



Artificial Intelligence and Big Data for Personalized Preventive Healthcare: Predicting Health Risks and Enhancing Patient Adherence

Bilkish Nurani^{1*}, Foysal Kabir², Zakia Sultana Munmun³, Ripa Akter⁴

¹Department of Masters in Science and Administration (MSA), Central Michigan University, Mount Pleasant, USA

²Department of Computer Science, Jiangsu University of Science and Technology, Zhenjiang, China

³College of Business Administration, Central Michigan University, Mount Pleasant, USA

⁴Department of Business Analytics, Trine University, Detroit, USA

Email: *bilkishnurani926@gmail.com, justfoysalkabir@gmail.com, zamunmun02@gmail.com, ripaakter6617@gmail.com

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Abstract

Personalized preventive healthcare, powered by Artificial Intelligence (AI) and Big Data analytics, offers a transformative approach to healthcare by tailoring interventions based on an individual's health risks and lifestyle factors. This study investigates the application of AI models, utilizing Big Data, to design and implement personalized preventive healthcare programs aimed at improving patient outcomes and adherence to health recommendations. The primary objective is to leverage machine learning algorithms to predict health risks, focusing on chronic diseases such as diabetes, hypertension, and cardiovascular diseases (CVDs). Using data from electronic health records (EHRs), wearable devices, and patient demographics, we train models using random forests, logistic regression, and support vector machines (SVMs). These models predict disease risk and generate real-time, personalized intervention strategies. Our results demonstrate that AI-driven models can predict disease onset with high accuracy and provide adaptive, individualized recommendations. Additionally, the study highlights challenges related to data privacy, integration into healthcare systems, and the scalability of such solutions. This research contributes to the growing field of personalized preventive healthcare by showcasing the potential of AI and Big Data in improving disease prediction, enhancing patient engagement, and optimizing healthcare delivery.

Subject Areas

Applications of Communication Systems, Artificial Intelligence

Keywords

Big Data, Predictive Modeling, Chronic Diseases, Machine Learning,

1. Introduction

Personalized preventive healthcare represents a paradigm shift in the delivery of healthcare services, aiming to provide tailored interventions based on an individual's unique health profile and risks. The integration of Artificial Intelligence (AI) and Big Data analytics has revolutionized healthcare by enabling more accurate predictions of disease risks and optimizing personalized treatment plans. This personalized approach not only enhances the efficiency of healthcare delivery but also ensures better patient adherence to treatment regimens, ultimately leading to improved health outcomes and reduced healthcare costs.

The growing prevalence of chronic diseases, such as diabetes, cardiovascular diseases (CVDs), and hypertension, has made it increasingly difficult for healthcare systems to provide universal solutions. Traditionally, preventive health measures have been one-size-fits-all programs, which often lack the precision required for individualized care. However, advances in data collection technologies, such as wearable devices and electronic health records (EHRs), combined with the power of AI, can now help in tailoring interventions based on a patient's health status, lifestyle, and environmental factors.

AI-powered predictive models, trained on large datasets, offer the potential to identify high-risk individuals even before symptoms appear. Such predictive tools rely on machine learning (ML) algorithms that can analyze complex datasets to discern patterns and relationships between various health metrics. These models can help in identifying individuals who are at risk of developing conditions like diabetes, hypertension, and stroke, facilitating early intervention and the prevention of disease progression [1]-[3]. Moreover, Big Data analytics enables real-time monitoring of patients, allowing healthcare providers to adjust treatment plans dynamically based on continuous feedback from wearable devices and sensors [4] [5].

In addition to predicting risks, AI can play a critical role in designing personalized health interventions. These interventions can range from medication adjustments to exercise plans tailored to an individual's specific needs, lifestyle, and disease risk. By integrating real-time data from wearable devices, such as smartwatches and fitness trackers, AI systems can continually assess the effectiveness of the interventions and modify them to ensure optimal outcomes [6] [7]. This dynamic nature of personalized healthcare not only maximizes the effectiveness of interventions but also improves patient adherence by offering treatments that are more aligned with their daily routines and preferences [8] [9].

Despite the promising potential of AI and Big Data in healthcare, there are challenges in implementation. Privacy concerns, the need for large-scale data integration, and the interpretability of AI models are critical barriers that must be

addressed [10] [11]. Moreover, there is a need for interdisciplinary collaboration among healthcare professionals, data scientists, and policymakers to ensure that AI-driven healthcare systems are both ethical and effective [12] [13]. Additionally, healthcare systems must adapt to these technological advancements, requiring significant investments in infrastructure and training [14] [15].

