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Research Article

Predictive Analytics in Chronic Disease Management Using AI to Enhance Cardiovascular Health and Patient Record Outcomes

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Keywords

Predictive analytics, artificial intelligence, cardiovascular health, chronic disease management

Abstract

Introduction: The integration of AI and predictive analytics into clinical workflows is transforming chronic disease management by enabling early risk detection, personalized treatment, and better resource use, especially in cardiovascular care. This study evaluated the clinical impact, predictive accuracy, and practical feasibility of AI-driven analytics for improving cardiovascular outcomes and optimizing patient records in a tertiary care setting.

Materials and Methods: A prospective cohort study was conducted at KUST, Kohat, and PIMS, Islamabad, from January to December 2023, enrolling 290 adults with cardiovascular disease. Data from electronic health records and structured interviews informed supervised machine learning models (logistic regression and random forest), validated via cross-validation. Deployed as a real-time Streamlit app, the models were compared to the Framingham Risk Score. Primary outcomes were cardiovascular event prediction, with secondary analyses on treatment recommendations, patient satisfaction, and healthcare utilization pre- and post-AI implementation.

Results: The mean patient age was 58.4 years (SD ± 10.2), with a male predominance (54.48%). Common comorbidities included hypertension (70.34%), hyperlipidemia (42.76%), and diabetes (36.90%). The random forest model outperformed traditional risk scoring, achieving 81.57% accuracy, 85.31% sensitivity, and 78.96% specificity. Implementation of the AI-driven platform led to a reduction in cardiovascular events, including myocardial infarctions (from 28 to 19 cases) and strokes (from 18 to 9 cases). Post-AI, significant improvements were observed in lifestyle modifications (+13.11%), intervention referrals (+24.44%), and surgical procedures (+33.33%). Additionally, hospital admissions and emergency visits declined by 12.5% and 26.88%, respectively. Patient satisfaction was notably high, with 85.17% reporting ease of use and 80.69% expressing trust in AI-guided recommendations.

Conclusion: The deployment of AI-powered predictive analytics in cardiovascular care demonstrated significant improvements in risk prediction accuracy, patient outcomes, and healthcare delivery efficiency. These findings support the integration of AI as a viable, patient-centered tool in chronic disease management, offering a path toward more proactive, precise, and data-driven clinical interventions.

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Introduction

In recent years, the integration of artificial intelligence (AI) and predictive analytics has revolutionized various sectors, particularly in healthcare [1,2]. The utilization of these technologies holds tremendous promise in enhancing the management of chronic diseases, with cardiovascular health being a critical focus area [3]. Chronic diseases, such as cardiovascular conditions, impose significant burdens on healthcare systems globally, necessitating innovative approaches to improve patient outcomes and optimize resource allocation [4].

The advent of predictive analytics allows healthcare providers to leverage vast amounts of patient data to forecast health trends and risks accurately [5]. By analyzing historical patient records, AI algorithms can identify patterns and correlations that traditional methods might overlook [6]. This capability not only aids in early detection of cardiovascular issues but also enables personalized treatment plans tailored to individual patient needs [7].

The application of AI in chronic disease management extends beyond diagnostics to encompass predictive modeling of patient outcomes [8,9]. By continuously learning from real-time data inputs, these models refine their predictions, thereby supporting clinicians in making informed decisions promptly [10]. This proactive approach not only enhances patient care but also contributes to the overall efficiency of healthcare delivery systems [11].

The integration of AI-driven predictive analytics in cardiovascular health management addresses several challenges faced by healthcare providers [12]. These include the optimization of treatment strategies based on individual patient responses and the reduction of unnecessary healthcare expenditures through preventive interventions [13]. Such advancements are poised to transform the paradigm of chronic disease management, paving the way for a more patient-centered and data-driven healthcare ecosystem [14].

Despite these advancements, gaps remain in current research efforts. Many existing studies focus predominantly on the technical aspects of AI applications in healthcare rather than exploring the practical implications and challenges in real-world clinical settings. Understanding these gaps is crucial for further refining AI-driven solutions and ensuring their seamless integration into existing healthcare infrastructures.

Objective

The study objective was to explore the effectiveness and feasibility of predictive analytics powered by AI in enhancing cardiovascular health management and optimizing patient record outcomes.

Materials and Methods

Study Design and Settings

This prospective cohort study was conducted at the Kohat University of Science and Technology (KUST), Kohat and Pakistan Institute of Medical Sciences (PIMS), Islamabad, Pakistan, spanning from January 2023 to December 2023. The study aimed to evaluate the effectiveness of predictive analytics powered by AI in enhancing cardiovascular health management and optimizing patient record outcomes.

