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Original Article

Bayesian and Stochastic Modeling Approaches to Coronary Artery Disease Progression: A Systematic Review of Methods, Applications, and Clinical Implications

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Abstract *- Bayesian and stochastic models in coronary artery disease extend beyond prediction to clinical implications, including adaptive trial designs, personalized medicine, and enhanced risk stratification. Using a systematic review of literature approach, this study examines Bayesian and stochastic modeling approaches to coronary artery disease progression. The study selects literature using the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) framework, which led to the selection of 17 articles from five databases using some specified inclusion and exclusion criteria. Results show that Bayesian modeling approaches were more prevalent in the predictive landscape of Coronary Artery Disease (CAD), especially when it concerns risk estimation and prognostic modeling. Findings show that while Bayesian techniques focus on probabilistic inference and statistical learning, stochastic techniques prioritize time evolution, physical simulation, and biological plausibility. Results show that Bayesian models perform in individualized risk prediction and calibration, whereas stochastic approaches have strength in providing a deeper understanding of disease dynamics and longitudinal progression patterns. Findings show that Bayesian applications are more patient-specific, while stochastic models support longitudinal and cohort-level management. Results show that Bayesian models are more mature for deployment in predictive clinical environments, while stochastic models provide insight into disease evolution and mechanistic underpinnings. The study establishes that there is a difference between the predictive strength of Bayesian models and the mechanistic interoperability of stochastic models, highlighting the need for integrative modeling frameworks.*

Keywords *- Bayesian models, Cardiovascular disease, Coronary Artery Disease(CAD), Stochastic models, Applications.*

1. Introduction

Over the years, coronary artery disease has been an example of cardiovascular disease, which has been on an increasing trend. Aside from accounting for a third of global deaths, the disease is one that causes over 75% of the deaths in low- and middle-income countries (WHO, 2025). Coronary Artery Disease (CAD) is one of the major causes of morbidity and mortality all over the world. It is characterized by a progressive stenosis in coronary arteries due to atherosclerosis, which eventually could lead to acute events such as myocardial infarction or stroke (Shao et al., 2020). The CAD progression is a complicated and multi-faceted process with dynamic interplay of lifestyle, haemodynamic and genetic influences, which makes the prediction and management of it very difficult (Ralapanawa & Sivakanesan 2021). However, conventional deterministic models typically do not account for such inherent uncertainties and variabilities in disease trajectories; this has led to the use of probabilistic frameworks, including Bayesian formulation and stochastic modeling, in order to improve forecasting, deepen understanding, and guide clinical decision-making (Matsushita et al., 2022).

Bayesian modeling technique is based on Bayes' theorem, which describes the probability of an event, based on prior knowledge of conditions that might be related to the event (Van-de-Schoot et al., 2021). Bayesian models update those probabilities as new data is observed. Using Bayes' theorem, we can do predictions and calculate risk by updating our beliefs in the likelihood of events as we gain more evidence about these events. For example, Bayesian networks can estimate the probability of cardiovascular risk by modeling dependencies between Modifiable Risk Factors (MRF) and Non-Modifiable Risk factors (NMR), e.g., genetic factors, hypertension & diabetes mellitus (Steyvers et al., 2022). Support vector machines using Bayesian optimization predicted CAD with great accuracy. This was done by selecting features and hyperparameters jointly. It was also found to perform better than traditional classifiers such as random forest and logistic regression. Features that helped predict CAD include age, EF, and chest pain (Ismaila and Suleman 2025).

Furthermore, the Bayesian age-period-cohorts' models are gradually projecting the trends in CAD-related mortality, which estimate a decrease in "ischemic heart disease" rates but an increase in heart failure (Du et al., 2020). The authors established that the burden of heart failure is forecasted for 2035 in the United States, based on the historical data from 2000 to 2019, to predict the projections.

Yuan et al. (2023) indicated that the approaches to genomic and clinical predictions through the use of Bayesian frameworks like "ALADYNOULLI" have progressively improved the disease progression modeling across multiple conditions, clearly outperforming the clinical risk scores by incorporating the genetic relationship and progression speeds. This shows that there is a research gap and there is a need to understand the methods, applications, and clinical implications of Bayesian and stochastic modeling approaches to coronary artery disease progression.

Simultaneously, the Bayesian modeling has the ability to handle incomplete data and prior distributions, and this facilitates personalized risk stratification (Li et al., 2024). The authors established that in predicting the transitions from stable coronary heart disease to acute coronary syndrome, the use of electronic health records is required.

This probabilistic updating consistently reduces uncertainty in clinical trials, where Bayesian methods incorporate prior information to enhance device evaluation, potentially decreasing sample sizes while controlling error rates (Barati et al., 2024). Complementing Bayesian approaches, stochastic modeling introduces randomness to simulate the unpredictable nature of CAD progression, such as transitions in plaque stability or episodic disease flares (Kopa & Rusý 2021). Markov chains serve as foundational stochastic tools for modeling transitions in atherosclerosis, capturing non-linear progression and sudden plaque ruptures inspired by chaos theory and probabilistic frameworks (Brahma et al., 2024).

Advanced applications include cohort analytics that apply time-variant stochastic models to longitudinal data, outlining transition probabilities in cardiovascular diseases to support monitoring and intervention planning (Gonzalez-Jaramillo et al., 2022). Multiscale agent-based stochastic models simulate low-density lipoprotein transport, hemodynamics, and cellular dynamics, offering patient-specific insights into mechanobiological pathways driving coronary plaque progression.

