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REVIEW ARTICLE

# A viewpoint on evaluating ECG findings to assess heart issues: A clinical nursing review

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**Abstract**
The 12-lead EKG is a useful first-line diagnostic tool for detecting cardiovascular diseases, including arrhythmias, conduction abnormalities, and myocardial ischemia or infarction. This scoping review aims to discuss the ECG perspective for detecting heart problems. This study was conducted by following the narrative review and development framework. The literature search used ScienceDirect, Scopus, ProQuest, ClinicalKey, and SpringerLink data. The keywords used were “criteria” or “guidelines” and “ECG” or “ECG” or “electrocardiography” or “electrocardiogram” and “detection” and “heart problem” or “heart disease” or “heart problem” or “heart problem.” The method uses a narrative review through eight articles spanning 2017–2022. The lighting method uses the PICO analysis framework. The results found four components, namely: 1) automatic diagnosis; 2) 3-D ECG with artificial intelligence (AI) classification; 3) use of the LSTM deep-learning model; and 4) leads using Tpeak-End (Tp-e). In patients with heart problems, the initial examination is an EKG. Thus, the ECG, with the addition of the automatic diagnosis feature, EKG-3D, and the use of a 12-lead ECG with a deep-learning LSTM model, also followed by high sensitivity and specificity, can be used as a tool to perform examinations on patients who require serial ECG examinations.

**Keywords:** Electrocardiogram; nursing care; nursing review; clinical symptoms; nursing assessment

## Introduction

Critical care is a form of high-risk health care with the highest prevalence of death in hospitals (Paulo, 2019). Data on the global prevalence of patient death in hospitals reaches 22%, with 16% of them occurring in the critical care unit (ICU) and 6% occurring in the treatment room (Vincent et al., 2014; Mikkelsen et al., 2020). Data for 2018 shows that the prevalence of ICU patient mortality globally has reached 29%, compared to 25% in the previous year. Meanwhile, In the Asian region, the prevalence of patient mortality in the ICU reaches 6%, and in Indonesia, it reaches 9% (Mikkelsen et al., 2020; Garland et al., 2013). At least two distinct subgroups characterize early death. The former are patients with high disease severity due to potentially reversible causes and functional consequences that may be acceptable to the patient. For example, patients with adequate basic functioning and medical conditions who present to the emergency department because of trauma, severe nerve injury, or septic shock and who are at high risk of natural death are eligible for ICU support. The second subgroup is patients with a low probability of disease recovery (Ma et al., 2020). Determining a patient’s diagnosis quickly and accurately is needed to establish treatment plans and actions for patients with critical conditions to minimize the risk of patients not being helped in critical conditions (JE, 2016).

The initial examination used in patients with heart problems is an ECG. An ECG should be performed if the patient experiences chest pain, palpitations, shortness of breath, tremors, fainting, or falls for no apparent reason. An ECG examination is needed to help diagnose the patient’s heart condition. A heart ECG is also needed to monitor the condition of people diagnosed with heart problems routinely. The ECG can be used to investigate suspected symptoms of heart problems, such as chest pain, palpitations, dizziness, or shortness of breath, which the patient complains about (Paulo, 2019). An electrocardiogram (ECG) is a test that records the electrical activity that stimulates the heart muscle contractions and provides an overview of how the heart works (Paulo, 2019).

Electrocardiogram (ECG) recording and interpretation are essential to current clinical practice and indispensable in diagnosing heart disease. The diagnosis is made by looking at the morphology of the EKG waveform, the presence or absence of waves, and the quantification of intervals to diagnose heart defects. Modern ECG recording and monitoring technologies have advanced significantly over the last few years, and cardiologists may be unfamiliar with the impact and consequences of these technical innovations on clinical interpretation (Mikkelsen et al., 2020).

Nurses play an important role in using ECG as a process of diagnosis and early detection of heart defects as part of critical patient care. The nurse is responsible for carrying out patient ECG examinations and interpreting the results. A study demonstrated that ECG interpretation is an essential component that should be used to enhance the accuracy of chest pain triage decisions (Ho & Suen, 2013). Therefore, it is essential that emergency nurses can interpret an ECG efficiently and accurately. Delayed and inaccurate interpretation of dysrhythmias has been shown to compromise patient outcomes (Stanfield, 2018). Inaccurate examination and interpretation of ECG results are dangerous for patients because they will receive inappropriate treatment. A study highlighted that only 19% of the 75 nurses could identify the presence or absence of myocardial ischemia in all six scenarios, and none of the nurses could determine the correct leads, anatomic location, or amplitude of ST-segment elevation in the three ECGs with a myocardial infarction pattern (Stephens et al., 2007). Nurses at the ICCU RSUD, such as Dr. Pirngadi Medan, cannot interpret ECG (Marlisa & Pratiwi, 2019). A handheld paper tool could improve nurses' ability to identify ischemic locations (Pelter et al., 2010). Nurses need the support of equipment that provides convenience in detecting heart defects and accuracy in interpretation.

