100652

Dyspnea is a common and nonspecific symptom among various medical conditions, such as cardiac and noncardiac conditions.[1,2] When a patient presents with dyspnea in the emergency department (ED), it is important to promptly differentiate whether the symptoms are cardiac or noncardiac in origin. Cardiac dyspnea is typically due to elevated left ventricular (LV) filling pressures (FP), whereas noncardiac causes may stem from pulmonary or metabolic conditions. Accurate differentiation optimizes diagnostic and therapeutic approaches and may reduce evaluation time and cost.

Electrocardiogram (ECG) is a simple standardized test that is performed in many patients who visit the ED with dyspnea. Recent advancements in artificial intelligence-enabled 12-lead ECG (AI-ECG) have reported the ability to detect cardiovascular disorders that may escape expert human interpretation.[3,4] The AI-ECG algorithm has shown good performance in screening for LV systolic dysfunction.[5,6] Furthermore, we recently developed an AI-ECG algorithm using a neural network to predict diastolic function and FP.[7] The model has an excellent ability for identifying patients with high LVFP.

From the Department of Cardiovascular Medicine (H.T.Y., E.L., M.A., S.W., G. T., K.K., F.L-J., P.F., Z.A., J. K.), and Department of Emergency Medicine (L.E. W.), Mayo Clinic, Rochester, MN; and Division of Cardiology, Department of Internal Medicine, Yonsei University College of Medicine, Seoul, Republic of Korea (H.T.Y.).

In cardiac dyspnea, whether from LV systolic dysfunction, diastolic heart failure, valve disease, or coronary artery disease, increased FP is common. Invasive right heart catheterization provides the most precise measurement but is impractical, particularly on the timeline of an ED visit. Traditionally, noninvasive assessment through echocardiography is time-consuming and often cannot be completed in the ED. Simplified bedside echocardiogram protocols have been developed for use in the ED[8]; however, this still requires additional training and time at the bedside.

When a reason for dyspnea is not clear, a battery of tests is performed to identify the cause. Because of the broad nature of the differential, some of these tests may not be necessary if we had a sense as to whether dyspnea is related to a cardiac condition or not. ED throughput and crowding are persistent issues in the health care system.[9] There is an important need for innovative diagnostic tools that can facilitate quicker and more effective assessments in the ED. Recent studies have explored the application of AI-ECG in differentiating cardiac and pulmonary etiologies of dyspnea[10] and proposed interpretable deep learning models based on comprehensive health system data,[11] underscoring growing interest in AI-assisted triage. Building on this evolving field, we aimed to evaluate the effectiveness of the AI-ECG for diastolic function in determining whether dyspnea in patients presenting to the ED is of cardiac or of noncardiac origin.

PATIENTS AND METHODS

Study Population

We aimed to enroll 2400 patients aged 18 years or older who presented with dyspnea or shortness of breath to the ED and who had an ECG performed at the time of evaluation from January 2020 to December 2022 using the Mayo Clinic Unified Data Platform. Patients were excluded if they did not consent to data sharing, had a pacemaker or mechanical circulatory support (left/right ventricular assist devices), or had undergone heart transplantation. In addition, patients with missing or nonanalyzable ECG data (eg, missing digital ECG file, corrupted format, or poor signal quality) were excluded, accounting for the most exclusions. All ECGs were measured with 250 Hz or 500 Hz sampling rate using a GE-Marquette electrocardiogram machine for a standard 10-second 12-lead ECG and were stored in the GE-MUSE system (Marquette). The ECGs with original sampling rate of 250 Hz were up-sampled to 500 Hz before analysis. The correlation between AI-ECG-estimated diastolic function grades and the final clinical diagnosis was analyzed for the final cohort of 2412 patients (Figure 1). The Mayo Clinic internal review board approved waiver of the requirement to obtain informed consent per 45 CFR 46.104d and waiver of Health Insurance Portability and Accountability Act (HIPAA) authorization per applicable HIPAA regulations.

