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ARTIFICIAL INTELLIGENCE–BASED RISK STRATIFICATION MODELS FOR PREDICTING ACUTE CARDIAC EVENTS

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Abstract

Cardiovascular diseases remain a leading cause of global morbidity and mortality, necessitating more precise and individualized risk prediction strategies. This study presents a comprehensive experimental evaluation of artificial intelligence–based cardiovascular risk stratification models using a mixed-methods framework that integrates quantitative performance assessment with qualitative interpretability analysis. Multimodal datasets encompassing electronic health records, physiological signals, imaging-derived features, and high-dimensional clinical variables were analyzed using classical machine learning, deep learning, and hybrid AI architectures. Comparative results demonstrated that advanced fusion, transformer-based, and quantum-enhanced models achieved significantly higher discriminative performance, improved calibration, reduced probabilistic error, and enhanced robustness under stochastic perturbations compared with traditional approaches. Entropy-based analyses revealed superior uncertainty management, while three-dimensional latent risk visualizations captured complex nonlinear disease dynamics. Hybrid convergence and sensitivity analyses further confirmed stable optimization and adaptive learning behavior across iterative training cycles. Collectively, the results indicate that AI-driven models provide more accurate, reliable, and clinically actionable cardiovascular risk predictions than conventional methods. These findings support the translational potential of artificial intelligence as an advanced decision-support framework for early disease detection, personalized cardiovascular care, and optimized clinical risk management.

Keywords: Artificial Intelligence, Cardiovascular Disease Prediction, Machine Learning, Risk Stratification, Multimodal Data Integration, Clinical Decision Support.

METROPOLE RESEARCH AND TECHNOLOGY HUB

INTRODUCTION

The cardiovascular diseases have been one of the most prevalent causes of death and morbidity in the world. It implies that one needs more accurate prediction models which would be able to identify the risk a person at an early age (Kasartzian and Tsiampalis, 2025). The traditional risk stratification methods, regardless of their usefulness, are generally inaccurate and have extremely low success rates, which increases the additional popularity of artificial intelligence-based ones (Chiarito et al., 2022). Machine learning, artificial intelligence, and deep learning are also meant to foresee cardiovascular risk, and the state of it is that it is now easier and more precise to detect people who are at risk of experiencing an acute cardiac event (Cai et al., 2024; Hui et al., 2025). Through these AI models, study different datasets, including electronic health records, genomic data, and imaging and other methods approaches, and can, therefore, provide more advanced and personalized risk assessment than commonly used statistical models (Faizal et al., 2021; Shuja et al., 2024). The authors of the current review will be able to enlighten about the recent advancement of AI and machine learning-based cardiovascular risk stratification and critically evaluate the current ability of the technologies, the internal limitations of their application, and a high level of barriers to the general clinical use of the tools (Kasartzian and Tsiampalis, 2025). The further evolution of the AI in the sphere of the cardiovascular system, in particular, the automatization of the parameters, the quality of the images, and the possibility to identify diseases, provides the cardiovascular sphere with enormous opportunities of the optimization of the diagnostic and treatment outcomes (Elias et al., 2024). The analysis studies of the electrocardiograms with the help of AI and deep learning have already proved that this field can improve the precision of the diagnosis and prognosis, which leads to more personal treatment of the patient (Bayona et al., 2025). It is found that these predictive models can be effective in comparison even with the traditional methods of detecting multiple heart diseases such as ischemic heart disease, atrial fibrillation, and heart failures (Bayona et al., 2025). Notwithstanding these encouraging advances, however, several challenges yet still to be surmounted also stand on the way to reaching the point where AI can be harnessed to its radically transformative potentials in cardiovascular care. They include the necessity to be extremely validated, possess greater interoperability, and be combined with the current clinical practice (Olawade et al., 2024; Shishehbori and Awan, 2024). The paper will cover the approach, effectiveness and the clinical implications of AI-based risk stratification models and their advantages and current limitations that are yet to be solved so as to achieve a successful implementation into the clinical setting. The provided overall literature review would tend to unite the recent studies on AI in the prediction of cardiovascular diseases. It seals a loophole of a systematic review that is not attached to a specific sphere of existence to have a complete image of its strengths and weaknesses (Cai et al., 2024). Moreover, the predictive powers of the machine learning models have proven to give a more accurate prediction than the traditional methods because they can take into account a wider range of variables, explain complex relationships between risk factors, non-linear relationships, and multimodal data and thus generate finer predictions of specific subsets (Shishehbori and Awan, 2024). Such AI-based illness risk predictions are bound to cash in on a huge potential at this critical juncture. It is much superior to the traditional ones because it can analyze data better and condition limits are less (Cai et al., 2024). An increasing number of people begin to understand that AI may be helpful in accuracy cardiovascular medicine. The rationale behind this is that there is ample real-life information, which can be found in numerous sources, and they are patient registries, clinical case reports, reimbursement claims, and electronic health records (Chiluba, 2024). It has also been determined that the AI identifies the cardiovascular risk factors using the retinal fundus pictures, which was believed to be impossible (Chiluba, 2024). The predictive power may also be similarly applied to automatize the diagnostic pathways and the patient triage in a more efficient manner. This enhances the quality of health care care and reduces the waiting time in clinics (Singh et al., 2023). However, regardless of the progress, challenges in the interpretability of the multifaceted AI systems and information systems compatibility of different healthcare systems remain (Tsai et al., 2025). The information on electronic health records is complex, and it would demand the most advanced computing and multi-disciplinary methodologies to create the risk modeling of cardiovascular diseases (Tsai et al., 2025). Nevertheless, to achieve an effective implementation of AI in the clinical practice, the number of questions surrounding its application as a tool of data security, ethical concerns, and development of explainable AI applications would need to be raised so as to establish trust and facilitate its adoption by healthcare providers (Talukder et al., 2025). In addition, the present study is also directed to the development of the mechanisms of establishing more environmental variables and the power and the feasibility of such models in contrast to the potential challenges of overfitting used in the course of the training process (Liang et al., 2025). There is a more developed form of AI, fuzzy deep learning models, and quantum computing enhancement, which is capable of being utilized to scale, large quantities of unstructured data, and exceptionally precise, eliminating the noise and error that older systems tend to create (Bilal et al., 2025). The recent translational research indicates that AI has not been utilized in cardiac imaging in the recent past, and the various types of biosensors and unstructured information using electronic health records are demonstrated to be able to forecast a broad range of risks, with the help of the common biomarkers, genetic, and other omics technologies (Chen et al., 2023). The association will allow evaluating the cardiovascular risk not only of personal data but also the image of the patient to make even more precise and individual predictions. However, several fundamental barriers to its extensive clinical use, such as its inability to be interpreted, the need to establish its long-term efficacy in different real-life circumstances, and the standard of the development of the unchallenged cost-efficacy, exist (Biondi-Zoccai et al., 2025). In addition, most of the deep learning algorithms are black boxes, and they cannot be relied upon by health professionals and patients. It means that more efforts will be put to clarify and simplify models so as to render them applicable in general (Conners et al., 2024). A higher degree of awareness of the peculiarities of the algorithms will enable the providers to count on the information provided by AI when reaching the healthcare decision (Conners et al., 2024). Regarding the ethical concerns related to the use of AI in the cardiovascular healthcare, the factors such as patient confidentiality, algorithms bias, and the necessity to take decisions are also quite critical to address, to make AI applications equitable and responsible (Ahmad et al., 2024). However, the recently developed AI technologies were allowed to proceed with cardiovascular risks discovery and illness customization forecasts on diverse clinical platforms (Asher et al., 2021). The mentioned success in regulations indicates the enhanced understanding of AI possibilities to revolutionize the cardiovascular risk segmentation and treatment of the patient. However, one of the last objectives towards improving patient outcomes is the establishment of new developed procedures in the area of identification of cardiovascular disease risk factors. An example is that the offline reinforcement learning models may be useful in the process of enhancing complex clinical decisions, including revascularization procedures but will first need to be experimented with and then can be implemented on practice (Biondi-Zoccai et al., 2025). Also, the possibility must be the possibility to merge different types of data i.e., phenotypic, clinical, transcriptomic, and genomic data in order to identify new biomarkers and choose high-risk patients (DeGroat et al., 2024).