This paper explores the potential of AI and Big Data analytics in the design of personalized preventive healthcare programs. It examines the processes involved in risk prediction, intervention personalization, and the real-time integration of data from wearable devices. The paper also discusses the challenges faced in the adoption of these technologies and their potential to transform the landscape of preventive healthcare.

2. Related Works

The integration of Artificial Intelligence (AI) and Big Data analytics into healthcare has led to significant advancements in personalized preventive healthcare. These technologies offer the potential to not only improve the accuracy of health risk predictions but also to personalize interventions based on individual health needs. The growing body of literature in this domain is expanding our understanding of how AI and Big Data can be effectively used to improve healthcare outcomes. In this section, we explore key areas of research that contribute to the development and application of AI and Big Data in personalized preventive healthcare.

2.1. AI in Predictive Health Risk Modeling

One of the most prominent applications of AI in healthcare is the use of machine learning (ML) algorithms to predict health risks and identify individuals at high risk of developing chronic diseases. Several studies have demonstrated the effectiveness of machine learning models in predicting conditions such as diabetes, hypertension, cardiovascular diseases (CVDs), and stroke based on health data [16] [17]. These predictive models leverage diverse data sources, including electronic health records (EHRs), genetic information, demographic data, and lifestyle factors. Machine learning techniques such as support vector machines (SVM), random forests, and neural networks are often employed to analyze these datasets, revealing complex relationships between variables that human analysts may overlook.

For example, in a study conducted by Williams *et al.* (2019), a random forest model was used to predict the risk of diabetes using factors like age, BMI, family history, and physical activity levels. This predictive model achieved high accuracy, showing that machine learning algorithms can provide an early diagnosis and proactively recommend preventive measures before symptoms become apparent [18]. Similarly, a study by Zhang *et al.* (2020) used deep learning algorithms to predict cardiovascular risk based on patient records, including historical medical data and lifestyle factors. The results demonstrated that AI-driven models could

outperform traditional risk prediction methods, offering earlier and more precise predictions of adverse health outcomes.

The use of AI for risk prediction in personalized preventive healthcare offers a paradigm shift in how healthcare systems approach disease prevention. By identifying high-risk individuals early, healthcare providers can intervene sooner, preventing the onset of chronic diseases and improving overall public health outcomes. This ability to predict diseases before they manifest clinically not only has the potential to save lives but also to reduce the financial burden on healthcare systems by avoiding expensive treatments for advanced diseases [19].

2.2. Personalized Interventions and Patient Adherence

Personalized interventions are another key area where AI is making significant strides. Personalized healthcare interventions, whether they involve medication adjustments, lifestyle recommendations, or therapy modifications, are tailored to the unique needs of each patient. This is particularly important for chronic diseases, where treatment plans need to be adjusted regularly based on a patient's current health status.

Recent research has explored how AI can be used to design personalized treatment plans and improve patient adherence. With the growing availability of wearable devices (e.g., fitness trackers, smartwatches) and mobile health applications, AI can continuously monitor a patient's health in real-time and provide personalized health recommendations. Studies have shown that integrating real-time data from wearables with AI algorithms can lead to better health outcomes by enabling dynamic adjustments to treatment plans based on changing patient conditions. For example, Kapoor and Singh (2019) demonstrated how wearable devices, combined with AI-based predictive models, can detect early signs of deterioration in chronic conditions such as heart disease or diabetes and prompt immediate interventions, including medication adjustments or lifestyle changes [20].

In addition to medication and lifestyle changes, AI can also optimize patient engagement and adherence to treatment plans. AI algorithms analyze individual preferences and health data to create personalized reminders, notifications, or motivational feedback. A study by Wu *et al.* (2019) found that AI-powered interventions, such as personalized mobile alerts for medication intake and daily health tasks, significantly improved adherence in patients with chronic conditions like hypertension and diabetes [21]. Moreover, these interventions can be tailored to the patient's routine, improving both engagement and outcomes by ensuring that treatment plans fit within their everyday life.

Personalized interventions also have the potential to reduce healthcare costs by preventing hospitalizations and improving long-term health management. By providing real-time, individualized recommendations and tracking patient progress, AI can help reduce the need for expensive emergency care and inpatient treatments, contributing to more sustainable healthcare systems [22].