Overview of AI-ECG Model

Details on the development and validation of the AI-ECG algorithm for assessing LV diastolic function and FP among a nonselective study population were recently published.[7] Briefly, the AI-ECG team implemented convolutional neural networks of the ResNet-18 as model architecture. Each ECG has a 12×5000 matrix that consists of 12-lead ECG by 10 seconds sampled at 500 Hz. For network input, we split the ECG by 2 seconds and averaged the output values from 5 splits. The network was trained with a learning rate of 0.001 and Adam optimizer for 20 epochs. The validation performance converged before the 20th epoch. The model was trained as a multi-class model with 4 outputs representing the 4 grades of diastolic function and the sum of 4 outputs was 1. Normal and grade 1 were considered normal filling pressure, and grades 2 and 3 were considered increased filling pressure. The model was evaluated using the area under the curve (AUC) of the receiver operating characteristic curve, and its prognostic performance was compared with echocardiography. The AUC for detecting increased filling pressure was 0.911. The AUCs to identify diastolic dysfunction grades ≥ 1, ≥ 2, and 3 were 0.847, 0.911, and 0.943, respectively. This model was developed using over 270,000 patients who had paired ECG and echocardiographic diastolic assessments within 14 days, without any exclusion criteria. It was trained to predict diastolic function and elevated LV

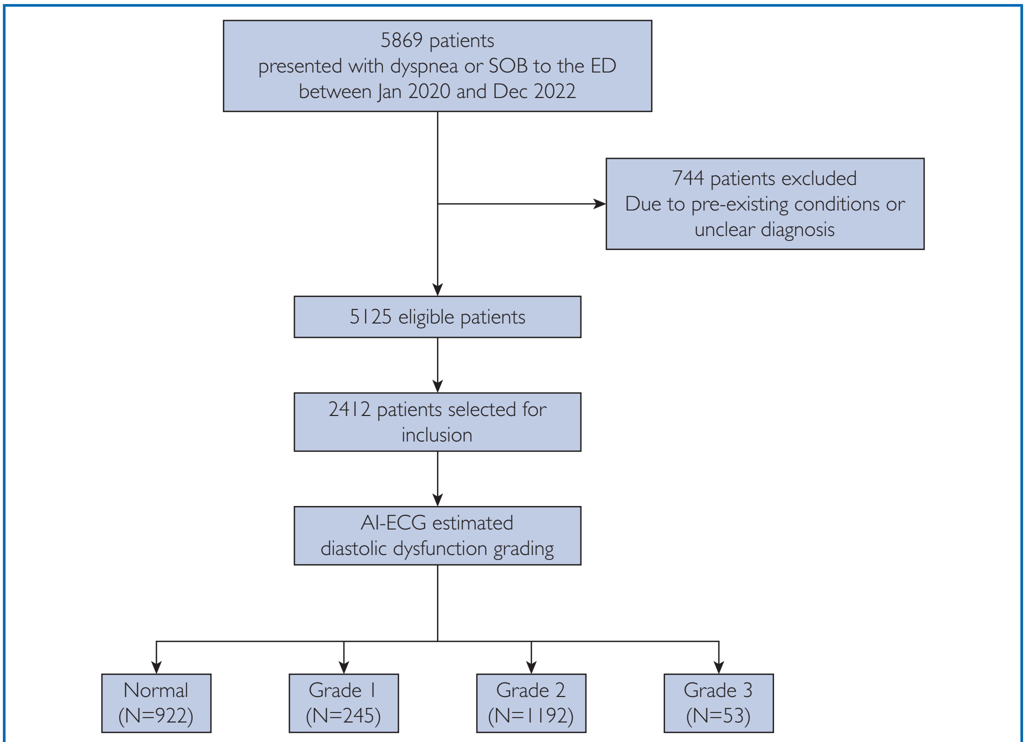

FIGURE 1. Flow chart of the study.

filling pressure using convolutional neural networks and was tested in both standard and indeterminate echocardiographic cases. Beyond its diagnostic performance, the model reported strong prognostic value, with AI-predicted increased filling pressure being associated with considerably higher mortality during long-term follow-up, comparable to echocardiographic assessments.