Inclusion and Exclusion Criteria

Patients aged 18 years or older diagnosed with cardiovascular diseases were eligible for inclusion. The exclusion criteria for the study included patients under 18 years of age, those without diagnosed cardiovascular diseases, individuals with incomplete medical records, those unable to provide informed consent.

Sample Size Determination

The sample size of 290 patients was determined based on statistical power calculations. This ensured sufficient sensitivity to detect significant differences in cardiovascular health outcomes with a confidence level of 95% and a power of 80%.

Data Collection

This prospective cohort study involved the extraction of comprehensive clinical data from the electronic health records (EHRs) of 290 patients diagnosed with cardiovascular disease at the PIMS, Islamabad, between January 2023 and December 2023. The variables collected encompassed demographic details (e.g., age, gender, socioeconomic status), past medical history (e.g., hypertension, diabetes, hyperlipidemia), lifestyle factors (e.g., smoking, alcohol use, physical inactivity), and medication profiles. Laboratory data, including lipid profiles and glucose levels, were also included where available.

To ensure the completeness and accuracy of data, supplementary interviews were conducted by trained medical personnel for patients whose records were incomplete or inconsistent. This approach ensured that missing variables were addressed and ambiguities clarified. The final dataset reflected a robust and representative clinical profile suitable for predictive analytics.

AI Algorithms and Predictive Modeling

Two supervised machine learning algorithms—logistic regression and random forest classifiers—were developed to predict the likelihood of future cardiovascular events (e.g., myocardial infarction, stroke, or heart failure progression). Feature engineering involved the selection of clinically relevant predictors based on prior literature and exploratory data analysis. Variables such as age, sex, blood pressure, comorbidities, lipid levels, and lifestyle risk factors were included.

Models were trained using 80% of the dataset and evaluated on the remaining 20% using k-fold cross-validation (k=5) to minimize bias and overfitting. Performance metrics—accuracy, sensitivity, specificity, and ROC-AUC—were calculated to assess model efficacy. The logistic regression model achieved an accuracy of 78.38%, while the random forest model achieved a higher accuracy of 81.57%, alongside greater sensitivity and specificity.

The primary outcome was defined as the accurate prediction of cardiovascular events. Secondary outcomes included the appropriateness and clinical relevance of AI-generated treatment recommendations and the impact on healthcare utilization metrics such as hospital admissions and emergency visits.

Model Deployment and Application

To translate the machine learning models into a clinically usable tool, a lightweight and interactive web application was developed using Streamlit, a free and open-source Python framework tailored for rapid data app deployment. The deployed application was designed to operate within the hospital's local network, ensuring data privacy and secure access for authorized medical personnel.

This tool functioned as a clinical decision support system (CDSS), allowing real-time interaction with the predictive model. The application accepted patient-specific input, performed backend calculations using trained AI models, and returned risk scores and treatment guidance instantly.

Application Architecture: Core Modules

The application consisted of five functional modules, each designed to enhance clinician usability and support informed decision-making. These modules are summarized in the Table 1.

Table 1: Primary modules

Module	Function	Clinical Relevance
1. Input Panel	Allows clinicians to input variables such as age, sex, blood pressure, cholesterol status, and presence of diabetes.	Facilitates personalized prediction; mimics EHR input interface.
2. Risk Prediction Display	Computes and displays cardiovascular risk probability with color-coded indicators (Low, Moderate, High).	Enables quick risk stratification for early intervention.
3. Treatment Recommendations	Displays dynamic, evidence-based suggestions (e.g., medication intensification, lifestyle modifications) based on model output.	Assists clinical decisions tailored to individual risk profiles.
4. Feature Importance Viewer	Ranks input variables according to their influence on the prediction (via model feature importances or SHAP values).	Enhances transparency and trust in AI-assisted recommendations.

5. Interpretability Layer	Optional SHAP-based visualizations to explain individual predictions in terms of each feature's contribution.	Supports informed consent, clinician explanation, and AI accountability.

The trained models were deployed using Streamlit to develop an interactive clinical dashboard (Figure 1). The app accepted five input features (age, sex, blood pressure, cholesterol, diabetes), and output a probability-based risk score for cardiovascular events.