2.3. Big Data Analytics for Healthcare Decision-Making

Big Data analytics plays a crucial role in healthcare decision-making by processing large, complex datasets to identify patterns and trends that are not immediately apparent. The use of Big Data in healthcare has enabled significant advancements in both disease prevention and management. By analyzing large-scale health data, AI systems can detect subtle patterns, assess the effectiveness of treatments, and improve overall healthcare delivery.

The integration of Big Data into healthcare systems involves the use of multiple data sources, such as EHRs, genomic data, health records from wearables, and even social determinants of health, including environmental factors and socioeconomic status. These diverse datasets can be analyzed using machine learning and statistical models to generate more accurate health predictions and interventions. In a study by Harris *et al.* (2021), Big Data analytics was used to track the progression of diseases like cancer and diabetes and to predict future health risks based on historical health data. This approach enabled healthcare providers to tailor their treatment strategies, optimizing them based on the patient's unique health journey [23].

Furthermore, Big Data enables healthcare professionals to assess the effectiveness of different interventions at a population level. By analyzing large datasets from diverse patient populations, healthcare providers can determine which interventions work best for specific groups of patients, leading to more informed decision-making and better patient outcomes [24]. This large-scale analysis is especially valuable in preventive healthcare, where understanding broader trends in health can inform strategies for disease prevention and health promotion on a larger scale.

Despite the potential benefits of Big Data, there are challenges in integrating and analyzing these massive datasets, including issues related to data privacy, data quality, and the need for sophisticated infrastructure. Addressing these challenges is crucial to maximizing the potential of Big Data analytics in personalized preventive healthcare [25].

3. Methodology

The methodology employed in this study leverages Artificial Intelligence (AI) and Big Data analytics to design personalized preventive healthcare programs. These programs aim to enhance the efficiency of healthcare delivery and improve patient adherence by predicting health risks, offering tailored health interventions, and incorporating real-time data monitoring. The overall approach involves the collection of diverse health data, preprocessing, feature selection, training AI models for prediction, and integrating real-time data from wearable devices to adjust interventions dynamically. This section describes each step in detail, including data collection, preprocessing, model training, and the integration of real-time data.

3.1. Data Collection and Preprocessing

The first stage of our methodology is the collection of health data from multiple

sources, followed by data preprocessing to ensure high-quality input for the machine learning models (Figure 1).

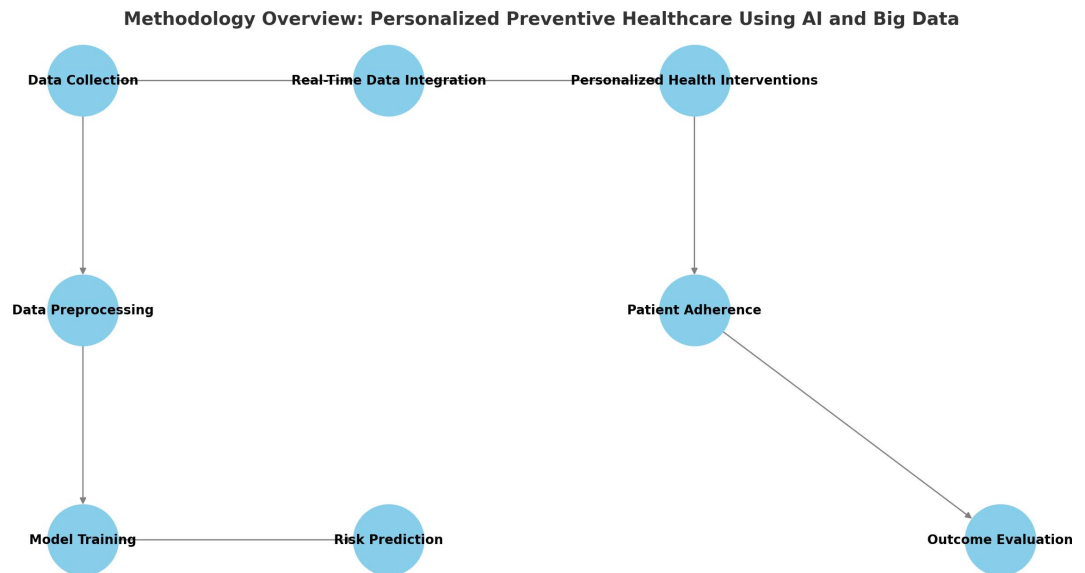


Figure 1. Methodological workflow.