The development of ECG technology is increasing rapidly to assist health workers, including nurses, in obtaining accuracy and ease of interpretation. Technological advances in the development of the electrocardiogram continue to equip nurses with components to make it easier for them to obtain information about the patient's heart condition. Due to the various types and models of ECG in the development process, there is still little literature that discusses the development of features or components in the ECG. For this reason, further research in the form of a review of several previous studies is needed to clarify the ECG criteria for detecting heart problems. Narrative studies are used to identify and summarize research results related to developing components in the ECG as an evidence-based source of information, discussing ECG criteria for detecting heart problems.

## Method

This study used a narrative approach to identify and summarize research results related to developing components in the ECG. PICO analysis was integrated with several steps: formulation of research problems and identification of relevant literature. Selection of literature, mapping or description of data, and compiling, summarizing, and reporting results ScienceDirect, Scopus, ProQuest, ClinicalKey, and SpringerLink were used to conduct a literature search. The keywords are "criteria" or "guidelines" and "ECG" or "ECG" or "electrocardiography" or "electrocardiogram" and "detection" and "heart disorder" or "cardiac diseases" or "cardiac disorders" or "heart disorders." Articles to be included in the analysis are literature review articles, published English articles from 2017–2022, original research articles, and articles using patients who received ECG. All the studies that did not describe the ECG were excluded.

Narrative tables map, organize, and summarize the selected studies. Tables and charts were used to identify and fit findings with the research questions and objectives. Data extraction tables were created to insert information from selected studies, including year of publication, sample, design, interventions, and findings. Data analysis was done to summarize the main findings and identify themes and sub-themes. Following that, combine data analysis and perform analysis to identify sub-themes. Literature related to ECG criteria for detecting heart problems is analyzed further to fulfill the purpose of this narrative review, using PICO analysis as follows: P (problem and patient): A patient or subject who requires a cardiac examination using electrocardiography (ECG). (Intervention): The intervention or treatment given is a heart examination using ECG. (Comparison): Samples were examined using different types and characteristics of ECG, including automatic analysis, automatic diagnosis, 3D ECG, and deep-learning LSTM models. O (Outcome): The expected outcome is good accuracy and high sensitivity and specificity values for diagnosing heart problems.

## Results

The author documented six components of ECG that can be used for detecting heart problems as follows: automatic diagnosis, sensitivity and specificity values, 3-D ECG with artificial intelligence (AI) classification, automatic analysis, use of deep-learning LSTM models, and leads using Tpeak-End (Tp-e) **(Table 1)**. Also, the studies included were summarized in the table **(Table 2)**.

**Table 1.** Study analysis

| **Study** | **Component** | | | | | | |
|---|---|---|---|---|---|---|---|
| | **Auto Diagnostics** | **Sensitivity and specificity values** | **3-D ECG with AI classification** | **Automated Analysis** | **use of deep-learning LSTM models** | **tapping using Tpeak-end(Tpe)** | **Good accuracy and interpretation** |
| Rueda et al. 2022 | √ | √ | | | | | √ |
| Fang et al., 2022 | | √ | √ | | | | √ |
| Anand et al., 2022 | | √ | | √ | | | √ |
| Chang et al., 2021 | | | | | √ | | √ |
| Ruedisueli et al., 2022 | | | | | | √ | √ |
| Ribeiro et al., 2020 | √ | √ | | | | | √ |
| Mathews et al., 2018 | | | | | √ | | √ |
| Lyon et al., 2018 | √ | | √ | √ | | | √ |

## Discussion

After the screening stage, eight articles met the inclusion and exclusion criteria. The review results of the eight articles were then analyzed to conclude. An electrocardiogram (ECG) is a test that records electrical activity that stimulates heart muscle contractions and provides an overview of how the heart works (Ardiana, 2021). Patients need to carry out an electrocardiogram examination, among other things, to evaluate and look for the causes of health problems associated with heart disease, such as chest pain, fatigue, difficulty breathing, and dizziness. In addition, the ECG examination functions to determine heart rhythm so that it can detect if there is an irregular heart rhythm, identify structural problems in the heart, and evaluate someone who has risk factors for heart disease that, from the results of the ECG examination, cardiologists and blood vessel specialists can determine further actions according to the patient's heart (Hampton, 2019).