In predictive contexts, stochastic elements in machine learning models, such as random forests, identify risk factors like systolic blood pressure and NT-proBNP for rapid coronary lesion progression post-percutaneous coronary intervention, enabling online platforms for clinical forecasting (Tyralis & Papacharalampous, 2024). Cyclical arguments underscore the integration of stochastic processes with real-world variability in vascular models, refining boundary conditions using velocity data for real-time predictions.

Stochastic models also address population-level impacts through simulations evaluating interventions on heart disease mortality over extended periods (Ruggeri et al., 2025). Collectively, Bayesian and stochastic models in CAD extend beyond prediction to include clinical implications, such as adaptive trial designs, personalized medicine, and enhanced risk stratification (Esmaeili et al., 2024). In pharmaceutical research, Bayesian models facilitate adaptive clinical trials by updating priors with accumulating data, optimizing dose-finding, and reducing patient exposure to suboptimal treatments.

Clinically, these models inform revascularization choices, such as preferring bypass surgery over percutaneous intervention in diabetic patients with multivessel disease, by compounding trial results with prior distributions to reinforce evidence-based recommendations (Mazumder et al., 2022).

Glanzer and Pflug (2020) asserted that stochastic methods support the multi-scale simulation for device optimization, and commemorate the stability assessment, and this implication plummets the trial duration in medical device evaluations. Correspondingly, these frameworks facilitate uncertainty quantification in healthcare predictions, based on what is established by Bayesian neural networks in chronic disease management (Abdullah et al., 2022). The foregoing deliberations may metamorphose into probabilistic outputs, an ethical guide, and efficient decision-making using Bayesian and stochastic modeling for the evaluation of Coronary Artery Disease (CAD).

However, there are still some persistent challenges in validating the specific models and deploying the diverse sources, accentuating the need for experimental research for these models to be adopted into the routine clinical practices, so that there will be a positive result in Coronary Artery Disease (CAD). Based on the foregoing, using a systematic review of the literature, this study seeks to examine the methods, applications, and clinical implications of using Bayesian and stochastic modeling approaches to coronary artery disease progression. The specific research questions for the study are to:

1. Identify the Bayesian and stochastic modeling approaches applied to the progression of coronary artery disease.
2. Examine the techniques used in Bayesian and stochastic models for coronary artery disease progression.

3. Compare the performance and strengths of Bayesian versus stochastic modeling approaches to coronary artery disease progression.
4. Evaluate the reported clinical applications of Bayesian and stochastic models in coronary artery disease management.
5. Analyze the clinical implications of the Bayesian and stochastic approaches used for coronary artery disease progression.

2. Methodology

The study adopts a qualitative systematic review design, which is aimed at understanding the methods, applications, and clinical implications of Bayesian and stochastic modeling approaches to coronary artery disease progression. The systematic review research design allows for the formulation of research questions, searching for relevant literature from credible databases, downloading literature that meets the set inclusion criteria, assessing the qualities of the final selected literature, extracting needed information from the final selected literature/studies, and analyzing the information collected from the final selected literature to generate themes (Schut et al., 2024). This structured approach makes the systematic review scientific in nature (Adeyemi et al., 2025), demonstrating the prevailing methods, applications, and clinical implications of Bayesian and stochastic modeling approaches to coronary artery disease progression.

In order to answer the research questions of this study, a structured and scientific approach was adopted to enhance repeatability and credibility. This brought about the use of specific search terms and techniques to ascertain the relevant literature. This allowed the return of search results providing relevant information for this study. This study used the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA). This is a framework designed to ensure structured and credible data collection in systematic reviews (Adeyemi et al., 2025), which is widely used for systematic reviews of literature.

The framework has 27 items, which are categorized into identification, screening, eligibility, and inclusion (Helach et al., 2023). The identification stage concerns literature search, including the sources and databases consulted; the screening stage concerns the evaluation of the abstracts and titles of the literature downloaded; the eligibility stage concerns the examination of the final selected literature using the inclusion and exclusion criteria; and the inclusion stage indicates the final selected literature for the study. In this study, the PRISMA framework was used to select sixteen (16) literature/studies from which bibliographic details and relevant evidence were extracted.

A total of five (5) databases were consulted for relevant literature on the study's research questions. These databases include Scopus, Google Scholar, Taylor and Francis, Emerald, and Web of Science. These databases were considered owing to their relevance to provide information resources on the topic of discourse. To retrieve optimum and relevant information, different search terms were used for the literature search, which are core to the major aim of this study and the specific research questions identified.

Some of the search terms used include "Bayesian modeling approach to coronary artery disease progression", "stochastic modeling approaches to coronary artery disease progression", "Methods of Bayesian AND stochastic modeling approaches to coronary artery disease progression", "Applications of Bayesian AND stochastic approaches to coronary artery disease progression", and "Clinical implications of Bayesian and stochastic approaches to coronary artery disease progression". The study used the "AND" Boolean operator to widen the search scope. After all the literature was retrieved, they were scanned to see those that meet up with the inclusion and exclusion criteria.

Meanwhile, the search period was between 2015 and 2026. Thus, timeliness or lack thereof does not have any significant effect on the study's findings. All the collected or extracted evidence from the final selected literature was analyzed using the "a priori" thematic analysis, which involves using some predetermined themes to analyze the data (Adeyemi et al., 2025).