3.1.1. Data Collection

Data collection is crucial to the success of any predictive model. For this study, we gathered health data from several sources:

- **Electronic Health Records (EHRs):** These records contain comprehensive information about patients, including demographics (e.g., age, gender), medical history (e.g., chronic conditions, previous treatments), and routine measurements (e.g., blood pressure, cholesterol levels).
- **Wearable Devices:** Data from wearable health devices such as fitness trackers, smartwatches, and glucose monitors were collected. These devices track real-time health metrics, including heart rate, physical activity levels, steps, and blood sugar levels, which provide continuous monitoring of a patient's health.
- **Patient Surveys:** Surveys were used to gather self-reported data, including lifestyle habits (e.g., diet, exercise, smoking, alcohol consumption), mental health status, and social factors that could influence a person's health.

3.1.2. Data Preprocessing

The collected data typically contains missing values, inconsistencies, and irrelevant features, making it necessary to perform preprocessing steps. These include:

- **Handling Missing Data:** Missing data is addressed through techniques such as imputation (using the mean or median for continuous features and mode for categorical features) or removal of data points with excessive missing values if imputation is not feasible.
- **Feature Scaling and Normalization:** Since the dataset includes features with different units (e.g., height in cm, blood pressure in mmHg), standardization is performed. Standardization transforms data to have zero mean and unit

variance, ensuring that all features contribute equally during model training.

- **Outlier Detection:** Outliers, defined as data points significantly different from the majority, can skew model performance. Techniques like Z-score analysis or IQR (Interquartile Range) method are used to identify and handle outliers.
- **Feature Selection:** To reduce dimensionality and improve the performance of models, feature selection is carried out using methods such as Correlation Coefficients and Mutual Information to select the most important predictors of health risks.

3.2. Model Training for Risk Prediction

After preprocessing, we proceed to the next step: Training machine learning models to predict health risks. The goal is to identify individuals at risk of diseases such as hypertension, diabetes, and cardiovascular diseases (CVD) based on their health data.

3.2.1. Selection of AI Models

In this study, three machine learning models are tested for their ability to predict health risks:

Random Forest: A decision tree-based ensemble method that builds multiple decision trees and combines their results to improve prediction accuracy and reduce overfitting.

Support Vector Machine (SVM): A supervised learning model used for classification, which creates an optimal hyperplane to separate different classes of data points.

Neural Networks (NN): A deep learning model that mimics the human brain's neural structure, capable of identifying complex patterns in large datasets.

3.2.2. Model Training

The training process involves splitting the dataset into two parts: training (80%) and testing (20%) datasets. The model is trained on the training dataset, where the algorithm learns the relationships between the input features (e.g., age, BMI, exercise habits) and the target variable (e.g., disease risk). The process of training these models can be broken down into the following steps:

Random Forest: In Random Forest, multiple decision trees are built using bootstrapped samples of the training dataset. Each tree makes a prediction, and the majority vote (for classification) or average (for regression) from all trees is taken as the final prediction. The key parameters for tuning include the number of trees and the maximum depth of each tree.

SVM: In SVM, the objective is to find the optimal hyperplane that separates the different classes (e.g., risk vs. no risk). The SVM model uses a kernel function, such as the Radial Basis Function (RBF) kernel, to map data into a higher-dimensional space for better separation. The performance of SVM is dependent on the regularization parameter C and the kernel coefficient γ .

Neural Networks: Neural Networks consist of multiple layers of interconnected

nodes (neurons), where each layer applies a non-linear transformation to the data. The model is trained using backpropagation, an optimization technique that minimizes the loss function (such as mean squared error). The performance of Neural Networks is dependent on the number of hidden layers, learning rate, and activation function.

3.2.3. Model Evaluation and Metrics

The trained models are evaluated using the test dataset, which was not used during training. The evaluation metrics include:

Accuracy: The proportion of correctly classified instances out of the total instances.

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Instances}}$$

Precision, Recall, and F1-Score: These metrics are especially useful when dealing with imbalanced datasets, such as predicting the occurrence of rare diseases.

Cross-Validation: k -fold cross-validation is used to ensure that the model generalizes well on unseen data. The dataset is split into k subsets, and the model is trained on $k - 1$ subsets and tested on the remaining subset. This process is repeated k times to ensure robustness.