Subclassification of Diagnosis for Cardiac and Noncardiac Causes

The determination of the cause of dyspnea in the study subjects was based on the primary and secondary diagnoses recorded in the ED medical records, along with a chart review of the evaluations conducted in the ED and subsequent outpatient visits. For patients who were admitted, the hospital course was also reviewed to ensure accurate determination of the final cause of dyspnea. Cardiac causes were further classified into the following subcategories: (1) heart failure, (2) atrial fibrillation/tachyarrhythmia, (3) acute coronary syndrome, (4) angina, (5) bradyarrhythmia, and (6) pericarditis/pericardial effusion. Noncardiac causes were categorized as follows: (1) noncardiac general weakness/fatigue, (2) pneumonia/coronavirus disease-related, (3) chronic obstructive pulmonary disease /asthma/interstitial lung disease, (4) infections or sepsis from other organs except lungs, (5) chronic kidney disease and its acute exacerbation, (6) anemia, (7) pulmonary thromboembolism, (8) pleural effusion, (9) anxiety, (10) ascites/gastrointestinal symptoms, (11) hypoglycemia/other metabolic causes, (12) pneumothorax, and (13) miscellaneous cases that were difficult to clearly categorize.

Statistical Analyses

The primary outcome was the ability of the AI-ECG to identify LV diastolic dysfunction and filling pressure to classify patients as having cardiac or noncardiac cause of dyspnea, using the final diagnosis of the study patients based on usual-care evaluation. Baseline characteristics of the study population as means (standard deviations) or medians (interquartile range) for continuous variables (according to variable distribution), counts, and percentages for categorical variables. For continuous variables, groups were compared using Student's *t*-test. For categorical variables, χ^2 tests were used. A two-tailed *P*-value<.001 was considered significant.

RESULTS

We screened 5869 patients for inclusion in the study. Those with pre-existing conditions that exclusion criteria were omitted and ultimately 2412 patients were randomly selected for inclusion in the study, maintaining consistent ratios of diastolic dysfunction grades with the entire population eligible for inclusion. Baseline patient characteristics are summarized in Table 1. The mean age was 70.5 years with standard deviation of 14, and 53.4% of the patients were men. Of the total, 55.7% of patients had a history of previous heart failure, and 44.6% had a history of chronic pulmonary disease. As a result of applying the 12-lead ECG performed at the time of the ED visit to our AI-ECG algorithm, AI-ECG estimated diastolic function was divided into 4 groups, with 922 (38.2%) patients in normal, 245 (10.2%) in grade 1 function, 1192 (49.4%) in grade 2, and 53 (2.2%) in grade 3 (Figure 1).

TABLE 1. Baseline Patient Characteristics[a,b]

Characteristics	Overall (N=2412)
Sex (Male)	1288 (53.4%)
Age at event	70 (18-90)
Ethnicity	
N-Miss	31
Hispanic or Latino	101 (4.2%)
Not Hispanic or Latino	2280 (95.8%)
Weight	86.9 (34.8-303)
Height	170.02 (121.9-210.8)
BMI (kg/m^2)	29.8 (13.2-103.2)
BSA (m^2)	2 (1.2-3.6)
Myocardial infarction	556 (23.1%)
Congestive heart failure	1344 (55.7%)
Peripheral vascular disease	1194 (49.5%)
Cerebrovascular disease	359 (14.9%)
Dementia	78 (3.2%)
Chronic pulmonary disease	1075 (44.6%)
Peptic ulcer disease	110 (4.6%)
Diabetes without complications	222 (9.2%)
Diabetes with complications	635 (26.3%)
Renal disease	1003 (41.6%)
Cancer	374 (15.5%)
Moderate or severe liver disease	110 (4.6%)

[a]Continuous variables summarized as median (minimum, maximum). Categorical variables summarized as count (%).
[b]Abbreviations: BMI, body mass index; BSA, body surface area.