3. Results and Discussion

On the research question one, which is about Bayesian and stochastic modeling approaches applied to Coronary Artery Disease (CAD) progression, the study showed that Bayesian modeling approaches were more prevalent in the predictive landscape of CAD, especially in risk estimation and prognostic modeling. For instance, Suo et al. (2024) showed the ability of a Bayesian network-based model to handle missing data and censored observations in Electronic Health Records (EHRs) for coronary artery disease.

Jian et al. (2024) applied a Bayesian network to predict atrial fibrillation among CAD patients and showed a strong discriminative performance (AUC $\approx$ 0.90), which reinforces the suitability of Bayesian interference for multivariate cardiovascular risk modeling. Gupta et al. (2019) further indicated the flexibility of probabilistic graphical modeling in coronary artery disease.

Three of the final selected seventeen (17) studies advanced a Bayesian approach through Dynamic Bayesian Networks (DBN). Orphanou et al. (2015) extended DBNs with temporal abstractions to capture longitudinal disease evolution, which demonstrates that temporal integration enhances prognostic precision. Aside from its usage in probabilistic networks, Bayesian optimization techniques were also used in hybrid machine learning contexts, such as Fractional Flow Reserve (FFR) modeling (Yin et al., 2019) and hyperparameter-tuned SVM classification (Baratpur et al., 2025). In comparison, stochastic approaches were mainly used to model disease progression dynamics rather than static risk prediction.

Brahma et al. (2024) implemented a Continuous-Time Markov Chain (CTMC) model to estimate time-variant transition probabilities between cardiovascular states, thereby capturing progression pathways over a 16-year period. Warren et al. (2025) used an agent-based multi-physics simulation model integrating hemodynamics, tissue mechanics, and pathophysiology to represent coronary artery disease modeling processes. Unlike Bayesian predictive models, these stochastic models emphasized mechanistic and temporal realism.

On the research question two, which focuses on the techniques used in Bayesian and stochastic models, the findings indicate that Bayesian approaches rely heavily on probabilistic graphical structures and statistical learning techniques. Some of the techniques used include feature selection methods such as LASSO regression, which was integrated prior to network construction (Jian et al., 2024); while calibration curves and decision curve analysis were incorporated to validate clinical utility (Suo et al., 2024). Baratpur et al. (2025) showed that Bayesian hyperparameter tuning enhanced classification accuracy and robustness.

Moreover, Yin et al. (2019) demonstrated that uncertainty quantification and global sensitivity analysis in FFR modeling indicate that Bayesian models can quantify physiological variability. In contrast, stochastic modeling techniques were more about time-dependent state transitions and simulation.

The CTMC approach was used by Brahma et al. (2024) to estimate hazard-like transition probabilities between disease states, which provides interpretable progression metrics. Warrant et al. (2025) used agent-based modeling to incorporate computational fluid dynamics and finite element analysis to simulate vascular remodeling, which helps bridge biological processes with biomechanical stress patterns. Mazumder et al. (2022) adopted an in-silico cardiac computational model to generate synthetic PPG signals, which combines mechanistic modeling with statistical classification.

On the research question three, which focused on comparative performance and strength of Bayesian and stochastic modeling approaches to coronary artery disease progression, there are differences in their level of performance and strengths. Results on the comparative analysis revealed a distinction between predictive discrimination and mechanistic interpretability. The findings provide that Bayesian-based models have higher AUC values and strong classification metrics. For example, Gupta et al. (2019) showed AUC ≈ 0.93, while Baratpur et al. (2025) showed AUC ≈ 0.99 with 97.67% accuracy. This implies that the Bayesian models have superior performance in diagnostic prediction tasks and risk stratification.

In contrast, the strength of stochastic models lies in their capacity to estimate clinically meaningful transition probabilities and simulate pathophysiological processes. This means that they are not basically evaluated using classification metrics. Brahma et al. (2024) identified distinct transition rates between myocardial infarction, stroke, angina, and heart failure states, which offer insights into disease trajectories rather than classification accuracy.

On the fourth research question, which focuses on the clinical applications of Bayesian and stochastic models in coronary artery disease management, findings show distinct applications for the two approaches. The study’s findings showed that Bayesian models are more aligned with decision support systems.

For instance, Suo et al. (2024) showed that Bayesian network models enhance EHR-based prediction and decision curve utility. Gupta et al. (2019) highlighted the adaptive decision-making under uncertainty, while Bertsimas et al. (2020) proffered a personalized prescriptive algorithm, named ML4CAD, which improved time-to-adverse-event outcomes by over 24%. This suggests that the applications are ready for real-world clinical integration.

In contrast, stochastic approaches contribute at the systems and planning level. Brahma et al. (2024) developed a cohort analytics tool that serves as an eHealth monitoring artifact for guiding intervention strategies. Warrant et al. (2025) provided predictive insights into vascular remodeling, which may inform surgical or interventional planning.

On research question five, which focuses on the clinical implications of the Bayesian and stochastic approaches used for coronary artery disease progression, results show different implications for the two approaches. For the Bayesian approach, the clinical implication lies in precision cardiology. This concerns their ability to handle missing data, quantify uncertainty, and maintain probability calibration, which makes them suitable for real-time clinical decision support. These tools enhance diagnostic confidence, optimize treatment selection, and personalize long-term management strategies.