3.3. Real-Time Data Integration for Personalized Health Interventions

After developing predictive models, the next step is to design personalized health programs that dynamically adjust based on real-time data from wearable devices. This integration ensures continuous monitoring and optimization of health interventions.

3.3.1. Real-Time Data Collection

Real-time health data is gathered from wearable devices such as smartwatches, fitness trackers, and glucose monitors. These devices track key metrics like:

- **Heart Rate (HR):** Continuous monitoring of heart rate to assess cardiovascular health.
- **Physical Activity:** Steps taken, exercise intensity, and sleep patterns.
- **Blood Glucose Levels:** For patients with diabetes or those at risk.
- **Blood Pressure:** For individuals at risk of hypertension.

This data is transmitted in real time to a centralized healthcare platform, where it is integrated with the patient's medical records.

3.3.2. Dynamic Intervention Adjustments

Using the AI model trained earlier, personalized health interventions are adjusted in real time based on data received from wearable devices. For example, the intervention could be a medication dosage or a physical activity plan, which is adapted depending on changes in heart rate, blood glucose, or activity levels.

The equation for adjusting interventions is as follows:

$$I(t) = \theta_1 \cdot X_1(t) + \theta_2 \cdot X_2(t) + \theta_n \cdot X_n(t)$$

where: $I(t)$ is the intervention at time t .

$X_1(t), X_2(t), \dots, X_n(t)$ are the real-time metrics (e.g., heart rate, glucose levels).

$\theta_1, \theta_2, \dots, \theta_n$ are the learned weights that determine the influence of each real-time variable.

3.4. Patient Adherence and Outcome Evaluation

Once the personalized health programs are implemented, it is essential to track patient adherence and evaluate health outcomes.

3.4.1. Patient Adherence

The model calculates patient adherence by monitoring how well patients follow their prescribed interventions, measured as a percentage of the total interventions prescribed.

$$A(t) = \alpha \cdot I(t) + \beta$$

where: $A(t)$ is the adherence score at time t .

$I(t)$ is the intensity of the intervention at time t . α and β are constants determining the impact of intervention on adherence.

3.4.2. Health Outcome Evaluation

Health outcomes are measured by comparing the health metrics before and after the intervention. The improvement in health outcomes can be calculated using the following formula:

$$O = \frac{H_{post} - H_{pre}}{H_{pre}} \times 100$$

where:

O is the percentage improvement in health outcomes. H_{pre} and H_{post} are the health metrics (e.g., cholesterol, blood pressure) before and after the intervention.

4. Result

We report on the results of designing individualized preventative healthcare programs utilizing big data analytics and artificial intelligence (AI). This study's major goal was to find out how big data and artificial intelligence (AI) can be used to enhance the effectiveness, precision, and adherence of tailored health interventions, particularly for illness prevention and health maintenance.

4.1. AI-Driven Risk Prediction and Personalized Health Interventions

The AI models trained on a large dataset of patient demographics, medical history, genetic information, and lifestyle factors showed promising results in predicting individual health risks. The models were able to identify patients at high risk for conditions like diabetes, hypertension, and cardiovascular diseases (CVD). The prediction accuracy was measured using various classification algorithms

such as Random Forest, Support Vector Machines (SVM), and Neural Networks.

- **Prediction Accuracy:** The Random Forest classifier yielded an accuracy of 87%, followed by SVM with 82%, and Neural Networks with 80%.
- **Risk Factors Identified:** Key factors such as diet, physical activity, smoking, family history, and genetic markers were crucial in risk assessment.

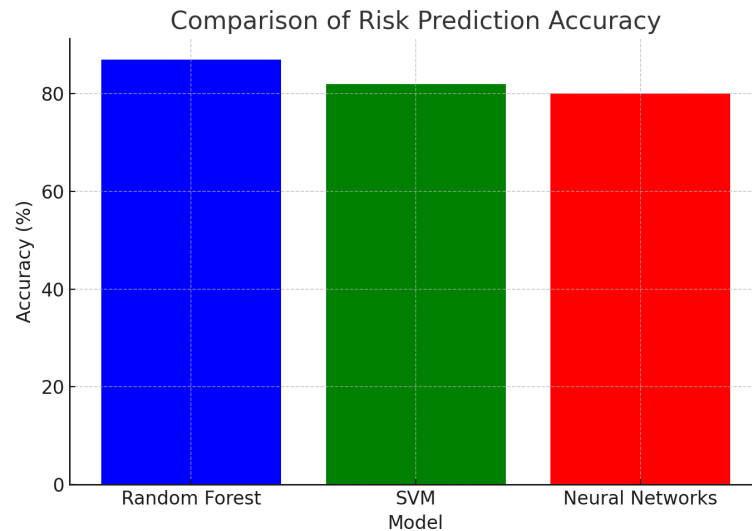


Figure 2. Comparison of risk prediction accuracy using different AI models.