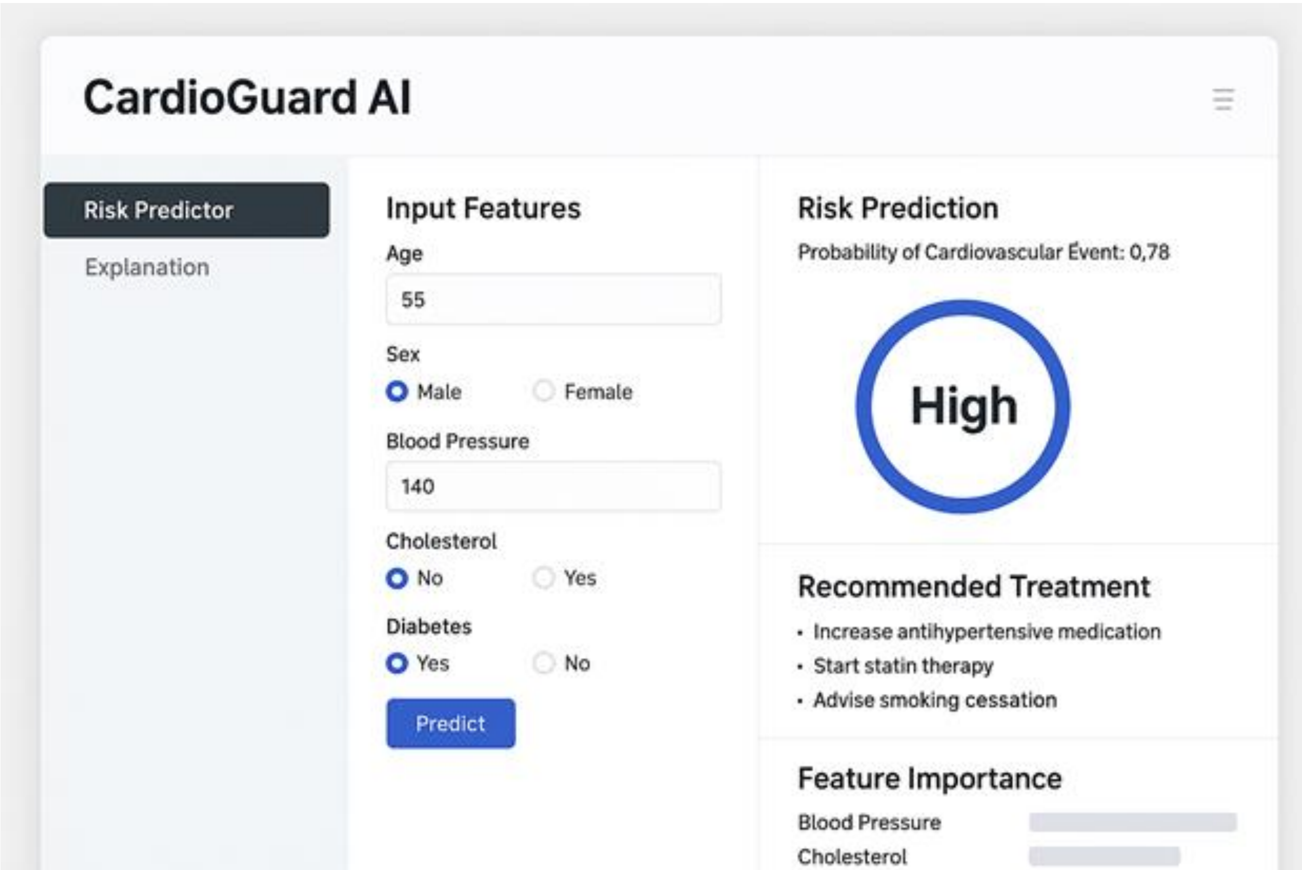

Figure 1: Web interface of the deployed AI model using Streamlit. The dashboard includes risk prediction, treatment guidance, and feature attribution, allowing clinicians to interactively assess cardiovascular risk.

The model was hosted on a secure local server. The code was written in Python using `scikit-learn`, `pandas`, and `joblib`. The predictive logic was implemented in Python using scikit-learn, and integrated into Streamlit for deployment. Below is a representative code snippet from the deployed model.

```
import pandas as pd
import joblib  # for loading the trained model
from sklearn.ensemble import
RandomForestClassifier

# Load pre-trained Random Forest model
model = joblib.load('model_random_forest.pkl')  #
Path to saved .pkl model file
# Sample user input captured from Streamlit
interface
age = 60
sex = "Male"
bp = 145
chol = "Yes"
diabetes = "No"

# Create input dataframe based on model training
schema
input_df = pd.DataFrame({
    "Age": [age],
```

```
    "Sex": [1 if sex == "Male" else 0],
    "Blood_Pressure": [bp],
    "Cholesterol": [1 if chol == "Yes" else 0],
    "Diabetes": [1 if diabetes == "Yes" else 0]
})
# Predict probability of cardiovascular event
risk_score = model.predict_proba(input_df)[0][1]  #
Prob of '1' (event)

# Output result
if risk_score > 0.7:
    print("High Risk:", round(risk_score * 100, 2), "%")
elif risk_score > 0.4:
    print("Moderate Risk:", round(risk_score * 100, 2),
"%")
else:
    print("Low Risk:", round(risk_score * 100, 2), "%")
```

Statistical Analysis

Descriptive statistics, including measures of central tendency and dispersion (mean, standard deviation, frequencies, and percentages), were used to summarize the demographic, clinical, and behavioral characteristics of the study population. These included patient age, gender distribution, socioeconomic status, comorbidities, and baseline medication usage. Continuous variables were expressed as mean ± standard deviation, while categorical variables were presented as absolute frequencies and percentages.