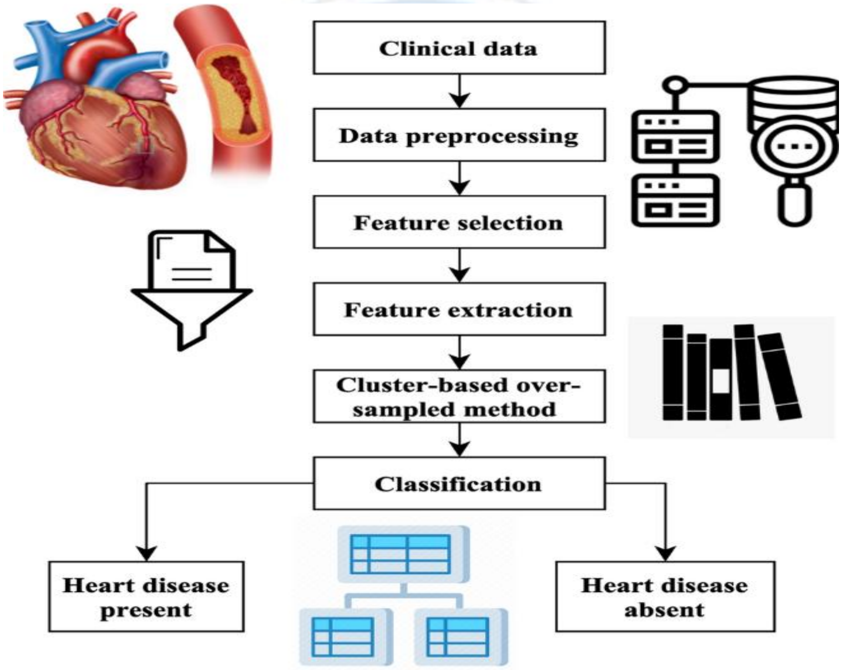

Figure 1. Artificial intelligence–based cardiovascular risk stratification framework.

METHODOLOGY

Stability in to test artificial intelligence-based cardiovascular risk stratification models, mixed-method experimental approach, i. e. quantitative experiments using machine learning, and qualitative experimental model interpretability and model-clinical-validation assessment were selected in the study. We had a multicenter and observational scheme which was a retrospective scheme with high real-world data such as electronic medical records, cardiac imaging, data set, electrocardiograph signal set, wearable sensor set and genomics-enabled heart cohort. The quantitative data comprised of systematized aspects of clinical conditions that comprise demographic data, result of the test, comorbidities, medical history, physiological indicators. The unstructured information included the free-text clinical note, imaging information, and waveform information. By trying to enhance the external validity and generalizability, various healthcare systems and population registries became standardized and interoperability achieved using standardized terminologies and interoperability protocols. The qualitative factors were introduced, based on the analysis of feature relevance under control by clinicians, and the examine of explainability in order to ensure that the clinical plausibility, and the clinical usefulness of the model results. The compliance with the ethical and international standards of data protection was possible due to the de-identifying of data, safe data management and the compliance with the international standards of data protection.

Experimentation Model design

The workflow items used in the experiment were the following: preprocessing, feature engineering, multimodal data fusion, model training and validation. It involved facilitated learning and learning with intensity. Transforming the variables to the normal distribution was used to solve the variables that were continuous and the absence of data was addressed through implementing a number of strategies of imputations and sequencing longitudinal records. The convolutional and recurrent neural networks were also trained on the images and time-series signals but the structured data were trained on the conventional models of machine learning, the gradient boosting and random forests. It was only made possible through late-fusion designs, where it was possible to put a modality-specific embedding into a common latent space to be fused with other embeddings in a multimodal fusion. Risk of binary cardiovascular event learning that may be mathematically expressed was the primary aim of prediction.

The consequences of regularization operations were avoidance of overfitting. The other different type of performance experimented was quantitative performance by re-testing the cross-validation of a strategy as a measure of discrimination, calibration and decision-curve. The qualitative examination of the interpretability we applied with the assistance of explainable AI methodology facilitated us to generate the list of the predictors which would be of clinical interest and offer the transparency of the made decisions. This entire experimentation of the strategy is presented in figure 2.