Cause of Dyspnea According to AI-ECG Estimated Diastolic Function Grade

Of the 2412 patients, 966 (40%) were found to have heart failure or dyspnea due to cardiac causes, and the remaining 1446 (60%) were diagnosed with dyspnea of noncardiac origin (Figure 2A, B). Among 966 patients with cardiac dyspnea, 130 (13.5%) were classified as normal, 51 (5.3%) as grade 1, 741 (76.7%) as grade 2, and 44 (4.6%) as grade 3 by the AI-ECG determined diastolic function grading. On contrary, among 1446 patients with noncardiac dyspnea, 792 (54.8%) were classified as normal, 194 (13.4%) as grade 1, 451 (31.2%) as grade 2, and 9 (0.6%) as grade 3 diastolic function on AI-ECG.

When analyzing the frequency of dyspnea of cardiac origin according to AI-ECG estimated diastolic dysfunction in the 4 grades, it was 130 of 922 normal group, 51 of 245 grade 1 group, 741 of 1192 grade 2 group, and 44 of 53 grade 3 group (Figure 2C). The probability for the dyspnea of cardiac origin was higher in patients with grade 2 (62.2%±48.5%) and 3 (83%±37.9%) diastolic function compared with normal (14.1%±34.8%) and grade 1 (20.8%±40.7%) diastolic function on AI-ECG. In addition, the incidence of cardiac dyspnea increased as the probability of increasing filling pressure increased by AI-ECG (Figure 2C). The probability for the dyspnea of cardiac origin was significantly higher in patients with high filling pressure compared with those with normal filling pressure (53.1% vs 11.6%, *P*<.001).

To further evaluate the discriminative performance of AI-ECG, we grouped patients into those with high (grade 2-3) and normal (grade 0-1) filling pressure. This binary classification yielded an AUROC of 0.63 (95% CI,