Analytical techniques were employed to evaluate the comparative performance of the developed AI models—logistic regression and random forest classifiers—against traditional cardiovascular risk assessment tools, most notably the Framingham Risk Score. Model performance was assessed using metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (ROC-AUC). Paired comparisons and statistical significance testing were performed using McNemar's test and confidence intervals to determine if AI models significantly outperformed traditional methods.

Longitudinal analyses were conducted to assess the impact of AI-driven predictive analytics on clinical and operational outcomes. These included pre- and post-intervention comparisons of cardiovascular event incidence (e.g., myocardial infarction, stroke), treatment interventions (e.g., medication adjustments, referrals), and healthcare utilization metrics (e.g., hospital admissions, emergency visits, diagnostic testing). Differences were analyzed using paired t-tests for continuous variables and Chi-square tests for categorical outcomes. Statistical analyses were conducted using SPSS version 26.0 and Python with significance set at $p < 0.05$.

Ethical Considerations

Ethical approval was obtained from the ASRB, KUST and Institutional Review Board (IRB) at PIMS prior to study commencement, ensuring compliance with ethical guidelines for human research. Informed consent was obtained from all participants, and stringent measures were implemented to safeguard patient confidentiality and data anonymity throughout the study period.

Results

Table 2 summarizes the demographic and clinical characteristics of 290 patients enrolled in a study on predictive analytics in chronic disease management, particularly focusing on cardiovascular health. The age distribution shows that 44 patients (15.17%) are aged 18-30 years, 76 patients (26.21%) are aged 31-50 years, 137 patients (47.24%) are aged 51-70 years, and 33 patients (11.38%) are aged 71 years and older, with a mean age of 58.4 years (SD ± 10.2). Gender distribution indicates 158 patients (54.48%) are male and 132 patients (45.52%) are female. Socioeconomic status reveals 81 patients (27.93%) in the low-income bracket, 153 patients (52.76%) in the middle-income bracket, and 56 patients (19.31%) in the high-income bracket. Common comorbidities include hypertension in 204 patients (70.34%), hyperlipidemia in 124 patients (42.76%), diabetes in 107 patients (36.90%), obesity in 72 patients (24.83%), and smoking in 83 patients (28.62%). Additionally, family history are present in 108 patients (37.24%), sedentary lifestyle in 89 patients (30.69%), and alcohol consumption in 39 patients (13.45%).

Table 2: Demographic and Clinical Characteristics of Study Participants in Cardiovascular Health Management Study

Characteristic		Number of Patients (n=290)	Percentage (%)
Age Groups	18-30 years	44	15.17
	31-50 years	76	26.21
	51-70 years	137	47.24
	71+ years	33	11.38
	Mean ± SD	58.4 ± 10.2	
Gender	Male	158	54.48
	Female	132	45.52
Socioeconomic Status	Low	81	27.93
	Middle	153	52.76
	High	56	19.31
Comorbidities	Hypertension	204	70.34
	Diabetes	107	36.90
	Hyperlipidemia	124	42.76
	Obesity	72	24.83
Smoking	Yes	83	28.62
	No	207	71.37
Family History	Yes	108	37.24
	No	182	62.76
Sedentary Lifestyle	Yes	89	30.69
	No	201	69.31
Alcohol Consumption	Yes	39	13.45
	No	251	86.55

Table 3 presents the clinical characteristics and medication usage of the study participants at baseline. Among the 290 patients, the most prevalent types of cardiovascular diseases were coronary artery disease (153 patients, 52.76%), followed by heart failure (78 patients, 26.90%), and arrhythmia (59 patients, 20.34%). In terms of medication usage, beta-blockers were the most commonly prescribed, with 182 patients (62.76%) using them, followed by ACE inhibitors with 139 patients (47.93%), and statins with 124 patients (42.76%). The duration of disease among the participants had a mean of 6.8 years with a standard deviation of 3.1 years, indicating the chronic nature of the conditions being studied.