For stochastic approaches, they deepen the understanding of coronary artery disease as a progressive, multi-state disease. By modeling temporal transitions and biomechanical interactions, they inform preventive strategies and intervention timing. Their implications extend to public health planning and chronic disease surveillance.

Table 1. Electronic Search Strategy (Extract from five databases)

S/N	Search Terms	Web of Science	Scopus	Google Scholar	Emerald	Taylor and Francis
		Number of hits				
S1	Bayesian modeling approach to coronary artery disease progression	5821	4732	1293	2405	4095
S2	Stochastic modeling approaches to coronary artery disease progression	4532	5320	1384	1930	3281
S3	Methods of Bayesian AND stochastic modeling approaches to coronary artery disease progression	4000	3000	7000	2300	5200
S4	Applications of Bayesian AND stochastic approaches to coronary artery disease progression	7100	15000	21000	1800	4300
S5	Clinical implications of Bayesian and stochastic approaches to coronary artery disease progression	19000	1500	5000	1540	3100
Databases search limits adopted.						
Duplicates removed		107	113	181	85	95
Titles and abstracts checked		83	88	120	45	71
Secondary research		50	54	83	40	38
Peer-reviewed articles/journals		07	05	07	05	02
English language only		NA	N/A	02	N/A	N/A
Final selected		3	3	5	5	0

Source: Author's Literature Search (2026)

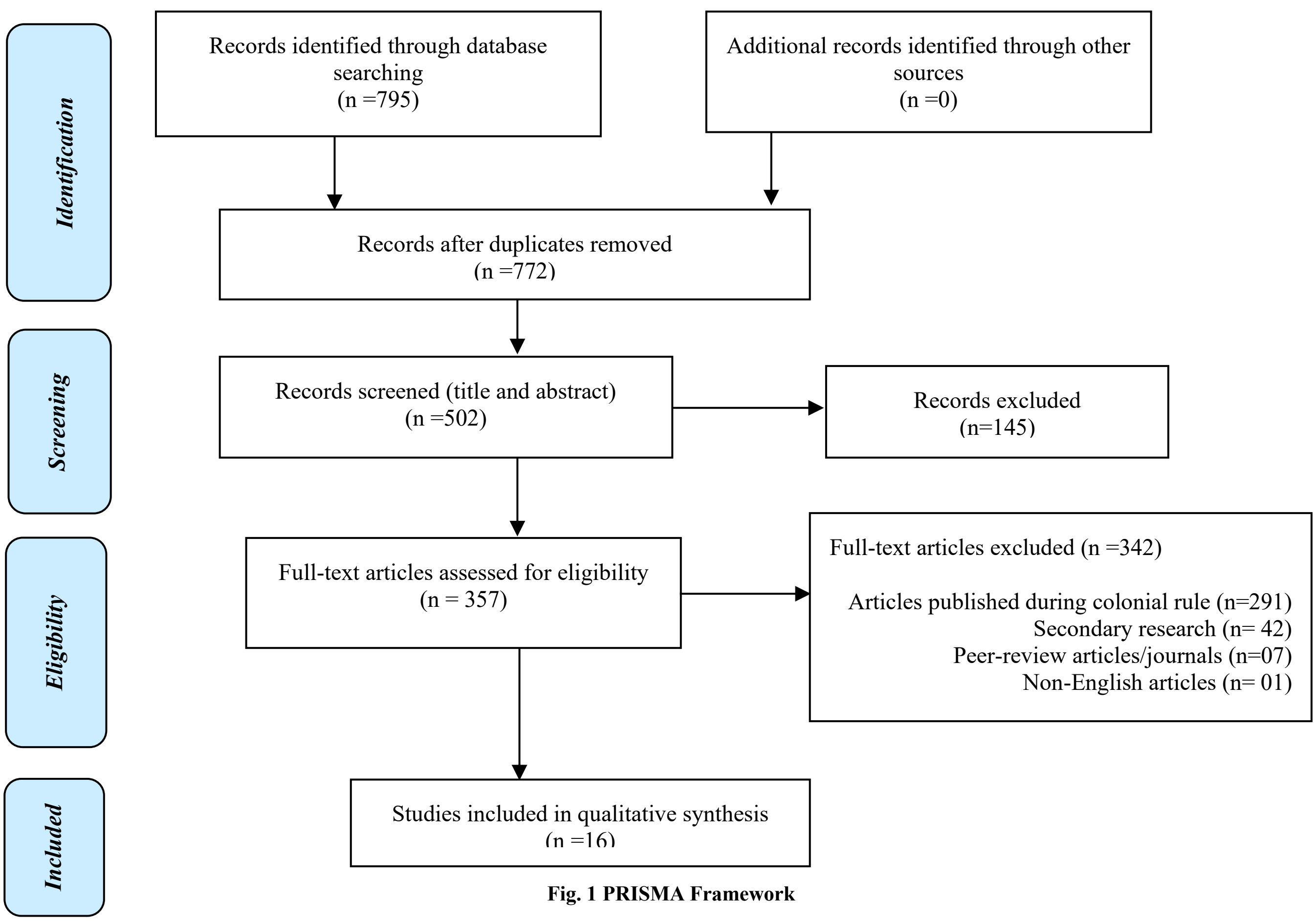

Fig. 1 PRISMA Framework

4. Implications

The study suggests that Bayesian and stochastic modeling approaches can enhance data-driven cardiovascular care. Thus, policymakers in healthcare systems should develop policies that support the integration of advanced predictive analytics into clinical infrastructure, especially through electronic health record-based decision support systems. Since Bayesian models demonstrate predictive performance and can handle incomplete clinical data, health policy frameworks should be designed to ensure the adoption of such models in hospital information systems.