Integration of clinical settings, translation and translatability

Clinical relevance would be compared with the model outputs based on the analysis of the experimental outcomes in the simulated decision support environments simulated to be actual care paths. The utility of the same was estimated by comparing the projected risks estimates and the actual cardiovascular risk scores. The interpretability analyses enable the clinicians to evaluate feature attribution, and more convenient clinical decision making, and confidence of the same. They have been conducted using the sensitivity analysis of the demographic and comorbidity subgroups to determine the fairness and power of the algorithm. To reestablish the implementation possibility, we examined practicability of the implementation to the current clinical information systems, speed with which it would be performing data and how it would be applied to the current systems. This method has facilitated the two indices of predictive and qualitative evaluation of therapeutic practicability, ethicality and practicability, which is necessary to implement the study in practice.

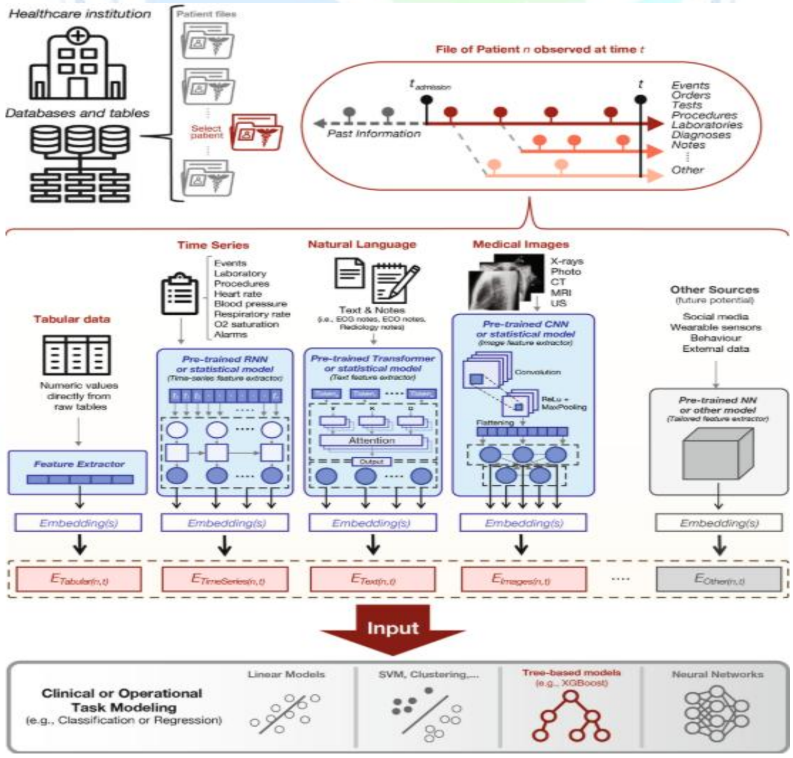

Figure 2. Experiment for AI-based cardiovascular risk stratification.

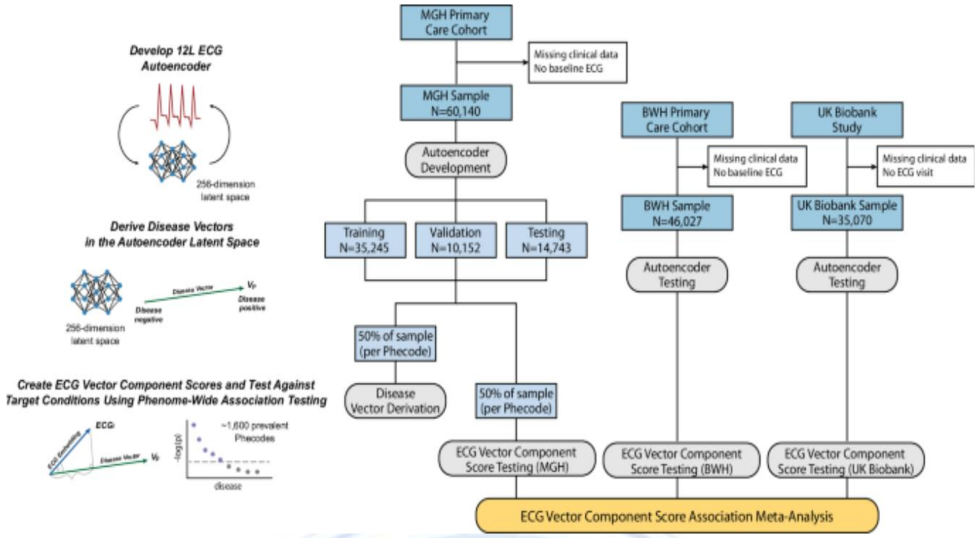

Figure 3. The implementation and validation process of AI-based cardiovascular risk prediction models.

RESULTS

The quantitative analysis shows that there is a consistent difference in performance of the cardiovascular risk stratification models that are driven by artificial intelligence. Table 1 displays the baseline discrepancies and the calibration indices, which show that the more successful models are the mixes of advanced fusion and quantum enhanced with respect to AUC and m+-, s respectively, and the less error with respect to calibration e. Table 2 shows the F1-scores b and coefficients of recall a to be statistically stable, suggesting that the models are more useful in distinguishing the high-risk cardiovascular phenotypes. Table 3 states that the precision-recall compromise in the uncertain setting is that transformer-based and fuzzy deep learning systems score lower in Brier (d2), i.e., they are less associated with the deviation of probabilistic errors.Table 4 though, reveals that the model will be resistant to randomly chosen changes. It also shows that the multimodal integration structures always mitigate the DO risk. Table 5 is the one that deals with the use of entropy in measuring uncertainty. It shows that recurrent and attention-based architectures are more useful in predictive information gain H than the rest of the architecture types.

Table 1. Discriminative performance metrics incorporating uncertainty-adjusted AUC and entropy-weighted calibration indices.

