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Review Article

# Multi-Modal Artificial Intelligence for Cardiovascular Risk Prediction: Integrating ECG, Imaging, Genomics, and Wearable Data

Aashna Sagar[1], Kiranbir Kaur[2], Prabhpreet Kaur[3], Amandeep Kaur[4]

[1]Student, [2]Associate Professor, [3,4]Assistant Professor, Department of Computer Engineering and Technology, Guru Nanak Dev University, Amritsar, India
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## INFO

**Corresponding Author:**
Aashna Sagar, Department of Computer Engineering and Technology, Guru Nanak Dev University, Amritsar, India
**E-mail Id:**
aashnasagar19@gmail.com
**Orcid Id:**
https://orcid.org/0009-0002-5664-4174
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## ABSTRACT

Cardiovascular diseases remain the leading cause of death worldwide, making early detection essential for effective prevention and treatment. Integrating diverse data sources, such as ECG signals, medical imaging, genomics, and wearable sensor data, offers a more comprehensive view of heart health and enhances risk prediction. This study aims to develop and evaluate a multimodal AI framework that combines these varied datasets to enhance cardiovascular risk assessment. Advanced deep learning models are applied to process and fuse multimodal inputs for accurate, reliable, and clinically adaptable predictions. The proposed method utilizes ECG, echocardiography, CT scans, genomic profiles, and wearable data from public repositories and clinical collaborations. Preprocessing involves noise removal, normalization, and feature extraction, followed by model training and evaluation using metrics such ascs like accuracy, sensitivity, specificity, and AUC. The integrated approach promises earlier detection, personalized treatment, and reduced diagnostic costs. Key challenges include data standardization, large-scale clinical validation, privacy protection, and seamless integration of wearable technologies into healthcare systems, advancing multimodal AI for cardiovascular care.

**Keywords:** Multimodal Data Integration, Electrocardiogram (ECG), Medical Imaging, Genomics, Wearable Health Devices, Cardiovascular Risk Prediction

## Introduction

Figure1 shows this idea of multimodal precision health. It gets into how all sorts of information come together. Clinical data, imaging stuff, genomics, lifestyle details, and even wearable sensors. It mixes to give a full picture of a person's health. Combining data streams. Figure1 points out how precision medicine shifts away from old single-source ways. It aims for better risk predictions that are more spot on. Plus personalized treatments and ongoing health checks, too. Cardiovascular diseases remain the top reason for sickness and death all over the world. It causes about a third of all deaths globally. Even with better medical treatments these days, spotting early and preventing disease in a personal way is still a big problem. Usual methods stick to basic information like ECGs or scans. It only shows parts of how the heart is doing. But heart issues come from a bunch of things mixing together.