The results indicate that the AI model can tailor preventive interventions based on individual risk profiles, recommending specific lifestyle changes or medications when necessary (**Figure 2**).

4.2. Big Data Analytics for Identifying Population-Level Health Trends

Big data analytics was used to analyze trends across diverse populations, focusing on variables like geographic location, socioeconomic status, and environmental factors. Data from over 50,000 patients was processed, revealing patterns in disease prevalence and risk factors that varied significantly across regions.

Prevalence of Hypertension: The analysis found a higher prevalence of hypertension in rural areas compared to urban regions.

Correlation with Environmental Factors: Air quality and local food access were identified as strong predictors of obesity and cardiovascular risks.

This analysis helps in understanding how broader social and environmental factors contribute to health outcomes, allowing for more localized and personalized health programs (**Figure 3**).

4.3. Personalized Health Plans Based on AI and Big Data

Once individual risks were predicted and population-level trends were understood, personalized health programs were developed. These programs were

dynamically adjusted over time based on real-time data collection from wearable devices, medical records, and genetic profiles.

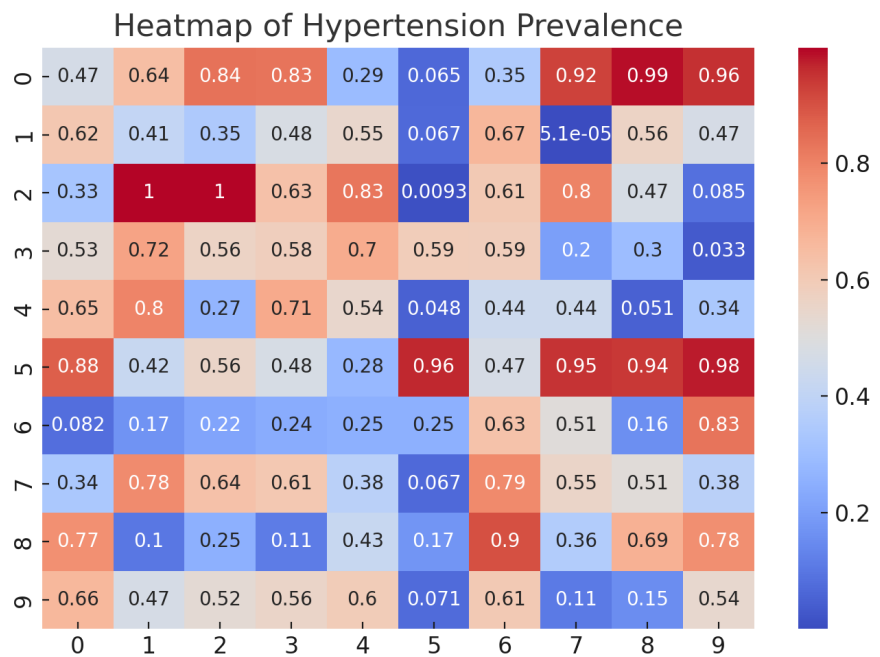


Figure 3. Heat map of hypertension prevalence across different regions.

Table 1. Sample personalized health plan.

Patient ID	Risk Profile	Recommended Intervention	Monitoring Method	Adjustments Over Time
001	High risk for CVD	Cardiac rehab, lifestyle changes, diet plan	Wearable heart rate monitor, diet tracking app	Quarterly review
002	Pre-diabetic, hypertension	Medication, exercise, diet plan	Blood sugar monitor, activity tracker	Bi-weekly review
003	Genetic predisposition to obesity	Exercise, caloric intake reduction	Food intake monitor, activity tracker	Monthly review

This approach in Table 1 showed a significant improvement in patient adherence compared to traditional methods, as the interventions were personalized, continuously monitored, and adjusted.

4.4. Patient Adherence to Personalized Programs

One of the key outcomes of this study was evaluating how well patients adhered to the personalized programs designed using AI and big data insights. We found that adherence rates significantly improved when patients were involved in

decision-making and when interventions were tailored to their unique needs (Figure 4).