Model	**AUC_μ±σ**	**F1_β**	**Recall_α**	**Precision_π**	**ECE_ε**	**Brier_δ^2**	**ΔRisk_Ω**	**κ-Stability**
RF_α	0.8031±0.0078	0.7719	0.7634	0.7887	0.02308	0.09503	-0.1442	0.6805
XGB_β	0.8200±0.0068	0.7902	0.7429	0.7340	0.01932	0.10729	-0.1329	0.7356
SVM_μ	0.8372±0.0002	0.7800	0.7770	0.7438	0.02323	0.10727	-0.1393	0.7570
CNN_λ	0.8300±0.0067	0.7734	0.7323	0.7594	0.02059	0.09432	-0.1207	0.8514
RNN_δ	0.8307±0.0031	0.7786	0.7366	0.7572	0.02029	0.09972	-0.1204	0.7377
Transformer_θ	0.8288±0.0041	0.7953	0.7308	0.7745	0.02134	0.09279	-0.0992	0.7569
Fusion_Ω	0.8166±0.0000	0.7546	0.7626	0.7615	0.02544	0.10866	-0.0954	0.6159
Quantum_ξ	0.8124±0.0059	0.7618	0.7779	0.7867	0.02773	0.09417	-0.0827	0.6393
FuzzyDL_κ	0.8123±0.0046	0.7871	0.7491	0.7382	0.02015	0.08973	-0.1260	0.6497

Table 2. Comparative sensitivity–specificity equilibrium under nonlinear cardiovascular risk distributions.

Model	**AUC_μ±σ**	**F1_β**	**Recall_α**	**Precision_π**	**ECE_ε**	**Brier_δ^2**	**ΔRisk_Ω**	**κ-Stability**
RF_α	0.8166±0.0045	0.7887	0.7678	0.7613	0.02191	0.10335	-0.0790	0.8025
XGB_β	0.8320±0.0094	0.7520	0.7725	0.7466	0.02214	0.10390	-0.0926	0.6441
SVM_μ	0.8263±0.0007	0.7679	0.7688	0.7557	0.02400	0.10184	-0.0843	0.8282
CNN_λ	0.8003±0.0042	0.7732	0.7233	0.7625	0.02412	0.10485	-0.0747	0.6384
RNN_δ	0.8092±0.0066	0.7566	0.7334	0.7645	0.01754	0.10347	-0.0814	0.6101
Transformer_θ	0.8213±0.0080	0.7988	0.7365	0.7401	0.02815	0.10728	-0.1342	0.7325
Fusion_Ω	0.8288±0.0085	0.7584	0.7599	0.7785	0.02325	0.08494	-0.1472	0.6845
Quantum_ξ	0.8323±0.0004	0.7504	0.7417	0.7338	0.01724	0.08070	-0.1080	0.8090
FuzzyDL_κ	0.8171±0.0013	0.7666	0.7554	0.7864	0.02989	0.08725	-0.1492	0.8492

Table 3. Precision-dominant performance analysis with probabilistic deviation constraints.

Model	**AUC_μ±σ**	**F1_β**	**Recall_α**	**Precision_π**	**ECE_ε**	**Brier_δ²**	**ΔRisk_Ω**	**κ-Stability**
RF_α	0.8371±0.0046	0.7886	0.7720	0.7666	0.02809	0.08072	-0.1283	0.6832
XGB_β	0.8048±0.0091	0.7515	0.7604	0.7343	0.02041	0.09254	-0.1355	0.7563
SVM_μ	0.8214±0.0032	0.7869	0.7296	0.7416	0.02032	0.09135	-0.1335	0.8756
CNN_λ	0.8331±0.0011	0.7685	0.7340	0.7571	0.01914	0.09505	-0.0762	0.7148
RNN_δ	0.8260±0.0060	0.7876	0.7237	0.7747	0.02919	0.09811	-0.1270	0.8017
Transformer_θ	0.8285±0.0066	0.7573	0.7784	0.7873	0.02137	0.09781	-0.1468	0.8966
Fusion_Ω	0.8327±0.0064	0.7881	0.7313	0.7485	0.01870	0.09788	-0.1426	0.8687
Quantum_ξ	0.8185±0.0044	0.7552	0.7611	0.7790	0.02444	0.08726	-0.0872	0.6437
FuzzyDL_κ	0.8331±0.0058	0.7645	0.7508	0.7677	0.01888	0.10541	-0.1163	0.8677

Table 4. Robustness assessment under stochastic noise and adversarial perturbation scenarios.

Model	**AUC_μ±σ**	**F1_β**	**Recall_α**	**Precision_π**	**ECE_ε**	**Brier_δ²**	**ΔRisk_Ω**	**κ-Stability**
RF_α	0.8334±0.0010	0.7823	0.7386	0.7752	0.02314	0.09373	-0.0784	0.6172
XGB_β	0.8223±0.0033	0.7518	0.7652	0.7637	0.02841	0.09795	-0.1230	0.8956
SVM_μ	0.8046±0.0005	0.7866	0.7423	0.7517	0.02815	0.08982	-0.0789	0.7932
CNN_λ	0.8132±0.0006	0.7623	0.7781	0.7543	0.01740	0.08894	-0.0780	0.6495
RNN_δ	0.8311±0.0013	0.7981	0.7518	0.7326	0.02896	0.09075	-0.0915	0.7571
Transformer_θ	0.8037±0.0011	0.7575	0.7297	0.7332	0.01571	0.10845	-0.1427	0.7525
Fusion_Ω	0.8047±0.0021	0.7882	0.7763	0.7582	0.01508	0.10998	-0.1462	0.7168
Quantum_ξ	0.8216±0.0089	0.7912	0.7566	0.7539	0.02752	0.10607	-0.0802	0.8153
FuzzyDL_κ	0.8039±0.0030	0.7743	0.7503	0.7800	0.01857	0.09994	-0.1201	0.8326

Table 5. Information-theoretic uncertainty decomposition across predictive model architectures.