Moreover, there is a need for healthcare ministries and/or agencies to design guidelines for validating and implementing machine learning-based clinical decision tools to ensure reliability, transparency, and patient safety. For stochastic models, their ability to simulate disease progression can inform cardiovascular health policies, prevention programs, and resource allocation. The policymakers can design population-level screening strategies and intervention initiatives that are aimed at reducing the burden of coronary artery disease.

The findings highlight the complementary value of Bayesian and stochastic modeling techniques in cardiology, which is a clinical practice. Bayesian models provide clinicians with high-performing predictive tools that support risk stratification, diagnosis, and personalized treatment planning. Bayesian models would be useful in clinical environments where data may be imperfect, as they quantify uncertainty and operate effectively with incomplete patient data. Therefore, clinicians should consider incorporating Bayesian models into routine clinical workflows. In contrast, stochastic modeling approaches offer clinicians a deeper understanding of disease dynamics and progression patterns over time. This can support clinical planning by forecasting potential disease trajectories and identifying transition points for intervention. Thus, cardiologists and clinical researchers can use stochastic simulations to improve preventive strategies, optimize treatment timing, and guide long-term disease management programs.

Theoretically, the study findings contribute to the development of theories in the area of computational cardiology and health analytics. The distinction between predictive strength of Bayesian models and mechanistic interoperability of stochastic models highlights the need for integrative modeling frameworks. The study underscores the idea that disease modeling benefits from combining probabilistic inference with dynamic system simulation. Future theoretical development may consider the integration of Bayesian predictive learning with stochastic state-transition modeling. This can help enhance both predictive accuracy and explanatory power, which would ultimately advance methodological innovation in biomedical data science and disease progression research.

For society, an improved modeling of coronary artery disease progression has the potential to enhance public health outcomes. The study highlights that more accurate risk prediction models can facilitate earlier detection of cardiovascular risks, which enables individuals to receive timely interventions and adopt healthier lifestyles. This could contribute to reducing mortality and healthcare costs associated with coronary artery disease. Furthermore, stochastic simulations can help government and public health organizations anticipate future healthcare demands by planning more efficient cardiovascular care services. Overall, the integration of these modeling approaches into healthcare systems can enhance quality of life, provide more equitable access to predictive healthcare technologies, and strengthen societal capacity to manage the growing burden of coronary artery disease.

5. Conclusion

The study recognized that Bayesian modeling approaches are more prevalent in the predictive landscape of Coronary Artery Disease (CAD), especially in risk prognostic modeling and risk estimation. The Dynamic Bayesian Networks (DBN) were advanced Bayesian approaches that help in temporal integration to enhance prognostic precision. Stochastic approaches were primarily used to model disease progression dynamics rather than static risk prediction. Unlike Bayesian predictive models, these stochastic models emphasized mechanistic and temporal realism. The study established that Bayesian approaches rely on probabilistic graphical structures and statistical learning techniques, while stochastic modeling techniques are more about time-dependent state transitions and simulation. The study concludes that there is a distinction between predictive discrimination and mechanistic interpretability in Bayesian modeling approaches, while the strength of stochastic models is in their capacity to estimate clinically meaningful transition probabilities and simulate pathophysiological processes. The study emphasized that Bayesian models are more aligned with decision support systems, while stochastic approaches contribute at the systems and planning level. The study recognized that, when it comes to the Bayesian approach, the clinical implication lies in precision cardiology. For stochastic approaches, the study established that they deepen understanding of coronary artery disease as a progressive, multi-state disease.

Conflicts of Interest

The author does not have any financial or non-financial interest in the study.

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APPENDIX I
DATA EXTRACTION TOOL
Bayesian and Stochastic Modeling Approaches to Coronary Artery Disease Progression: A Systematic Review of Methods, Applications, and Clinical Implications

S/N	Research titles and authors	Aims	Methodology	Findings
1	Development and validation of a Bayesian network-based model for predicting coronary heart disease risk from electronic health records Suo et al. (2024)	The study aims to develop and validate a Bayesian network-based model for predicting coronary heart disease risk from electronic health records.	This is a retrospective cohort study of coronary heart disease at Weihai Municipal Hospital on unique patients aged 18 to 96 years between 2013 and 2021.	– The proposed risk prediction model has demonstrated significant effectiveness in handling the complexities of electronic health record data, which often involve extensive missing data and censoring. This approach may offer potential assistance in the use of electronic health records to enhance patient outcomes. – The calibration curve demonstrated its good calibration ability, and the decision curve analysis showed its clinical usefulness.
2	The identification and prediction of atrial fibrillation in coronary artery disease patients: A multicentre retrospective study based on a Bayesian network Jian et al. (2024)	The study aims to identify and predict atrial fibrillation in coronary disease patients, using a Bayesian network.	A total of 12,552 patients with Coronary Artery Disease (CAD) were divided into the CAD patients with Atrial Fibrillation (AF) group (CHD-AF group) and the CAD patients without AF group (non-AF group). Univariate analysis and the LASSO regression method were used to screen for potential risk factors.	– Fourteen indicators were included in the Bayesian Network (BN), including age, gender, Systolic Blood Pressure (SBP), low-density lipoprotein cholesterol (LDL-C), serum Uric Acid (UA), Gamma-Glutamy Transferase (GGT), direct bilirubin (DBIL), lipoproteins [LP(a)], NYHA cardiac function grading, diabetes mellitus and hypertension, palpitation, dyspnoea, and the left atrial diameter. The BN model performs well on both the test set (AUC = 0.90) and internal 10-fold cross-validation (AUC = 0.89 ± 0.01).
3	Bayesian network analysis of factors influencing type 2 diabetes, coronary heart disease, and their comorbidities Kong et al. (2024)	The study examines the factors influencing coronary heart disease and its comorbidities.	Employing a case-control design, the study compared individuals with T2DM, CAD, and their comorbidities (case group) with healthy counterparts (control group). Univariate and multivariate Logistic regression analyses were conducted to identify disease-influencing factors. The study involved 3,824 participants, with 982 cardiovascular disease (CAD) cases.	– For CAD, factors with direct and indirect effects included age, smoking, Systolic Blood Pressure (SBP), exercise, meat, and fruit intake, while sleeping time and heart rate showed direct effects. Regarding CAD comorbidities, age, FBG, SBP, fruit, and sweet intake demonstrated both direct and indirect effects.