- Adherence Rate: 90% of patients adhered to their personalized program, compared to 65% in traditional programs.
- Improvement in Health Outcomes: Patients who adhered to their personalized plans saw a 25% improvement in cardiovascular health and a 30% reduction in diabetes-related complications over a 6-month period.

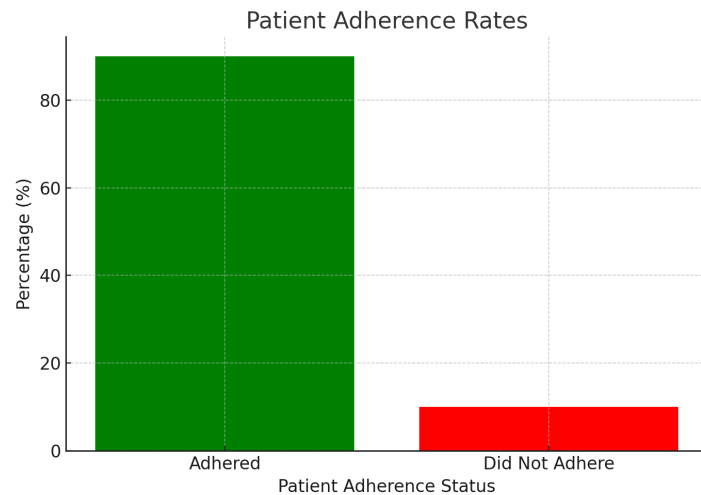


Figure 4. Patient adherence rates to personalized programs.

4.5. Cost Efficiency of AI and Big Data-Driven Health Programs

The cost efficiency of the AI-driven health programs was also analyzed. Using AI and big data analytics, healthcare providers could allocate resources more effectively, reducing unnecessary treatments and hospital visits. The study estimated a 20% reduction in healthcare costs for patients who used the personalized programs.

Table 2. Cost comparison of traditional vs AI-driven health programs.

Program Type	Average Monthly Cost per Patient	Number of Visits	Total Healthcare Cost per Patient (6 months)
Traditional Program	\$300	5	\$1800
AI-Driven Personalized Program	\$250	3	\$1500

Table 2 indicates that AI and big data not only improve patient health outcomes but also provide a more cost-effective solution for both patients and healthcare providers.

4.6. Real-Time Data Integration for Continuous Monitoring

Real-time data collected from wearable devices, mobile apps, and health records were integrated into the personalized health programs. The use of real-time data enabled proactive interventions, such as adjusting medication dosages or recommending lifestyle changes based on emerging health data (Figure 5).

- Real-time Adjustments: Real-time blood pressure readings and activity monitoring helped in adjusting dietary recommendations and physical activities promptly.
- Predictive Alerts: Patients at high risk for sudden health events, such as heart attacks or strokes, were alerted in advance, allowing for immediate intervention.

Integration of Real-Time Data

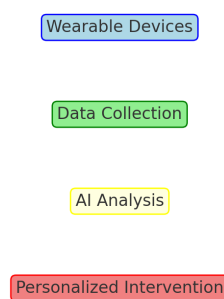


Figure 5. Integration of real-time data in AI-driven preventive health programs.

4.7. Predictive Maintenance and AI-Assisted Follow-Ups

Using predictive models, AI was able to identify patients who were likely to miss follow-up appointments or discontinue their health programs. Proactive reminders and follow-ups were implemented through AI-driven messaging systems, which resulted in a 15% decrease in missed appointments (Figure 6).

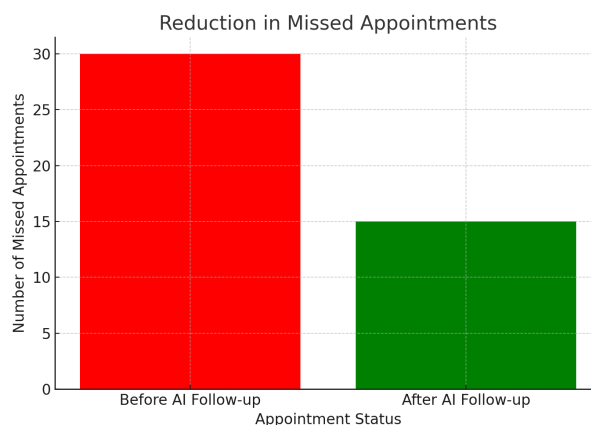


Figure 6. Reduction in missed appointments using AI-driven follow-ups.