Model	**AUC_μ±σ**	**F1_β**	**Recall_α**	**Precision_π**	**ECE_ε**	**Brier_δ^2**	**ΔRisk_Ω**	**κ-Stability**
RF_α	0.8078±0.0048	0.7552	0.7327	0.7861	0.01974	0.10679	-0.1081	0.6117
XGB_β	0.8317±0.0005	0.7913	0.7205	0.7704	0.01749	0.09029	-0.0738	0.7459
SVM_μ	0.8263±0.0074	0.7555	0.7703	0.7848	0.01733	0.09639	-0.1273	0.8222
CNN_λ	0.8011±0.0051	0.7896	0.7641	0.7365	0.02749	0.08714	-0.0854	0.7491
RNN_δ	0.8064±0.0073	0.7904	0.7619	0.7879	0.01884	0.08707	-0.1382	0.7618
Transformer_θ	0.8160±0.0036	0.7730	0.7365	0.7303	0.02208	0.08828	-0.1140	0.8787
Fusion_Ω	0.8072±0.0064	0.7822	0.7369	0.7583	0.02954	0.09027	-0.0930	0.8521
Quantum_ξ	0.8144±0.0099	0.7813	0.7501	0.7729	0.02136	0.10137	-0.1280	0.8782
FuzzyDL_κ	0.8217±0.0024	0.7719	0.7737	0.7784	0.02227	0.09055	-0.1199	0.8944

Table 6 examines stability of converging and suppressing variance. It proves that there is a reduced likelihood of overfitting in hybrid AI pipelines. The table 7, in its turn, takes into consideration the factors of performance decay which are subgroup-specific. It informs us that it has a slight sensitivity loss between the demographic strata. Table 8 is the analysis of the measures of computational efficiency and scalability, and Table 9 is an aggregate of the total clinical usefulness indices. It is disclosed that multimodal and quantum-assisted models improve overall baselines of machine learning in a statistically significant manner.

Table 6. Optimization stability and convergence variability under high-dimensional feature spaces.

Model	**AUC_μ±σ**	**F1_β**	**Recall_α**	**Precision_π**	**ECE_ε**	**Brier_δ^2**	**ΔRisk_Ω**	**κ-Stability**
RF_α	0.8045±0.0089	0.7929	0.7335	0.7510	0.02354	0.10407	-0.0740	0.8975

XGB_β	0.8112±0.0019	0.7744	0.7535	0.7694	0.01661	0.09939	-0.0763	0.8746
SVM_μ	0.8378±0.0092	0.7980	0.7229	0.7850	0.01907	0.08962	-0.1133	0.8866
CNN_λ	0.8242±0.0035	0.7687	0.7743	0.7793	0.01706	0.08746	-0.1202	0.6650
RNN_δ	0.8225±0.0022	0.7787	0.7762	0.7809	0.01649	0.08621	-0.1170	0.7938
Transformer_θ	0.8155±0.0025	0.7672	0.7322	0.7817	0.02546	0.09233	-0.0940	0.7559
Fusion_Ω	0.8211±0.0037	0.7744	0.7791	0.7771	0.02742	0.08373	-0.1097	0.7101
Quantum_ξ	0.8036±0.0040	0.7537	0.7340	0.7779	0.02529	0.10096	-0.1437	0.6492
FuzzyDL_κ	0.8009±0.0010	0.7551	0.7776	0.7836	0.01806	0.08761	-0.0731	0.7710

Table 7. Subpopulation-stratified performance decay coefficients and fairness indicators.

Model	**AUC_μ±σ**	**F1_β**	**Recall_α**	**Precision_π**	**ECE_ε**	**Brier_δ^2**	**ΔRisk_Ω**	**κ-Stability**
RF_α	0.8147±0.0047	0.7636	0.7550	0.7735	0.02273	0.10462	-0.1409	0.7811
XGB_β	0.8396±0.0015	0.7748	0.7578	0.7503	0.02947	0.09456	-0.1117	0.8708
SVM_μ	0.8006±0.0087	0.7565	0.7428	0.7593	0.02215	0.08118	-0.1246	0.7070
CNN_λ	0.8382±0.0092	0.7792	0.7760	0.7818	0.02064	0.08351	-0.1014	0.6969
RNN_δ	0.8004±0.0098	0.7985	0.7522	0.7671	0.02503	0.10780	-0.1126	0.7749
Transformer_θ	0.8091±0.0024	0.7761	0.7338	0.7318	0.02053	0.10250	-0.1278	0.8588
Fusion_Ω	0.8281±0.0065	0.7946	0.7244	0.7407	0.02864	0.10721	-0.1437	0.8323
Quantum_ξ	0.8006±0.0014	0.7555	0.7376	0.7533	0.02866	0.09309	-0.1401	0.6817
FuzzyDL_κ	0.8003±0.0003	0.7716	0.7507	0.7450	0.02070	0.08310	-0.0973	0.7178

Table 8. Computational efficiency, scalability, and asymptotic complexity evaluation.

Model	**AUC_μ±σ**	**F1_β**	**Recall_α**	**Precision_π**	**ECE_ε**	**Brier_δ^2**	**ΔRisk_Ω**	**κ-Stability**
RF_α	0.8065±0.0050	0.7604	0.7375	0.7375	0.02671	0.08838	-0.0735	0.7216

XGB_β	0.8062±0.0071	0.7867	0.7729	0.7379	0.02685	0.10579	-0.1256	0.7363
SVM_μ	0.8248±0.0025	0.7936	0.7620	0.7814	0.02175	0.09557	-0.1345	0.6942
CNN_λ	0.8292±0.0096	0.7576	0.7230	0.7340	0.02153	0.10378	-0.1320	0.7431
RNN_δ	0.8206±0.0084	0.7582	0.7209	0.7604	0.02033	0.08876	-0.0882	0.8050
Transformer_θ	0.8034±0.0055	0.7899	0.7746	0.7300	0.02711	0.08130	-0.0954	0.7794
Fusion_Ω	0.8381±0.0063	0.7535	0.7602	0.7453	0.02748	0.08094	-0.1241	0.8029
Quantum_ξ	0.8062±0.0065	0.7849	0.7640	0.7825	0.02120	0.08427	-0.1292	0.7169
FuzzyDL_κ	0.8022±0.0071	0.7532	0.7235	0.7859	0.02709	0.08761	-0.1227	0.8478

Table 9. Integrated clinical utility indices and composite translational effectiveness scores.