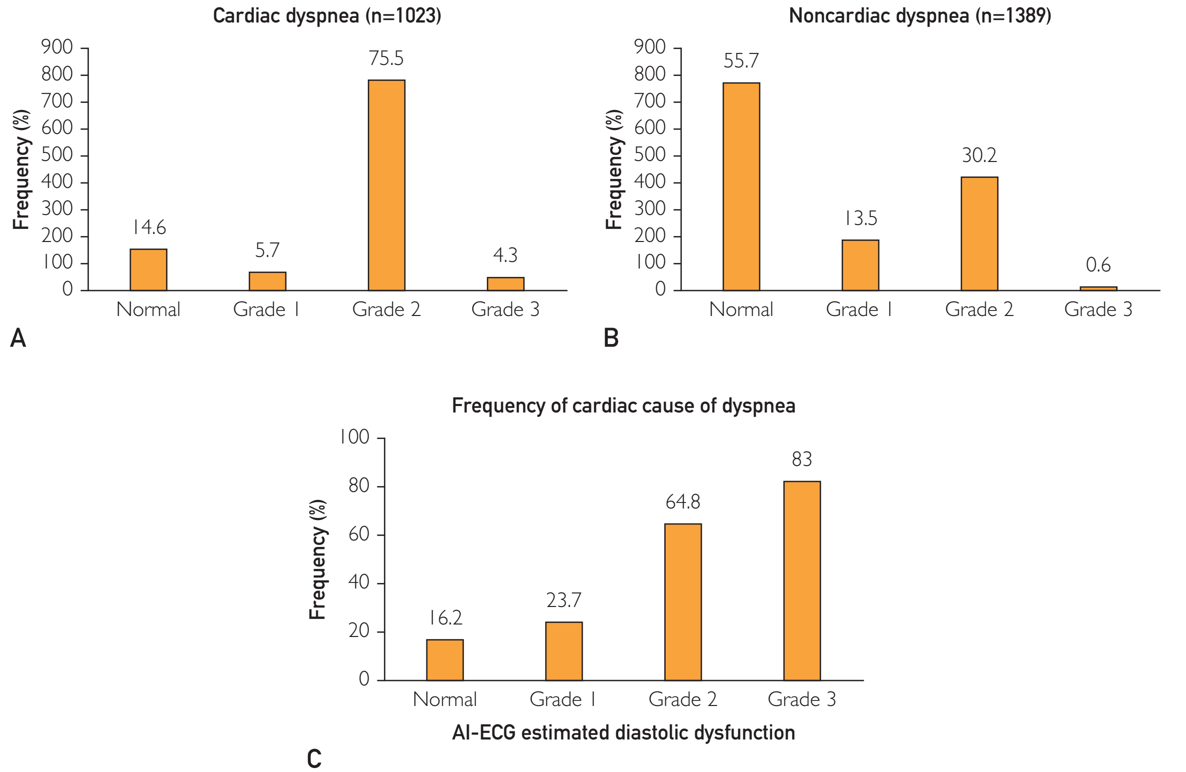

FIGURE 2. (A-B) Distribution of AI-ECG estimated diastolic function grade by cardiac/noncardiac cause and (C) frequency of dyspnea of cardiac origin according to AI-ECG estimated diastolic function grade.

0.59-0.68). At a threshold of 0.5, sensitivity was 93%, specificity 14%, positive predictive value 65%, negative predictive value 55%, and overall accuracy 64% (Table 2).

Diagnosis of Cardiac and Noncardiac Causes of Dyspnea

Table 3 s the major causes of cardiac and noncardiac dyspnea in order of frequency. Among cardiac causes, heart failure was the most common, with 59.8%, followed by atrial fibrillation or tachyarrhythmia (17.9%), acute coronary syndrome (11.3%), stable angina (6.4%), bradyarrhythmia requiring intervention such as atropine injection or pacing (2.4%), and effusive pericarditis (2.2%). The causes of noncardiac dyspnea appear to be more diverse. The most common noncardiac diagnosis was general weakness/fatigue (49.3%), followed by pneumonia or coronavirus disease-related symptoms (29.2%), primary lung disease, such as chronic obstructive pulmonary disease, asthma, or interstitial lung disease (18.6%), infections or sepsis from other organs except lungs (10.4%), chronic kidney disease with acute exacerbation (9.6%), anemia (8.7%), pulmonary thromboembolism (5.9%), pleural effusion (5.3%), anxiety (4%), ascites or gastrointestinal symptoms (3%), hypoglycemia or other metabolic causes (1.8%), pneumothorax (0.4%), and miscellaneous (3.5%).

DISCUSSION

Main Findings

Our study reported that there is a considerable higher rate of cardiac conditions responsible for dyspnea in patients presenting to the ED with shortness of breath when AI-ECG indicates increased LV diastolic filling pressure. The AI-ECG algorithm showed a significant correlation between higher diastolic dysfunction grades and cardiac-related dyspnea

TABLE 2. Frequency of Diagnosis of Cardiac and Noncardiac Causes of Dyspnea

Cardiac Cause (n=966)	n (%)
Heart failure	578 (59.8%)
AF/Tachyarrhythmia	173 (17.9%)
ACS	109 (11.3%)
Stable angina	62 (6.4%)
Bradyarrhythmia	23 (2.4%)
Pericarditis/effusion	21 (2.2%)
Noncardiac cause (n=1446)	**n (%)**
General weakness/fatigue	476 (49.3%)
Pneumonia/COVID	282 (29.2%)
COPD/asthma/ILD	180 (18.6%)
Other infection/sepsis	100 (10.4%)
Renal failure	93 (9.6%)
Anemia	84 (8.7%)
Pulmonary thromboembolism	57 (5.9%)
Pleural effusion	51 (5.3%)
Anxiety	39 (4%)
Ascites/GI symptoms	29 (3%)
Hypoglycemia/metabolic	17 (1.8%)
Pneumothorax	4 (0.4%)
Miscellaneous	34 (3.5%)

Abbreviations: AF, atrial fibrillation; ACS, acute coronary syndrome; COVID, Coronavirus disease; COPD, chronic obstructive pulmonary disease; ILD, interstitial lung disease; GI, gastrointestinal.

($P<.001$). Specifically, patients classified as having grade 2 or grade 3 diastolic function indicating increased filling pressure had a notably higher probability of cardiac origin dyspnea (62.2% and 83%, respectively) compared with those with normal (14.1%) or grade 1 dysfunction (20.8%). This finding highlights the potential of AI-ECG as a valuable tool in the rapid and effective assessment and triage of patients who present with dyspnea to the ED.