4	One-dimensional modeling of fractional flow reserve in coronary artery disease: Uncertainty quantification and Bayesian optimization Yin et al. (2019)	The study evaluated a one-dimensional modeling of fractional flow reserve in coronary artery disease using uncertainty quantification and Bayesian optimization.	The study developed a predictive probabilistic model of fractional flow reserve (FFR), which quantifies the uncertainty of the predicted values with significantly lower computational costs. Based on global sensitivity analysis, we first identify the important physiologic and anatomic parameters that impact the predictions of FFR. Our approach is to employ one-dimensional blood flow simulations of coronary trees that offer fast FFR predictions with uncertainty quantification in computing blood pressure and flow distributions within the coronaries.	– The nonlinear 1D FFR values are within 2% error of the 3D results for mean pressure and flow rates. – The global sensitivity analysis signifies the high impact of the segmentation error on the stenosis lumen radius. – Among the lumped network parameters, the aortic resistance accounts for most of the uncertainty in FFR. – Multifidelity surrogate models, along with Bayesian optimization, are shown to be efficient in addressing parameter inference problems.
5	DBN-extended: a Dynamic Bayesian Network (DBN) model extended with temporal abstractions for coronary heart disease prognosis. Orphanou et al. (2015)	The study extended the DBN model that integrates TA methods with DBNs applied for the prognosis of the risk for coronary heart disease.	More specifically, the study demonstrated the derivation of Temporal Abstractions (TAs) from data, which are used for building the network structure. It used machine learning algorithms to learn the parameters of the model through data. It applied the extended model to a longitudinal medical dataset and compared its performance to the performance of a DBN implemented without TAs.	– The results we obtain demonstrate the predictive accuracy of our model and the effectiveness of our proposed approach.
6	Coronary artery disease prediction using Bayesian-optimized support vector machine with feature selection Baratpur et al. (2025)	The study predicted coronary artery disease using a Bayesian-optimized support vector machine with feature selection.	A hybrid decision tree–AdaBoost method is employed to select 30 clinically relevant features. To prevent data leakage, SMOTE oversampling is applied exclusively within each training fold of a 10-fold cross-validation pipeline. The Support Vector Machine (SVM) model is optimized using Bayesian hyperparameter tuning and compared against the Sea Lion Optimization Algorithm (SLOA) and grid search. Shapley additive explanations (SHAP) analysis is utilized to interpret the feature contributions.	– The SVM_Bayesian model achieves 97.67% accuracy, 95.45% precision, 100.00% sensitivity, 97.67% F1-score, and 99.00% AUC, outperforming logistic regression (93.02% accuracy, 92.68% F1-score), random forest (95.45% accuracy, 93.33% F1-score), standard SVM (77.00% accuracy), and SLOA-optimized SVM (93.02% accuracy). Ablation studies and Wilcoxon signed-rank tests confirm the statistical superiority of the proposed model.

				– SHAP analysis reveals clinically meaningful feature contributions (e.g., Typical Chest Pain, Age, EFTTE). 95% bootstrap confidence intervals and temporal generalization on an independent test set ensure robustness and prevent overfitting.
7	Enhancing coronary artery disease prognosis: a novel dual-class boosted decision trees strategy for robust optimization Mahmood et al. (2024)	The study examined coronary disease prognosis using a novel dual-class boosted decision tree strategy for robust optimization.	This study used machine learning technology to predict early-stage CHD risk and identify risk factors. Advanced ML models analyze medical imaging, genetic markers, lifestyle, and environmental factors to accurately predict Coronary Heart Disease (CHD) onset and progression. Our research introduces four novel models based on two-class Logistic Regression (two-class LR), two-class Neural Network (two-class NN), two-class Decision Jungle (two-class DJ), and two-class Boosted DT (two-class BDT).	– Our comparative analysis reveals that the two-class Boosted DT model is the most effective, achieving an AUC score of 0.991. This model excels in real-time monitoring by predicting minor changes in patients' health markers, allowing for timely adjustments in treatment plans. It optimizes medication selection, dosing, and intervention timing based on patient characteristics, improving therapeutic efficacy and reducing side effects. – The study reveals the transformative potential of these advanced ML models in CAD prediction and management. By focusing on feature selection, algorithm improvement, and integration, our models analyze medical imaging, genetic markers, lifestyle, and environmental factors to predict the onset and progression of CHD accurately.
8	Bridging hemodynamics, tissue mechanics, and pathophysiology in coronary artery disease: A new agent-based model with tetrahedral mesh integration Warren et al. (2025)	The study aims to bridge hemodynamics, tissue mechanics, and pathophysiology in coronary artery disease, using a new agent-based model with tetrahedral mesh integration.	A volumetric 3D tetrahedral mesh of the artery is shared between computational fluid dynamics (CFD), agent-based models (ABM), and finite element analysis (FEA) to simulate geometrical and biological changes with continuity and consistency. The CFD and FEA modules, implemented with FEBio, calculate the wall shear stress and structural stress and strain, respectively. These biomechanical values are passed to the ABM,	– Initial results using multi-physics simulation (CAFe) suggest atherosclerotic arteries seek to maintain a hemodynamic threshold through preferential growth and remodeling downstream of a stenosis. The innovative approach described herein marks a significant step forward in predictive modeling of CAD progression and paves the way for powerful coupling of the