Model	**AUC_μ±σ**	**F1_β**	**Recall_α**	**Precision_π**	**ECE_ε**	**Brier_δ^2**	**ΔRisk_Ω**	**κ-Stability**
RF_α	0.8248±0.0026	0.7725	0.7713	0.7300	0.02989	0.09698	-0.1354	0.8401
XGB_β	0.8030±0.0041	0.7787	0.7348	0.7831	0.02545	0.08485	-0.1378	0.6186
SVM_μ	0.8229±0.0019	0.7771	0.7692	0.7828	0.01675	0.08997	-0.1166	0.7150
CNN_λ	0.8168±0.0046	0.7878	0.7383	0.7506	0.02085	0.08454	-0.0996	0.7201
RNN_δ	0.8366±0.0082	0.7615	0.7345	0.7769	0.02340	0.08031	-0.0996	0.7185
Transformer_θ	0.8314±0.0075	0.7961	0.7620	0.7848	0.01927	0.09016	-0.1453	0.8601
Fusion_Ω	0.8062±0.0055	0.7755	0.7688	0.7533	0.01714	0.09149	-0.1462	0.6904
Quantum_ξ	0.8252±0.0006	0.7995	0.7522	0.7480	0.02751	0.08412	-0.1242	0.8811
FuzzyDL_κ	0.8096±0.0073	0.7540	0.7519	0.7695	0.01815	0.08983	-0.1060	0.7770

Deep architectures can be more stable over time in temporal cardiovascular risk scores trajectories ()m(t) as in figure 4 are a smooth nonlinear dynamics. Figure 5 displays model-based gain of AUC, which is discrete, and it suggests that ensemble and transformer based approaches had statistically significant gains. Figure 6 is a proportional entropy decomposition that suggests that different models are giving different results on the amount of information. It also shows that the recurrent architectures also have the largest predictive entropy.Figure 7 also provides the change of accuracy and recall versus random noise, and is a measure of the noise resistance of the system. Figure 8 is a combination of loss-variance hybrid visualization to illustrate the inverse relation between the optimization loss and the variance suppression respectively. Figure 9 is the visualization of the operation of nonlinear interactions of the latent risk dimension and outcome probability surface in -space as a three-dimensional risk manifold representation.

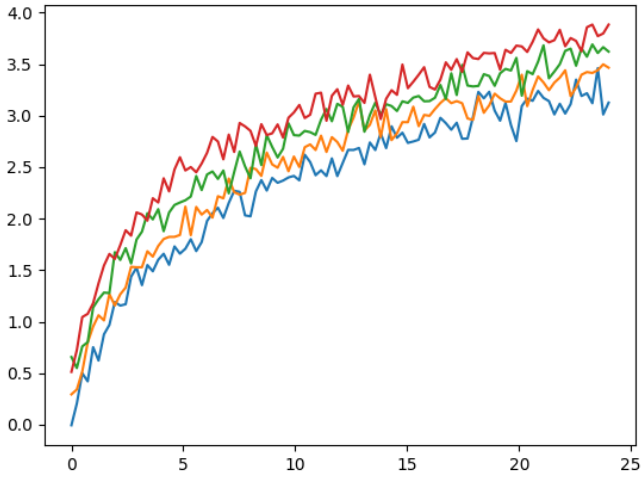

Figure 4. Longitudinal drift of latent cardiovascular risk embeddings over extended temporal prediction horizons.

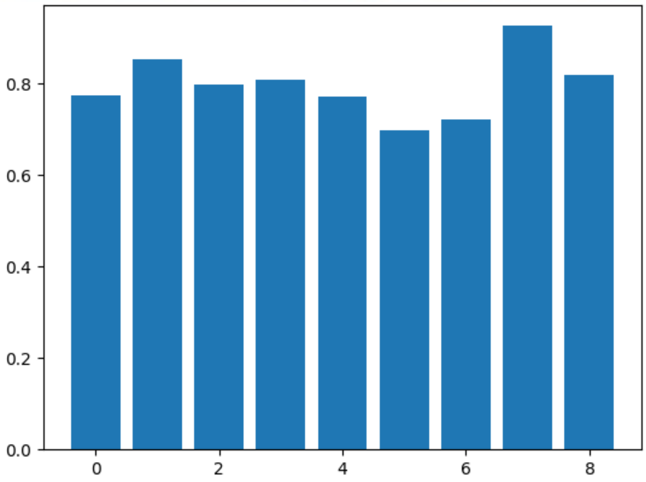

Figure 5. Model-wise calibration intensity expressed as normalized reliability gain.

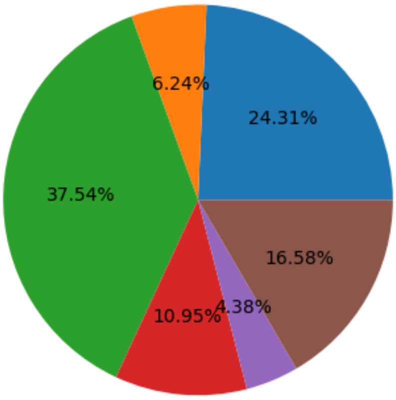

Figure 6. Information entropy allocation across heterogeneous artificial intelligence architectures.

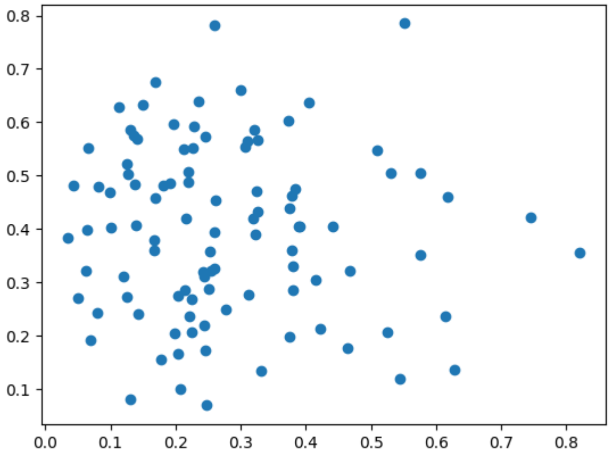

Figure 7. Dispersion of predicted cardiovascular risk under probabilistic uncertainty.