AI-ECG as a Screening Tool for Identifying Cardiac Dysfunction

Use of AI-ECG is a new and rapidly evolving field, and to date, AI-ECG as a diagnostic tool has primarily been deployed in the non-short-term setting. Few studies have described the application of AI-ECG in the ED, despite identifying the utility of AI-ECG in the ED.[12] Hyperkalemia and hypokalemia diagnosis by AI-ECG has been shown to be a clinically useful application,[13-15] expediting identification and treatment of a dangerous condition. Correlation between AI-ECG interpretation in combination with high-sensitivity troponin and postdischarge major adverse cardiac events have been studied retrospectively for use in improved risk stratification with promising results.[16] A recent study also found that in the correct clinical setting AI-ECG has similar diagnostic capabilities when compared with NT-proBNP levels.[15] Another study aimed to assess the diagnostic capabilities of AI-ECG as a unified screening tool for cardiac and noncardiac conditions as an explorative study in emergency care utilizing a total of 253 ICD codes and found that their model could reliably predict these conditions with an AUROC score of 0.8 in a statistically significant manner.[16] In our study, we found that higher diastolic dysfunction grades and LV diastolic FP correlates with a higher incidence of cardiac-related dyspnea in ED patients. Our study not only examined heart failure as an etiology for shortness of breath, rather we sought to be comprehensive and include a wide range of conditions encountered on a day-to-day basis in the ED. Furthermore, rather than using only ICD codes to identify patients, we manually reviewed the charts and included a symptom-based approach rather than a diagnosis based approach.

Although our study repurposed an AI-ECG model originally trained to estimate LV diastolic function and FP, this decision was guided by the strong pathophysiological link between elevated FP and cardiac causes of dyspnea. In this context, our findings support the feasibility of applying such a model to a broader triage task in the ED. However, it is possible that a model specifically trained to classify dyspnea etiology using labeled data for cardiac versus noncardiac causes might improve diagnostic accuracy. Future work should explore the development and comparison of task-specific AI-ECG models to determine the most effective approach in short-term care settings.

Impact of AI-ECG on ED Clinical Practice

Use of AI-ECG in ED clinical practice may help to initiate diagnosis-specific treatment in a timelier manner. Often, ED care follows multiple diagnostic threads simultaneously before landing on the etiology for symptoms. AI-ECG may change the pre-test probability such that

TABLE 3. Diagnostic Performance of AI-ECG in Predicting Cardiac Dyspnea for Binary Classification Model

Group	Threshold	AUROC (95% CI)	sen	spe	ppv	npv	Acc
Normal FP (threshold: 0.5)	0.50	0.63 (0.59-0.68)	0.01	1.00	0.25	0.85	0.84
High FP (threshold: 0.5)	0.50	0.62 (0.58-0.65)	0.93	0.14	0.65	0.55	0.64

Abbreviations: FP, filling pressure; AUROC, area under the receiver operating characteristic curve; sen, sensitivity; spe, specificity; ppv, positive predictive value; npv, negative predictive value; acc, accuracy.

pursuit of the cardiac or noncardiac diagnosis can be specifically targeted and the patient either discharged on diagnosis-specific treatment or admitted to the hospital on the appropriate hospital service. A typical ED workup to differentiate cardiac dyspnea from other causes includes a pro-brain natriuretic peptide and chest x-ray or point-of-care ultrasound, in addition to the ECG. With AI-ECG capabilities accurately reporting cardiac causes of dyspnea, an ED length of stay, time to treatment, time to admission, and other important throughput metrics and factors in patient satisfaction may be improved. Although our study did not include a head-to-head comparison with other diagnostic tools such as natriuretic peptides, chest radiography, or point-of-care ultrasound, future prospective studies will be essential to determine the relative utility of AI-ECG in comparison to these established modalities.