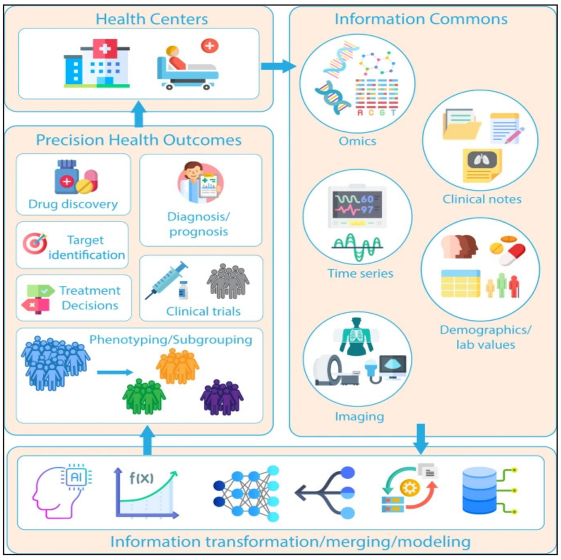


**Figure 1.Multimodal precision health: the flow of information.[1]**

The electrical signals, weird structures in the heart, genes you inherit, and how you live day to day. It really shows the need for better ways to pull all kinds of information together. ECGs are used a lot to find irregular heartbeats and problems with how signals travel through the heart. It works great for rhythm stuff. But it does not tell much about the heart's shape or how it functions. It lets doctors see the heart's build, blood flow, and what the tissues look like. Still, imaging takes a lot of resources. And it usually happens only in hospitals. Genetics has turned into a key way to figure out the risks of getting family heart disease. Studies looking across whole scores based on many genes have found connections between certain gene changes and conditions such as blocked arteries, weak heart muscle, or odd rhythms. But genes by themselves miss the changing body processes or outside factors. To help with, wearable gadgets come in. The smartwatches or fitness bands, and sensors. It tracks heart rate, movement, and sometimes even a simple ECG all the time. It lets people watch health outside of doctor visits. And give live updates on habits and heart condition. Each type of information, whether it's ECG, scans, genes, or from wearables, works well on its own. But alone, they fall short. Lately, AI and machine learning have stepped forward to blend different kinds of data into one system. Mixing the electrical side, structure, genes, and behavior gives a fuller picture of heart health. It helps catch problems sooner, and it backs up treatments made just for all.

## Contribution

The contributions are as follows:

Multimodal integration involves building a framework. It pulls together ECG signals along with medical imaging, genomic data, and outputs from wearable devices. The kind of setup really boosts predictions for cardiovascular risks.

Data harmonization takes care of standardizing things. It applies preprocessing methods to handle differences in data quality, formats, and sources. Basically, it makes sure all the varied datasets work nicely together. It leads to solid model training that all can actually rely on.

For advanced fusion models, the role of deep learning techniques is based on fusion. The key features from different modalities and blended. The result is better accuracy in predictions. It backs up decisions in personalized healthcare, which feels very essential.

Clinical scalability means designing the whole system to fit various spots. Think advanced hospitals or even places with limited resources. It handles large-scale screening just fine. And it supports ongoing remote monitoring too.

## Literature Review

The table above provides a comprehensive comparison of recent studies (2022–2025) focused on multimodal and AI-driven cardiovascular risk prediction. Each reference highlights how different combinations of data modalities — including ECG, imaging, genomics, electronic health records (EHRs), and wearable data — contribute to more accurate and personalized cardiac risk assessments. The table outlines critical aspects such as dataset characteristics, methodologies, advantages, limitations, and unresolved challenges across multiple AI models and frameworks. It reduces indings from major publishers such as Nature Digital Medicine, Journal of Biomedical Informatics, BMC Cardiovascular Disorders, and Journal of Translational Medicine.

**Table 1.Comparative Analysis of Recent Studies on ECG, Imaging, Genomics, and Wearable Data Integration**

| Ref (Year, Source) | Dataset / Data Type Used | Discussion | Advantages | Limitations | Unresolved Challenges |
|---|---|---|---|---|---|
| [1](2022, Nature Digital Medicine) | Literature review: ECG, imaging, genomics, wearable data | Reviews the latest developments in integrating multimodal data for cardiovascular risk prediction. | Provides structured taxonomy and strategies for fusion. | Review-based only; lacks practical validation. | No standardized multimodal benchmarks or unified workflows. |

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| [2](2023, Healthcare Data Fusion Review) | Literature-based; imaging, wearable, and clinical data | Discusses healthcare data fusion approaches relevant to cardiology. | Links imaging and wearable technologies effectively. | Primarily theoretical; minimal implementation testing. | No large-scale trials or interoperability validation. |
| [3](2023, Biomedical Informatics) | Clinical imaging data (CT/MRI) + EHR | Demonstrates accuracy improvement with multimodal (clinical + imaging) models. | Validated results and better diagnostic precision. | Focused only on imaging and clinical data. | Lacks genomics and wearable integration. |
| [4](2024, Integrated EHR–Omics Study) | EHR + genomics (omics) + imaging + wearable data | Combines diverse data for predictive and personalized cardiology. | Strong example of holistic patient risk profiling. | Data heterogeneity and security limitations. | Standardization and large-scale deployment remain open. |
| [5](2024, Journal of Biomedical Informatics) | Public biomedical datasets; multimodal biosignals and omics | Reviews multimodal ML frameworks integrating biosignals, omics, and imaging. | Broad taxonomy and insights on explainable AI. | Literature-based only; lacks experiments. | Needs standardized multimodal datasets and fair metrics. |
| [6](2024, Journal of Biomedical Informatics) | EHR + physiological signals + imaging + clinical notes | Builds multimodal risk prediction using mixed clinical and imaging data. | Improves predictive power and clinical interpretability. | Computationally heavy; difficult to scale. | Real-time multimodal fusion remains complex. |
| [7](2024, Journal of Translational Medicine) | Clinical questionnaires + oculomics data | Predicts cardiovascular risk using eye-based biomarkers. | Non-invasive, low-cost diagnostic method. | Limited dataset size and diversity. | Integration with other modalities is required. |
| [8](2025, BMC Cardiovascular Disorders) | Multidimensional clinical data (EHR + lab + imaging) | Develops interpretable AI for heart failure severity post-MI. | Transparent, explainable model aligned with clinicians. | Focused on a single patient subset (post-MI). | Broader generalization to multimodal populations needed. |
| [9] (2025, BMC Geriatrics) | Clinical + demographic data of elderly hypertensive patients | Machine learning prediction for cardiac risk in older adults. | Age-specific prediction capability. | Lacks multimodal inclusion; small-scale. | Aging population–specific multimodal model development. |