			implemented in MATLAB, which simulates vascular remodeling using molecular diffusion, cell migration, equations for cellular processes, and volumetric growth to update the geometry.	spatiotemporal-dependent remodeling paradigms exhibited by the disease.
9	Synthetic PPG signal generation to improve coronary artery disease classification: Study with a physical model of the cardiovascular system Mazumder et al. (2022)	The study used a physical model of the cardiovascular system to examine synthetic Photoplethysmogram (PPG) signal generation to improve coronary artery disease classification.	This paper presents a novel approach to generating synthetic Photoplethysmogram (PPG) data using a physical model of the cardiovascular system to improve classifier performance with a combination of synthetic and real data. The physical model is an in-silico cardiac computational model, consisting of a four-chambered heart with electrophysiology, hemodynamic, and blood pressure auto-regulation functionality. Starting with a small number of measured PPG data, the cardiac model is used to synthesize healthy as well as PPG time-series pertaining To Coronary Artery Disease (CAD) by varying pathophysiological parameters.	– Results are presented in two perspectives, namely, (i) using artificially reduced real disease data and (ii) using all the real disease data. In both cases, by augmenting with the synthetic data for training, the performance (sensitivity, specificity) of the classifier changes from (i) (0.65, 1) to (1, 0.9) and (ii) (1, 0.95) to (1, 1). – The proposed hybrid approach of combining physical modeling and statistical feature space selection generates realistic PPG data with pathophysiological interpretation and can outperform a baseline Generative Adversarial Network (GAN) architecture with a relatively small amount of real data for training. – This proposed method could aid as a substitution technique for handling the problem of bulk data required for training machine learning algorithms for cardiac healthcare applications.
10	Predictive performance and clinical implications of machine learning in early coronary heart disease detection Gowda et al. (2024)	The study aims to predict performance and clinical implications of machine learning in early coronary heart disease detection.	The study employed a large set of data containing patients' features: demographic characteristics, health history, test results, and diagnosis. The study used Random Forest, Support Vector Machine, and Neural Networks to estimate the probability of the incidence of CHD. Cohesion was performed using cross-validation for training and validation of the models with accuracy, precision, recall, F1 score, and ROC-AUC study parameters.	– The findings of this study show that through machine learning, the identification and diagnosis of CHD in its early stages can be significantly improved, with the RF model giving the highest accuracy. Challenges and possibilities of using these predictive tools in clinical practice are examined, with the focus on possible enhancements of patients' treatment and outcomes. Thus, the study proved that machine learning-based predictive

				models can be considered a promising avenue for the early diagnosis of CHD, which should be further explored and implemented.
11	Leveraging fuzzy embedded wavelet neural network with multi-criteria decision-making approach for coronary artery disease prediction using biomedical data Ragab et al. (2024)	The study examined how a fuzzy embedded wavelet neural network with a multi-criteria decision-making approach for coronary artery disease prediction using biomedical data.	The study presents a Leveraging Fuzzy Wavelet Neural Network with Decision Making Approach for Coronary Artery Disease Prediction (LFWNNDMACADP) technique. The presented LFWNNDMA-CADP technique focuses on the multi-criteria decision-making model for predicting CAD using biomedical data. In the LFWNNDMA-CADP method, the data pre-processing stage utilizes Z-score normalization to convert the input data into a uniform format. Furthermore, the Improved Ant Colony Optimization (IACO) method is used for selecting an optimum subset of features. Furthermore, the classification of CAD is accomplished by utilizing the fuzzy wavelet neural network (FWNN) technique. Finally, the hyperparameter tuning of the FWNN model is accomplished by employing the hybrid Crayfish Optimization Algorithm with the Self-adaptive Differential Evolution (COASaDE) technique.	– The simulation outcomes of the LFWNNDMACADP approach are investigated under a benchmark database. The experimental validation of the LFWNNDMA-CADP approach portrayed a superior accuracy value of 99.49% over existing techniques.
12	Development of a cohort analytics tool for monitoring progression patterns in cardiovascular diseases: Advanced stochastic modeling approach. Brahma et al. (2024)	The study developed a cohort analytics tool for monitoring progression patterns in cardiovascular disease using an advanced stochastic modeling approach.	Our data were sourced from 9 epidemiological cohort studies by the National Heart, Lung, and Blood Institute and comprised chronological records of 1274 patients associated with 4839 CVD episodes across 16 years. We then used the continuous-time Markov chain method to develop our model, which offers a robust approach to time-variant transitions between disease states in chronic diseases.	– Our study presents time-variant transition probabilities of CVD state changes, revealing patterns of CVD progression against time. We found that the transition from Myocardial Infarction (MI) to stroke has the fastest transition rate (mean transition time 3, SD 0 days, because only 1 patient had an MI-to-stroke transition in the dataset), and the transition from MI to angina is the slowest (mean transition time 1457, SD 1449 days).