Recent investigations have also emphasized broader challenges and opportunities in applying AI-ECG to clinical practice. Previous studies have reported the feasibility of using AI-ECG to distinguish cardiac from pulmonary causes of dyspnea in the ED setting[10] and explored interpretable deep learning models for system-wide diagnostic integration.[11] In parallel, important limitations such as generalizability, explainability, and clinical deployment have been outlined.[17] Emerging foundation models further point to a future in which ECG interpretation can support multiple diagnostic tasks across diverse populations.[18] While our study focused on a physiology-based model targeting filling pressure, these developments highlight the importance of continued model validation and refinement within real-world workflows.

Limitations

This is a retrospective study evaluating patients with dyspnea who presented to the ED. A prospective study would provide a more robust assessment of the performance of AI-ECG in this setting. Diastolic dysfunction is a common driver of dyspnea; however, it is one of many cardiac causes of dyspnea. Our study does not explore the role of AI-ECG in diagnosing other cardiac causes. In addition, there is diagnostic uncertainty for patients who have multiple underlying conditions that may cause dyspnea, such as chronic obstructive pulmonary disease, or malignancy. Some etiologies are difficult to classify as definitively cardiac or noncardiac, such as pleural effusion. Ongoing work should continue to evaluate the role of AI-ECG in diagnosing cardiac diseases and in the care for acute undifferentiated patients and exploring the full capabilities of AI-ECG in the ED. Furthermore, the exclusion of a substantial number of patients due to missing or unusable ECG data may have introduced selection bias. Although this limitation was partly mitigated by the large overall cohort size and consecutive sampling, it is possible that excluded patients differed systematically in clinical characteristics or acuity, which could affect generalizability.

CONCLUSION

Among patients who visited the ED presenting with dyspnea or shortness of breath, AI-ECG assessing diastolic function grades was able to strongly distinguish whether the cause was cardiac or not. AI-ECG has a promise to be a cost effective, efficient screening tool for patients who present to the ED with unexplained dyspnea. This may assist and facilitate clinical decision-making, reduce unnecessary emergency department testing, and decrease both patient costs and ED length of stay.

POTENTIAL COMPETING INTERESTS

Drs Oh, Lee, Friedman, Attia, and Lopez-Jimenez have potential competing interests related to commercialization of AI-ECG. The other authors report no competing interests.

ETHICS STATEMENT

The Mayo Clinic internal review board approved waiver of the requirement to obtain informed consent per 45 CFR 46.104d and waiver of Health Insurance Portability and Accountability Act (HIPAA) authorization per applicable HIPAA regulations.

Abbreviations and Acronyms: **AI-ECG,** artificial intelligence-enhanced 12-lead electrocardiogram; **AUC,** area under the curve; **ECG,** electrocardiogram; **ED,** emergency department; **FP,** filling pressures; **LV,** left ventricular

Correspondence: Address to Laura E Walker, MD, Department of Emergency Medicine, Mayo Clinic, 200 First St SW, Rochester, MN 55905 (walker.laura@mayo.edu).