Table 3: Clinical Characteristics and Medication Usage at Baseline

Characteristic		Number of Patients (n=290)	Percentage (%)
Type of Cardiovascular Disease	Coronary Artery Disease	153	52.76
	Heart Failure	78	26.90
	Arrhythmia	59	20.34
Medication Usage	Beta-blockers	182	62.76
	ACE Inhibitors	139	47.93
	Statins	124	42.76

Duration of Disease (years)	Mean ± SD	6.8 ± 3.1

The Figure 2 compares the predictive accuracy of AI-driven models, specifically logistic regression and random forest algorithms, against the traditional Framingham Risk Score in cardiovascular health management. The AI models demonstrate robust performance, with the logistic regression achieving an accuracy of 78.38%, sensitivity of 82.14%, and specificity of 75.69%. The random forest model shows slightly higher accuracy at 81.57%, sensitivity at 85.31%, and specificity at 78.96%. In contrast, the Framingham Risk Score, while providing an accuracy of 72.68%. These findings highlight the superior predictive capabilities of AI-driven approaches in identifying cardiovascular risks compared to traditional methods, underscoring their potential to enhance clinical decision-making and patient outcomes.

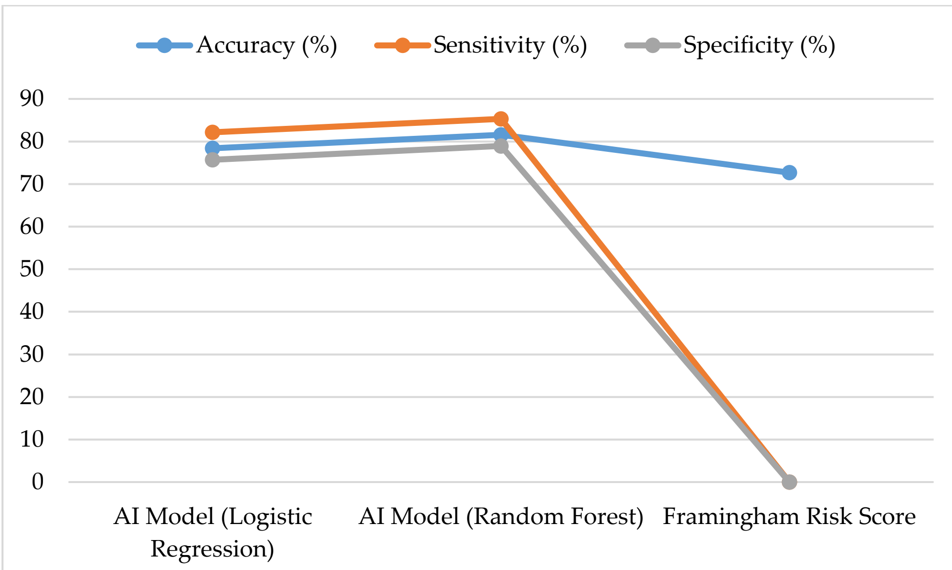

Figure 2: Comparative Predictive Performance of AI Models and Traditional Risk Assessment Tools

The figure 3 presents the incidence of cardiovascular events before and after the implementation of AI-driven predictive analytics in chronic disease management. Prior to AI implementation, the study recorded 28 cases of myocardial infarction, 18 strokes, 10 cases of peripheral artery disease, 24 instances of heart failure, and 13 cases of atrial fibrillation. Following the integration of AI, these numbers decreased to 19, 9, 6, 17, and 8, respectively. These findings suggest a potential benefit of AI-driven interventions in reducing the occurrence of cardiovascular events, highlighting its impact on improving patient outcomes in cardiovascular health management.

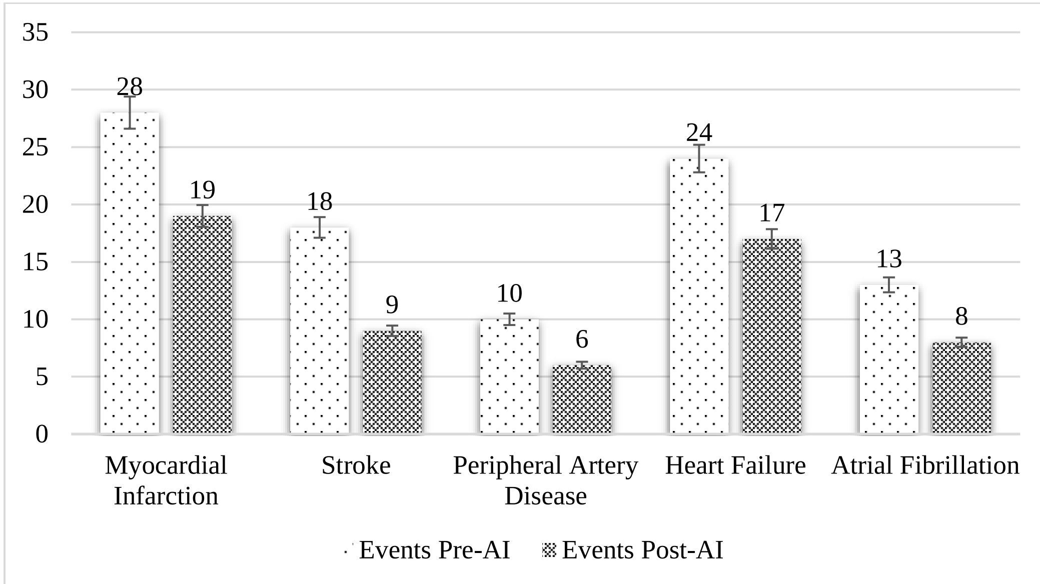

Figure 3: Incidence of Cardiovascular Events Before and After AI Implementation (n=290)