				– Congestive heart failure is the most probable first episode (371/840, 44.2%), followed by stroke (216/840, 25.7%). The resultant artifact is actionable as it can act as an eHealth cohort analytics tool, helping physicians gain insights into treatment and intervention strategies. Through expert panel interviews and surveys, we found 9 application use cases of our model.
13	Probabilistic graphical modeling for estimating risk of coronary artery disease: Applications of a flexible machine-learning method Gupta et al. (2019)	The study applied a flexible machine-learning method to estimate the risk of coronary artery disease using probabilistic graphical modeling.	The study used Bayesian Networks (BNs) to model the risk of CAD using the Z-Alizadehsani data set—a published real-world observational data set of 303 Iranian patients at risk for CAD. The study also described how BNs can be used for the incorporation of background knowledge, individual risk prediction, handling missing observations, and adaptive decision making under uncertainty.	– BNs performed on par with machine-learning classifiers at predicting CAD and showed better probability calibration. They achieved a mean 10-fold area under the receiver-operating characteristic curve (AUC) of 0.93 ± 0.04, which was comparable with the performance of logistic regression with L1 or L2 regularization (AUC: 0.92 ± 0.06), support vector machine (AUC: 0.92 ± 0.06), and artificial neural network (AUC: 0.91 ± 0.05). We describe the use of BNs to predict with missing data and to adaptively calculate prognostic values of individual variables under uncertainty.
14	Personalized treatment for coronary artery disease patients: a machine learning approach. Bertsimas et al. (2020)	The study used a machine learning approach to examine personalized treatment for coronary artery disease patients.	Using the electronic health records of 21,460 patients, the study created data-driven models for personalized CAD management that significantly improve health outcomes relative to the standard of care. It developed binary classifiers to detect whether a patient will experience an adverse event due to CAD within a 10-year time frame. For each treatment, we also create a series of regression models that are based on different supervised machine learning algorithms. The study estimates, with an average R^2=0.801, the	– The study showed that the methodology improves the expected TAE upon the current baseline by 24.11%, increasing it from 4.56 to 5.66 years. The algorithm performs particularly well for the male (24.3% improvement) and Hispanic (58.41% improvement) subpopulations. Finally, we create an interactive interface, providing physicians with an intuitive, accurate, readily implementable, and effective tool.

			outcome of interest: the time from diagnosis to a potential adverse event (TAE). Leveraging combinations of these models, the study presents ML4CAD, a novel personalized prescriptive algorithm.	
15	Coronary artery heart disease prediction: A comparative study of computational intelligence techniques. Ayon et al. (202)	The study compared a number of computational intelligence techniques for the prediction of coronary artery heart disease.	Seven computational intelligence techniques, named Logistic Regression (LR), Support Vector Machine (SVM), Deep Neural Network (DNN), Decision Tree (DT), Naïve Bayes (NB), Random Forest (RF), and K-Nearest Neighbor (K-NN), were applied, and a comparative study was conducted. The performance of each technique was evaluated using Statlog and the Cleveland and heart disease dataset, which were retrieved from the UCI machine learning repository database, using several evaluation techniques.	– In the comparative study, the deep neural network performed better and obtained an accuracy of 98.15% with the Statlog dataset. In the case of the Cleveland dataset, SVM achieved an accuracy of 97.36%, which is comparatively better than the others. This type of computational intelligence techniques plays an important role in medical diagnoses.
16	Machine learning predictive models for coronary artery disease Muhammad et al. (2021)	The study used machine learning predictive models for CAD that have been developed with a diagnostic CAD dataset obtained in the two General Hospitals in Kano State, Nigeria.	The medical expert diagnostic datasets for coronary artery disease obtained in the two General Hospitals in Kano State, Nigeria, were prepared in the appropriate format with the help of medical experts in the hospitals, and only data instances of the dataset without missing values were considered and collected. Therefore, there are only 506 data instances of the dataset without missing value. The dataset is labeled one with 18 features, including demographic, history, and clinical features of the patient's CAD.	– The dataset was applied to machine learning algorithms, which include support vector machine, K nearest neighbor, random tree, Naïve Bayes, gradient boosting, and logistic regression algorithms to build the predictive models, and the models were evaluated based on accuracy, specificity, sensitivity, and Receiver Operating Characteristic (ROC) performance evaluation techniques. In terms of accuracy random forest-based machine learning model emerged to be the best model with 92.04%, for specificity Naive Bayes based machine learning model emerged to be the best model with 92.40%, while for sensitivity support vector machine based machine learning model emerged to be the best model with 87.34% and

				for ROC, random forest-based machine learning model emerged to be the best model with 92.20%. The decision tree generated with the random forest machine learning algorithm, which happened to be the best model in terms of accuracy and ROC, can be converted into production rules and used to develop an expert system for the diagnosis of CAD patients in Nigeria.