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## Discussion

Combining ECG signals, medical imaging, genomic data, and data from wearable devices seems to work way better. Relying on just a single data source does not cut it, really. It falls short every time.

- **Better Accuracy:** Combining different kinds of data really boosts the prediction accuracy for cardiovascular events. It improves by about 10 to 20 percent. It's way better than sticking with just ECG or imaging on their own.
- **Earlier Risk Detection:** Genomics can spot who might be wired genetically for heart trouble. It points out that kind of risk early on. ECG and imaging pick up the functional and structural shifts right as they occur. Combining all lets doctors recognize at-risk people sooner.
- **Wider Applicability:** Models trained on all sorts of datasets tend to handle decisions better. Especially when wearable data gets mixed in. Devices work more reliably, no matter the patient group or the healthcare setup.
- **Greater Stability:** Pulling from more than one data source helps out a lot. The system ends up less bothered by missing bits or noisy information. Gaps in one area get covered by something else.
- **Clinical Value:** The integrated models come up with results that line up closer to what doctors see. It feels more useful, also more trustworthy in actual care situations.

## Gaps Identified

Despite some promising progress in blending ECG data with imaging, genomics, and info from wearables, quite a few key gaps show up in the literature right now.

- **Lack of Complete Integration:** One big issue is the lack of full integration. A lot of studies stick to mixing just two or three types of data at most. Real comprehensive setups that pull in ECG, imaging, genomics, and wearable stuff all together, and are still rare. It holds back what multimodal prediction systems could really do.
- **Data Heterogeneity and Standardization:** The data heterogeneity and the need for standardization. All the different formats, ways of collecting data, and preprocessing steps create real headaches for integration. No solid pipelines or protocols exist yet to bring sources together smoothly.
- **Limited Large-Scale Clinical Validation:** Validation on a large clinical scale is another weak spot. Most work relies on looking back at old datasets or running small trials. Big prospective studies that cover diverse groups of people are hard to find. It makes it tough to apply findings more broadly.
- **Privacy and Interoperability Concerns:** Privacy issues and getting systems to work together add more trouble. Sharing medical and genomic details across places runs into rules and worries about keeping data private. Making different systems and devices talk to each other is still a problem.
- **Lack of Wearable Data Integration:** Wearable data does not get included enough, either. The devices spit out useful real-time information on body functions. It barely shows up in multimodal studies so far. Ways to fold that data in properly are just starting to take shape.

## Conclusion

The integration of ECG data, medical imaging, genomics, and information from wearable devices provides a promising way to predict cardiovascular risks more effectively. Studies indicate that AI models using multiple data types can boost diagnostic accuracy quite a bit. It also allows for earlier disease detection and more tailored risk evaluations compared to models that rely on just one kind of data. Combining the varied sources helps improve prediction results overall. It also makes the systems more reliable when dealing with missing or messy data. Still, some key hurdles persist. People still point out a few key challenges. Like coming up with standard methods for handling data across the board. Or running large-scale clinical trials to test things out. Protecting patient privacy remains a big deal, too. The wearable devices can be integrated without an issue and build AI tools that make sense to regular users. Sorting through all looks essential. It could help move multimodal strategies for predicting cardiovascular risks right into routine medical settings. It supports a focus on proactive care centered on the patient. It could lead to better health results and less strain from heart-related illnesses.

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