ORCID

Laura E. Walker: https://orcid.org/0000-0002-1127-327X

REFERENCES

1. van Riet EE, Hoes AW, Limburg A, Landman MA, van der Hoeven H, Rutten FH. Prevalence of unrecognized heart failure in older persons with shortness of breath on exertion. *Eur J Heart Fail*. 2014;16(7):772-777. https://doi.org/10.1002/ejhf.110.
2. Kelly AM, Keijzers G, Klim S, et al. An observational study of dyspnea in emergency departments: The Asia, Australia, and New Zealand Dyspnea in Emergency Departments Study (AANZDEM). *Acad Emerg Med*. 2017;24(3):328-336. https://doi.org/10.1111/acem.13118.
3. Attia ZI, Harmon DM, Behr ER, Friedman PA. Application of artificial intelligence to the electrocardiogram. *Eur Heart J*. 2021;42(46):4717-4730. https://doi.org/10.1093/eurheartj/ehab649.
4. Siontis KC, Noseworthy PA, Attia ZI, Friedman PA. Artificial intelligence-enhanced electrocardiography in cardiovascular disease management. *Nat Rev Cardiol*. 2021;18(7):465-478. https://doi.org/10.1038/s41569-020-00503-2.
5. Attia ZI, Kapa S, Yao X, et al. Prospective validation of a deep learning electrocardiogram algorithm for the detection of left ventricular systolic dysfunction. *J Cardiovasc Electrophysiol*. 2019;30(5):668-674. https://doi.org/10.1111/jce.13889.
6. Attia IZ, Tseng AS, Benavente ED, et al. External validation of a deep learning electrocardiogram algorithm to detect ventricular dysfunction. *Int J Cardiol*. 2021;329:130-135. https://doi.org/10.1016/j.ijcard.2020.12.065.
7. Lee E, Ito S, Miranda WR, et al. Artificial intelligence-enabled ECG for left ventricular diastolic function and filling pressure. *NPJ Digit Med*. 2024;7(1):4. https://doi.org/10.1038/s41746-023-00993-7.
8. Del Rios M, Colla J, Kotini-Shah P, Briller J, Gerber B, Prendergast H. Emergency physician use of tissue Doppler bedside echocardiography in detecting diastolic dysfunction: an exploratory study. *Crit Ultrasound J*. 2018;10(1):4. https://doi.org/10.1186/s13089-018-0084-5.
9. Pearce S, Marchand T, Shannon T, Ganshorn H, Lang E. Emergency department crowding: an overview of reviews describing measures causes, and harms. *Intern Emerg Med*. 2023;18(4):1137-1158. https://doi.org/10.1007/s11739-023-03239-2.
10. Jang JH, Lee SW, Kim DY, et al. Use of artificial intelligence-powered ECG to differentiate between cardiac and pulmonary pathologies in patients with acute dyspnoea in the emergency department. *Open Heart*. 2024;11(2):e002924. https://doi.org/10.1136/openhrt-2024-002924.
11. Heyman ET, Ashfaq A, Ekelund U, et al. A novel interpretable deep learning model for diagnosis in emergency department dyspnoea patients based on complete data from an entire health care system. *PLoS One*. 2024;19(12):e0311081. https://doi.org/10.1371/journal.pone.0311081.
12. Muzammil MA, Javid S, Afridi AK, et al. Artificial intelligence-enhanced electrocardiography for accurate diagnosis and management of cardiovascular diseases. *J Electrocardiol*. 2024;83:30-40. https://doi.org/10.1016/j.jelectrocard.2024.01.006.
13. Kim D, Jeong J, Kim J, et al. Hyperkalemia detection in emergency departments using initial ECGs: a smartphone AI ECG analyzer vs. board-certified physicians. *J Korean Med Sci*. 2023;38(45):e322. https://doi.org/10.3346/jkms.2023.38.e322.
14. Lin C, Chau T, Lin CS, et al. Point-of-care artificial intelligence-enabled ECG for dyskalemia: a retrospective cohort analysis for accuracy and outcome prediction. *NPJ Digit Med*. 2022;5(1):8. https://doi.org/10.1038/s41746-021-00550-0.
15. Harmon DM, Liu K, Dugan J, et al. Validation of noninvasive detection of hyperkalemia by artificial intelligence-enhanced electrocardiography in high acuity settings. *Clin J Am Soc Nephrol*. 2024;19(8):952-958. https://doi.org/10.2215/CJN.0000000000000483.
16. De Michieli L, Knott JD, Attia ZI, et al. Artificial intelligence-augmented electrocardiography for left ventricular systolic dysfunction in patients undergoing high-sensitivity cardiac troponin T. *Eur Heart J Acute Cardiovasc Care*. 2023;12(2):106-114. https://doi.org/10.1093/ehjacc/zuac156.
17. Xue ZK, Chen KY, Li XM, et al. Clinical application of AI-ECG. In: Chen KY, Liu T, Tao HY, eds. *AI Augmented ECG Technology*. Springer Nature; 2024:37-122.
18. Tian Y, Li Z, Jin Y, et al. Foundation model of ECG diagnosis: Diagnostics and explanations of any form and rhythm on ECG. *Cell Rep Med*. 2024;5(12):101875. https://doi.org/10.1016/j.xcrm.2024.101875.