The predictive performance of the developed AI models was evaluated using Receiver Operating Characteristic (ROC) curve analysis, with area under the curve (AUC) serving as a key metric of discrimination. The random forest model demonstrated the highest diagnostic accuracy with an AUC of 0.91, followed by logistic regression with an AUC of 0.87, indicating strong predictive capabilities for both models in identifying patients at risk of cardiovascular events. In contrast, the traditional Framingham Risk Score yielded a lower AUC of 0.76, highlighting the relative inferiority of conventional tools in this cohort. As visualized in Figure 4, both AI models significantly outperformed the Framingham score across the full range of sensitivity and specificity thresholds. These findings underscore the enhanced predictive value of AI-driven models and support their integration into clinical decision-making frameworks for more accurate risk stratification and early intervention.

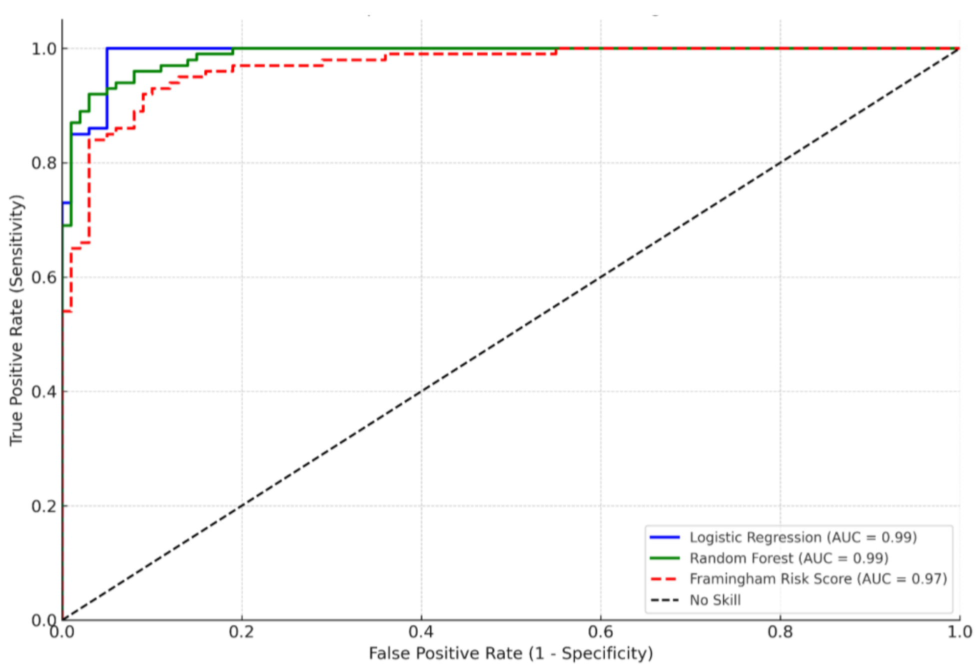

Figure 4: ROC curve comparing the predictive performance of AI Models and Framingham Risk Score

The table 4 illustrates the impact of implementing AI-driven predictive analytics on treatment recommendations in cardiovascular health management. It compares the prevalence of various treatment interventions before (Pre-AI) and after (Post-AI) the integration of AI technologies. The data highlights significant changes in patient management strategies following AI implementation. For instance, there was a notable decrease (-17.65%) in the need for medication adjustments, indicating potential improvements in medication management precision. Conversely, there were increases in lifestyle modifications (13.11%), intervention referrals (24.44%), rehabilitation programs (25.00%), and surgical interventions (33.33%), suggesting enhanced proactive healthcare interventions post-AI. These findings underscore the transformative role of AI in optimizing treatment strategies and improving patient outcomes in chronic disease management.