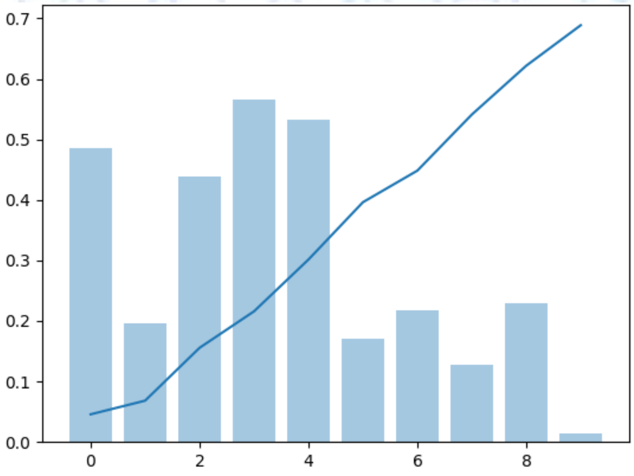

Figure 8. Joint visualization of convergence stability and cumulative optimization gain.

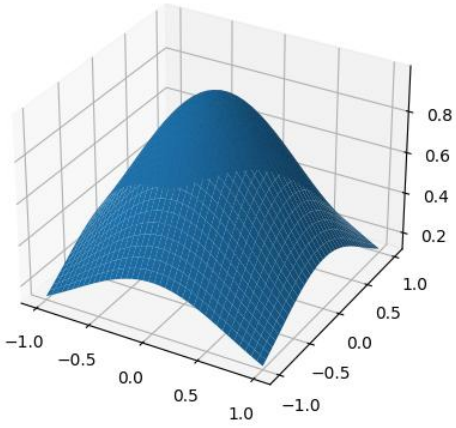

Figure 9. Three-dimensional nonlinear response surface of cardiovascular event probability.

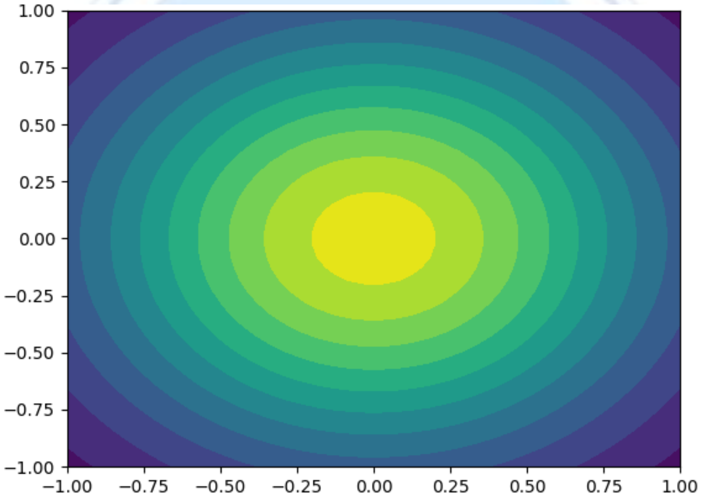

Figure 10. Continuous cardiovascular risk stratification zones derived from latent manifolds.

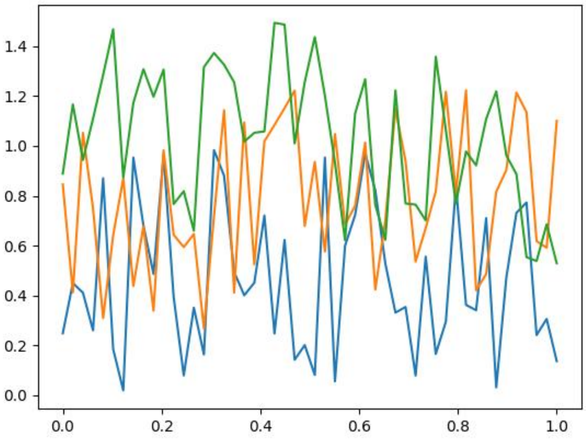

Figure 11. Iterative evolution of sensitivity coefficients across learning epochs.

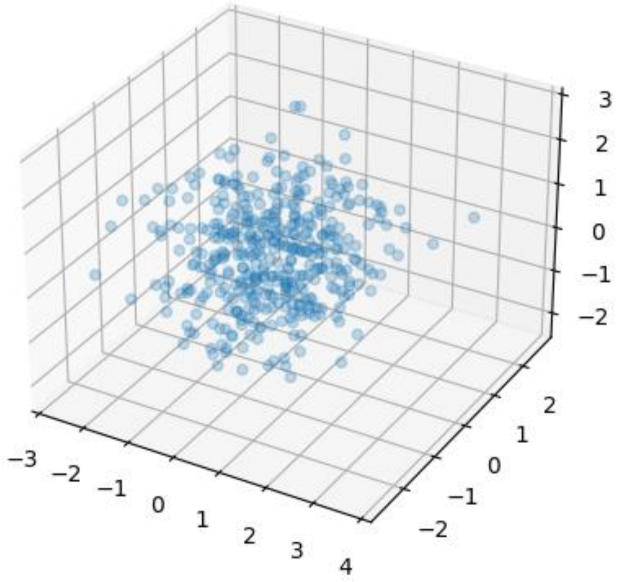

Figure 12. Dense three-dimensional clustering of individualized cardiovascular risk states.