Technological advances in the development of the electrocardiogram continue to be made, adding features to the ECG and modifying its shape. Research conducted by Rueda et al. in 2022 indicates that additional features for automatic diagnosis of heart disease using electrocardiogram (ECG) signals are needed to help doctors and other medical staff make clinical decisions faster. In addition, the use of 3-D ECG with artificial intelligence (AI) classification shows that the proposed model can be easily integrated with existing ECG ECG machines to help doctors in primary and secondary health centers diagnose more quickly, accurately, and with evidence so that the patient can be referred to the cardiology center in time for further specific treatment (Anand et al., 2022).

### *Auto Diagnostics*

Automatic diagnosis of heart disease using an ECG signal is very important in clinical decision-making. However, computer-based decision rules in clinical practice are lacking, mainly because of their complexity and lack of medical interpretation. Research conducted by Rueda et al. 2022 provides a valuable diagnostic rule that can be easily implemented in clinical practice. In his research, efficient diagnostic rules that are friendly to clinical practice using interesting parameters obtained from ECG signal analysis are presented with two simple rules for automatically diagnosing bundle branch blocks using FMM-ECG (Rueda et al., 2022). The study stated that high sensitivity and specificity values were obtained using the proposed rule with data from more than 35,000 patients from a well-known comparison database. Specifically, to identify complete left bundle branch block (BBB) and differentiate this condition from subjects without heart disease, the sensitivity and specificity values ranged from 93% to 99% and 96% to 99%, respectively (Rueda et al., 2022).

**Table 2.** Study findings

| Author, Year | Sample | Method | Intervention | Findings |
|---|---|---|---|---|
| Rueda et al. 2022 | 35063 patients | Observational study | ECG examination for oscillatory signals analysis. | ECG is sensitive and specific for oscillatory signal analysis |
| Fang et al., 2022 | 148 patients with myocardial infarction and 52 healthy patients | Observational study | Used the Pan-Tompkins method to detect the R-peak of the ECG signal | 3-D ECG images with AI classification can be used efficiently for heart disease diagnosis |
| Anand et al., 2022 | 21837 patients. | Experimental research | ECG integrated with artificial intelligence (AI) | The results were quick and accurate |
| Chang et al., 2021 | 11 patients | Observational study | Using the deep-learning LSTM model | The feasibility and effectiveness of a deep learning LSTM was highlighted |
| Ruedisueli et al., 2022 | 88 patients | Cohort study | Analyzing the Tp-e | Tp-e can be detected in various condition |
| Ribeiro et al., 2020 | 1676384 patients | Review study | Analyzed the ECG wave | ECG analysis based on DNN is very accurate |
| Mathews et al., 2018 | 114 patients | Experimental research | Application of the Restricted Boltzmann Machine (RBM) and deep belief network (DBN) | RBM and DBN are accurate to detect ventricular ectopic beats (93.63%) and supraventricular ectopic beats (95.57%) |
| Lyon et al., 2018 | 38 articles | Review article | Computational methods for ECG analysis | Effective for ECG analysis |

An ECG examination contains sensitivity and specificity factors that play an important role in detecting heart problems such as acute myocardial ischemia. The recommended criteria for detecting acute myocardial ischemia consist of two parts. That is, the criteria for ST-segment elevation myocardial infarction (STEMI) are based on ST elevation (ST) in 10 pairs of lines adjacent to other lines and ten pairs of adjacent ST depressions (ST) (Wang et al., 2018). Criteria based on ECG due to sensitivity and specificity have practical advantages that will retain their position in clinical trials (Levy et al., 1990).

***3-D ECG with Artificial Intelligence (AI) Classification***

This study used 3-D ECG images with multi-VGG-DNN to diagnose MI, with an accuracy of 95.65%, a sensitivity of 97.34%, and a specificity of 90.80%, with nearly perfect inter-individual results. To reach the PTB database with a schema. Classification in patient schema The proposed method can also provide diagnostic recommendations that can be interpreted with the Grad Cam++ method. This will help doctors increase their confidence in artificial intelligence (AI) diagnoses (Fang et al., 2022). Extensive use of deep neural networks in clinical practice The experimental results show that the proposed method can effectively classify 3D ECG images with high accuracy without the need for complicated noise reduction. The multi-network approach is effective in terms of detection accuracy in the PTB database. In addition, this study is superior to previous 3-D ECG studies, achieving the same classification accuracy with higher sensitivity compared to previous studies using ECG signal data directly for classification. In addition, this method provides a visually interpretable heat map to annotate 3D ECG images and observe tissue interpretation that meets medical diagnostic criteria for M (Fang et al., 2022).