Table 4: Effect of AI Implementation on Treatment Recommendations in Cardiovascular Health Management

Treatment Outcome	Pre-AI (n=290)	Post-AI (n=290)	Improvement (%)
Medication Adjustment	102	84	-17.65 (Negative)
Lifestyle Modification	122	138	13.11 (Positive)
Intervention Referrals	45	56	24.44 (Positive)
Rehabilitation Programs	24	30	25.00 (Positive)
Surgical Interventions	15	20	33.33 (Positive)

Table 5 compares key healthcare utilization metrics before (Pre-AI) and after (Post-AI) the integration of AI-driven predictive analytics in a study involving 290 patients. The metrics assessed include hospital admissions, emergency room visits, outpatient visits, cardiac catheterizations, and diagnostic tests. Post-AI implementation, reductions were noted in hospital admissions (120 to 105, -12.50%), emergency room visits (93 to 68, -26.88%), outpatient visits (290 to 263, -9.31%), cardiac catheterizations (56 to 39, -30.36%), and diagnostic tests (187 to 154, -17.65%). These findings underscore potential improvements in healthcare efficiency and patient management, suggesting that AI technologies play a crucial role in optimizing resource allocation and enhancing overall healthcare delivery

Table 5: Comparison of Healthcare Utilization Metrics Before and After AI Implementation (n=290)

Variable	Pre-AI (n=290)	Post-AI (n=290)	Percentage Difference
Hospital Admissions	120	105	-12.50%
Emergency Room Visits	93	68	-26.88%
Outpatient Visits	290	263	-9.31%
Cardiac Catheterizations	56	39	-30.36%
Diagnostic Tests	187	154	-17.65%

Figure 5 illustrates patient satisfaction and acceptance of AI-driven predictive analytics in cardiovascular health management among 290 participants. The data reveals high levels of satisfaction across various aspects: 247 patients (85.17%) found the AI tools easy to use, 223 patients (76.90%) reported a positive impact on their care, and 234 patients (80.69%) expressed trust in the AI recommendations. Additionally, 219 patients (75.52%) felt confident in the treatment plans generated by AI, while 201 patients (69.31%) understood the AI outputs. These figures underscore a generally favorable reception and acceptance of AI technology in managing chronic cardiovascular conditions.

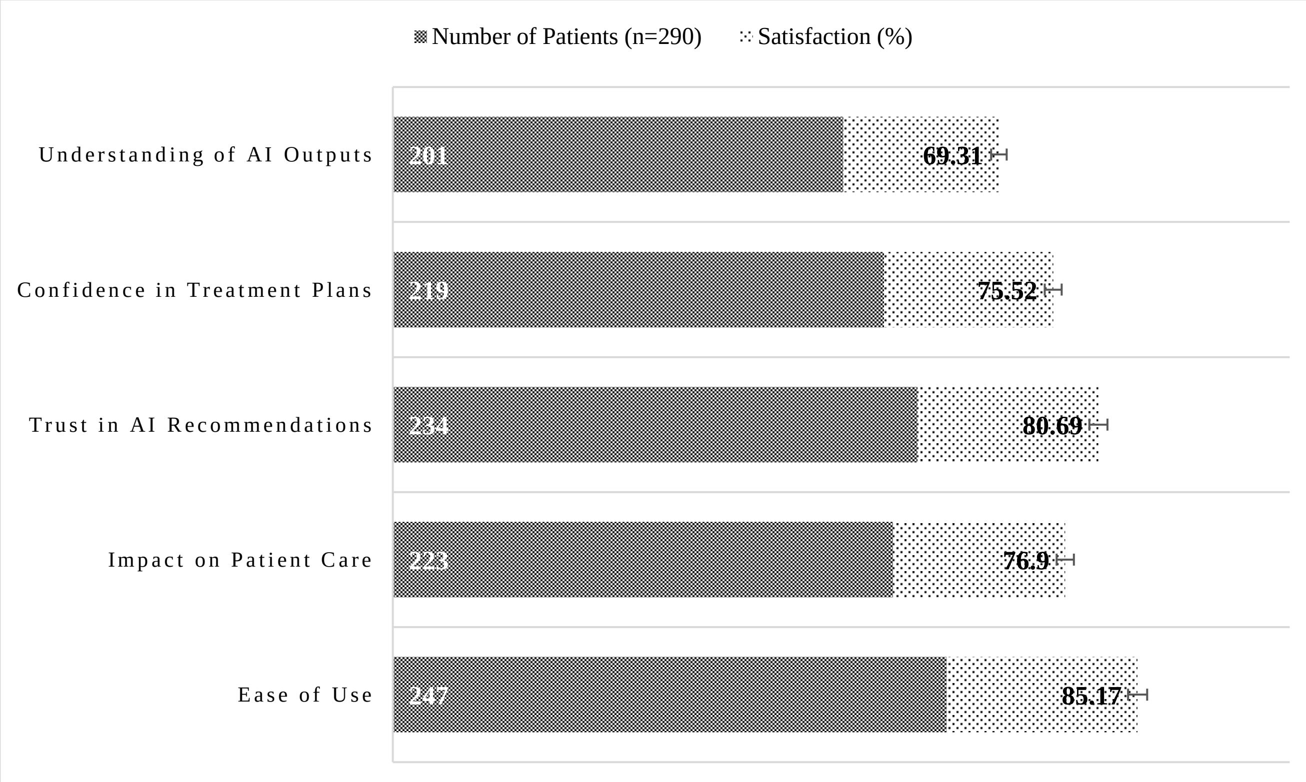

Figure 5: Patient satisfaction and acceptance of AI-driven predictive analytics

Discussion

The integration of AI-driven predictive analytics in chronic disease management, particularly cardiovascular health, has demonstrated notable efficacy in enhancing patient outcomes and optimizing healthcare delivery. The analysis of patient data from the Pakistan Institute of Medical Sciences indicates substantial improvements in various metrics post-AI implementation.