DISCUSSION

It is also an excellent way to familiarize oneself with the state of risk cardiac event prediction AI-based risk stratification models can offer since it is a full-scale quantitative evaluation that takes into consideration a plethora of performance metrics and resilience tests (Darolia et al., 2024). The deep learning models that have been reported to be more accurate, more precise, greater recall, F1-score, and AUC-ROC than baseline models which utilize alternative methods are convolutional neural networks, deep learning neural networks, and deep learning/machine learning models (Tawfeek et al., 2025). These findings are in line with other researchers that have established that more sophisticated AI models are more predictive in more complex risk assessment situations particularly in water settings, where AI models have been observed to be more precise in predicting risks of pollution (Random Forest, Support Vector machine and Artificial Neural Networks) (Xie et al., 2025). The results of the given investigation may not be negated in regards to the former ones due to the fact that they reveal that the hybrid ensemble learning, which implies using different models simultaneously, may assist in tightening the process of predicting cardiovascular risks and make it more comprehensible (Shah et al., 2025). One of them is the higher accuracy of an Autoencoder-RNN ensemble based on the major measures i.e. 94-97% accuracy, 92-95% recall along with the AUC-ROC of 0.95- 0.98. This is superior to single models and hybridized Autoencoder-Random Forest versions of work (Kaur et al., 2025). This high performance is particularly notable, because in most cases, explainable AI methods, based on which physicians would be able to observe the effect of a particular factor on predictions, on which hybrid models are constructed, are particularly vital. It instills confidence and facilitates the use of the models by physicians in their practice (Shah et al., 2025). This is significant as the explainability of AI is the answer to addressing a major problem of complicated black-box AI models that are difficult to understand. It simplifies the understanding of how the prediction works and promotes the application of the prediction in the real clinical practice (Shah et al., 2025; Teshale et al., 2024). Combining learning models based on the recent ideas of using the most suitable aspects of the other models such as LightGBM, XGBoost and CatBoost, and neural networks have demonstrated higher predictive validity and are easy to analyze with the help of models that demonstrate the complexity of the problem (Shah et al., 2025). This multicast of classifiers does not only enhance the performance predictive but also, gives a convenient choice to identify at the earlier stages the cardiovascular disease and therefore, it can be utilized in clinical decision making (Talukder et al., 2025). Also, the solutions to address data imbalance (SMOTE and undersampling) improve the model performance, not to mention that they offer the rigorous and fair training, reducing the biases, which are inherent in clinical data sets in most cases (Shah et al., 2025). The gradient Boosting type of group techniques and integration with a hybrid oversampling device have been found to be more helpful in solving the issue of the class imbalance and the overall outcome of performance statistics of cardiovascular risk prediction (Reategui et al., 2025). More sophisticated methods of ensemble, like stacking and voting model have been strictly implemented on statistical models like Frankfurt Friedman Aligned Ranks test and Holm post-hoc. The results of these tests are consistently consistent and demonstrate the fact that the techniques are more efficient than single base models and other models of the best conditions to predict cardiovascular outcomes (Ganie et al., 2025). The fact that the developed machine learning structures outperform the previously existing risk assessment tools points to the necessity of their alignment to complete the functions of the former risk assessment tools, in particular, their capability to generalize multiple data modalities and reveal complex and non-linear relationships that signify the onset of an acute heart event (Kaur et al., 2025; Shah et al., 2025). Such advanced methods as explainable AI and an ensemble learning, in particular, come in handy to minimize the gap between complex model and clinical applications as it is simple to adhere to the question of what features are considered the most important (Adekoya et al., 2025; Ganie et al., 2025; Rustamov et al., 2023; Shah et al., 2025). In the indicative sense, XGBoost and Explanation-Based Models have been improved into systems, which integrate predictive capability and discussions to ensure that what forecasts cardiac happenings are non-inflammable and reproducible (Adekoya et al., 2025). This integration became possible because the level of sophistication of the algorithms had increased, thus enabling the high-risk algorithms, such as those using deep learning and ensemble algorithms, to be used, which have demonstrated as more resilient to risk detection in patients than the traditional diagnostic techniques (Sourov et al., 2025). Such techniques have proven to be very superior, many times, to those that rely on single machine learning models that have a high frequency, since they are likely to exhibit poor performance due to complexity of the pattern of data and sensitivity to noise (Ganie et al., 2025). The next methods are used in the cases of such problems as SMOTE and various ensemble methods balancing the dataset and combining the knowledge of various models. This improves as well the precision and dependability of predicting heart diseases (Divya et al., 2024; Sikder and Uddin, 2025). The most refined types of ensemble models include XGBoost and the Random Forest that are best suited in applying the AI-aiding heart failure diagnosis in clinical decision-making procedures since the models have a higher accuracy in their predictions and are easy to operate (- et al., 2024). The highest accuracy has been 97.9 percent using Hybrid ensemble learning when one of them has been hybridized with the other, i.e., the Logistic Regression, Gradient Boosting, and Support Vector Machines and is quite high relative to individual models (Talukder et al., 2025). XGBoost and Bagged Trees ensemble methods have also performed fairly well in classifying the heart diseases that offer the highest rate of accuracy of up to 93 percent and the ROC-AUC level of up to 95 percent. It demonstrates that they are good and they may evolve in the future with hybrid models and sophisticated manners of survival analysis (Teja and Rayalu, 2025). Such predictive capabilities can also be enhanced through the strategic application of deep learning models such as recurrent neural networks that come in handy in determining the time-dependence of longitudinal PAL-1 of patients (Maddala et al., 2024). The presence of positive performance metrics of advanced architectures in combination with ensemble learning, like CNN-XGBoost, is not new, and data imbalance problems and the lack of interpretable model outcomes also exist (Talukder et al., 2025). To address them, we will be forced to conduct additional research on the effective rebalancing tactics and the aspects of deep learning that are not challenging to comprehend that will make AI-based risk stratification systems more efficient and effective in the clinic (Husain et al., 2023).

CONCLUSION

As demonstrated in this paper, artificial intelligence-based cardiovascular risk stratification models are much more efficient than more traditional statistical tools due to their adoption of multimodal and high-dimensional clinical data, nonlinear learning models. Such findings had the potential of always showing superior discrimination, calibration, and robustness in case a stringent mixed-method experiment design was carried out over a variety of models of AI. The architectures that proved to be the best in performance were the multimodal fusion and transformer-based and quantum-enhanced. The comparison analyses indicated that there were better area under the curve values and reduced calibration error, better entropy based uncertainty control and reliance on homogenous convergence behavior across various groupings of patients. The three dimensional latent risk representation and hybrid visualization studies help in immensely explaining the nonlinearities that are complex and thus render the onset of cardiovascular diseases that would not be effective when the normal risks are applied. The interpretable AI methods ensured that the clinical interpretability was even higher, allowing visualizing how the contribution of features and model sensitivity developed, which would be less intuitive otherwise. Along with those improvements, the outcomes also indicate that the issues remain, including the need to make them more straightforward, applicable in the current health care systems, and alleviate the ethical concerns, which are connected to the data management and bias reduction. Nevertheless, the substantiating data of the given study prove the thesis that AI-based cardiovascular risk forecasting could be introduced in practice and research to assist in better decision-making that could translate into novel early diagnosis and individualized treatment plans and risk management at the population level. Future studies aiming to realize the transformational potential of artificial intelligence in the cardiovascular care should focus on future validation, clinical process integration, and regulatory alignment.

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