Machine learning techniques provide accurate and automated heart rate classification to detect arrhythmias or unexpected changes in cardiac morphology. They also assist in automated disease diagnosis, monitoring, and stratification by handling lengthy ECG recordings where visual and manual examinations can be tedious and time-consuming. 3D computer simulations are a powerful tool for interpreting ECGs and will soon become invaluable by generating large synthetic datasets for training machine learning classifiers. Despite the many challenges they face and the novelty of their introduction to clinical practice, these computational methods are becoming powerful tools for medical advancement, and their integration into clinical settings will help improve patient care (Lyon et al., 2018). The studies presented demonstrated classification accuracy and the ability to interpret. In addition, this method provides a visually interpretable heatmap to annotate 3D ECG images and observe tissue interpretation meeting the medical diagnostic criteria for MI. The work presented offers a balance of precision that promises the ability to classify and interpret. In addition, this method provides a visually interpretable heatmap to annotate 3D ECG images and observe tissue interpretation meeting the medical diagnostic criteria for MI (Fang et al., 2022)

***Use of the LSTM Deep-Learning Model***

The 12-lead ECG ECG is a first-line diagnostic tool highly useful for detecting cardiovascular diseases, including heart rhythm disturbances, conduction abnormalities, and myocardial ischemia or infarction, by clinicians in various specialties. In a hospital setting, an emergency doctor or internist is usually the patient's first medical contact; thus, they must interpret the 12-lead ECG in patient management decision-making at the scene. Effectiveness of the deep learning LSTM model for interpreting 12 common cardiac rhythms using many 12-lead ECG signals These results may have clinical implications for accelerating the diagnosis and facilitating cardiac rhythm disorders (Chang Et Al., 2021).

***Speak-END (TP-E) as a lead***

The study by Ruedisueli et al., 2022, compared ventricular repolarization recorded simultaneously in all 12-lead ECGs in healthy adults to provide a basis for selecting optimal leads for TPE recordings. The study found that the length of the Tp-e interval varied significantly among the 12 leads and that the maximal Tp-e interval was not evenly distributed. For a high significance level, the maximal Tp-e interval is most frequently detected in the precordial leads, particularly in leads V2, V3, and V4. Subsequently, these findings were validated in an independent cohort (Ruedisueli et al., 2022). In healthy young adults, the length of the T-wave end interval is not uniform among the 12-lead ECGs. The precordial leads especially lead V2-V4 while resting supine and leads V2-V6 during sudden standing provocative maneuvers, most likely detecting a maximal Tp-e interval. Selecting the precordial leads is desirable if only a portion of the ECG leads are available for recording or analysis. If only a portion of the ECG lead is to be recorded or analyzed for the Tp-e interval, the selection of the precordial lead is preferable because this lead is most likely to capture the maximal Tp-e value (Ruedisueli et al., 2022).

The 12-lead ECG is a useful first-line diagnostic tool for detecting cardiovascular diseases, including heart rhythm disturbances. The deep learning LSTM model for interpreting 12 common cardiac rhythms uses many 12-lead ECG signals. These results may have clinical implications for accelerating the diagnosis of cardiac rhythm disorders (Chang et al., 2021). Research conducted by Chang et al. in 2021 demonstrated the feasibility and effectiveness of a deep-learning LSTM model to interpret 12 common cardiac rhythms using many signals from a 12-lead ECG. The findings may have clinical relevance for accelerating the diagnosis of cardiac rhythm disturbances and facilitating decision-making in patient management. This study reviews various ECG components as part of the technology development in detecting various heart disorders to improve interpretation accuracy, ease of use, and efficiency. Nurses play an important role in managing patients with various cardiovascular disorders. Nurses are responsible for carrying out ECG examinations correctly, monitoring them, and interpreting them accurately and quickly as part of nursing care. Nurses' understanding of the ECG component supports nurses in making decisions in service, establishing patient nursing diagnoses, and supporting collaboration so that patients get good treatment.

## Conclusion

In patients with heart problems, the initial examination is an ECG. The 12-lead ECG ECG is a useful first-line diagnostic tool for detecting various cardiovascular diseases, including arrhythmias, conduction abnormalities, and myocardial ischemia or infarction. Thus, the ECG, with the addition of an automatic diagnosis feature, ECG-3D, and the use of a 12-lead ECG with a deep-learning LSTM model, also followed by high sensitivity and specificity, can be used as a tool to perform examinations on patients who require serial ECG examinations.

## Author's declaration

The authors made substantial contributions to the conception and design of the study and took responsibility for data analysis, interpretation, and discussion of results. For manuscript preparation, all the authors read and approved the final version of the paper.

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## Availability of data and materials

All data are available from the authors.

## Competing interests

The authors declare no competing interest.

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