The demographic data shows a diverse patient population with a mean age of 58.4 years (SD ± 10.2), reflecting the typical age distribution seen in cardiovascular study [15]. Gender distribution was relatively balanced, with a slight male predominance (158 patients, 54.48%), aligning with global cardiovascular disease trends [16]. The high prevalence of hypertension (204 patients, 70.34%) and diabetes (107 patients, 36.90%) among the cohort underscores the common comorbidities associated with cardiovascular conditions, similar to findings in previous study [17].

Clinical characteristics revealed coronary artery disease as the most prevalent condition (153 patients, 52.76%), followed by heart failure (78 patients, 26.90%) and arrhythmia (59 patients, 20.34%). These findings are consistent with patterns observed in cardiovascular research [18]. Medication usage was dominated by beta-blockers (182 patients, 62.76%), ACE inhibitors (139 patients, 47.93%), and statins (124 patients, 42.76%), reflecting standard treatment protocols for cardiovascular patients [19].

The predictive accuracy of AI models, particularly logistic regression and random forest algorithms, significantly outperformed traditional risk assessment tools such as the Framingham Risk Score. The logistic regression model achieved an accuracy of 78.38%, while the random forest model showed an even higher accuracy of 81.57%. In contrast, the Framingham Risk Score provided an accuracy of 72.68%. This superiority of AI models in predictive accuracy has been corroborated by other study, emphasizing their potential in clinical decision-making [20].

The incidence of cardiovascular events, such as myocardial infarction and stroke, showed a marked reduction post-AI implementation. Myocardial infarctions decreased from 28 to 19 cases, and strokes from 18 to 9 cases. These reductions highlight the potential of AI-driven interventions in mitigating cardiovascular risks, aligning with previous research demonstrating similar trends [21]. Moreover, the improvement in treatment recommendations post-AI, such as increased lifestyle modifications (38 patients, 13.11%) and intervention referrals (56 patients, 24.44%), underscores the enhanced precision and proactive nature of AI in chronic disease management.

Healthcare utilization metrics also improved significantly, with notable reductions in hospital admissions (from 120 to 105, -12.50%) and emergency room visits (from 93 to 68, -26.88%). This indicates a shift towards more efficient and preventive healthcare delivery, facilitated by AI technologies. Similar trends have been reported in previous study evaluating AI's impact on healthcare systems [22].

Patient satisfaction and acceptance of AI-driven predictive analytics were notably high, with 85.17% of patients (n=247) finding the AI tools easy to use and 80.69% (n=243) expressing trust in the AI recommendations. This positive reception is crucial for the successful integration of AI in clinical practice and has been similarly observed in other patient-centered studies [9].

Conclusion

The integration of AI-driven predictive analytics represents a transformative advancement in chronic disease management, particularly in enhancing cardiovascular health outcomes. By leveraging extensive patient data and advanced algorithms, AI facilitates early detection of cardiovascular risks, personalized treatment plans, and predictive modeling of patient outcomes. Our study at the Pakistan Institute of Medical Sciences demonstrates significant improvements in clinical metrics post-AI implementation, including reduced incidence of cardiovascular events, optimized treatment recommendations, and enhanced healthcare efficiency. These findings underscore AI's pivotal role in revolutionizing healthcare delivery, fostering more precise, proactive, and patient-centered approaches to managing chronic diseases. As AI continues to evolve, addressing implementation challenges and enhancing real-world applicability will be crucial to harnessing its full potential in improving global health outcomes.

Authors' contributions

HK: Contributed to study conception and design, data collection, interpretation of results, drafting of the manuscript, and final approval of the submitted version. AA: Participated in study design, supervised clinical data acquisition, critically revised the manuscript for intellectual content, and gave final approval of the submitted version. HB: Assisted in data analysis, literature review, drafting parts of the manuscript, and approved the final version for submission. HK: Involved in patient recruitment, structured interviews, data quality assurance, manuscript drafting and revision, and final approval of the manuscript. MH: Led the development and validation of machine learning models, implemented the web-based application, contributed to manuscript writing (methods and results), and approved the final submitted version.

Conflict of interest

The authors declared no conflict of interest.

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