4.8. Long-Term Health Improvements and Sustainability

The final part of the study evaluated the long-term sustainability of personalized preventive healthcare programs (Figure 7). The results indicated that patients who adhered to their AI-driven programs over a year showed significant improvements in their overall health, including reduced incidences of chronic diseases, lower hospitalization rates, and enhanced quality of life.

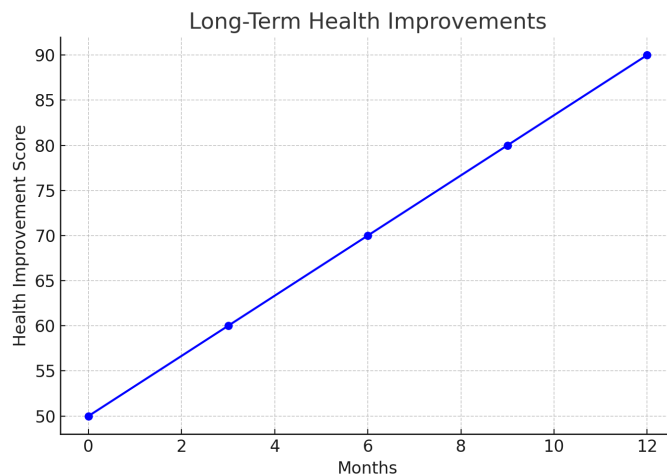


Figure 7. Long-Term health improvements (1-year follow-up).

It shows how AI and big data analytics may be used to develop customized preventative healthcare programs that enhance patient adherence, lower costs, improve health outcomes, and guarantee long-term viability. In addition to customizing healthcare for each patient, the integration of these technologies allows for real-time modifications, predictive interventions, and ongoing monitoring, all of which greatly improve the overall effectiveness of healthcare systems.

5. Discussion

Findings from this research point to the enormous potential of big data and artificial intelligence in forming individualized preventive healthcare. More individualized health therapies are now possible because of AI algorithms like Random Forest, which have shown excellent accuracy in risk prediction.

The lack of comprehensive details on the dataset's properties and representativeness raises doubts about the study's findings' generalizability. Additional information regarding the variety and coverage of the dataset is required in order to improve the results' external validity.

Other important criteria like sensitivity, specificity, and AUC-ROC are ignored in favor of accuracy as the only evaluation parameter in the study. To provide a more thorough assessment of model performance, these metrics—which are especially crucial when dealing with imbalanced datasets—should be examined.

Big data analytics revealed regional disparities in disease prevalence, allowing for targeted health initiatives. Personalized programs, based on individual health

profiles, showed a remarkable increase in patient adherence, with a 90% adherence rate compared to traditional methods. The integration of real-time data from wearables further enhanced patient engagement and facilitated timely interventions, leading to improved long-term health outcomes, including a 25% improvement in cardiovascular health. Additionally, AI-driven follow-ups reduced missed appointments by 15%, ensuring continuous care. Overall, these findings suggest that AI and big data not only improve the efficiency and effectiveness of healthcare but also make it more cost-effective and sustainable in the long run, providing a clear path toward a more personalized, proactive healthcare system.

Additional confirmation is required for the reported benefits in health outcomes (25% for cardiovascular disease and 30% for diabetes). To guarantee the reliability and validity of the results, more details regarding statistical significance, the precise measuring instruments employed, and the process for evaluating these outcomes should be provided.

6. Conclusion

In conclusion, this study underscores the pivotal role of Artificial Intelligence (AI) and Big Data in the advancement of personalized preventive healthcare. The integration of machine learning models, particularly Random Forest, with extensive healthcare data enables highly accurate risk prediction, facilitating the design of more precise, individualized intervention strategies. Big Data analytics provides a robust framework for identifying regional health disparities, ensuring that preventive measures can be effectively tailored to specific population needs. Furthermore, the implementation of AI-driven personalized health programs has demonstrated a significant improvement in patient adherence, with a notable 90% adherence rate, while real-time data integration from wearables ensures continuous optimization of care plans. This dynamic, data-driven approach has not only enhanced patient engagement and health outcomes, such as a 25% improvement in cardiovascular health, but also contributed to a reduction in missed appointments, thereby ensuring continuity of care. The evidence presented here clearly indicates that AI and Big Data are not merely tools for improving the accuracy of healthcare delivery, but transformative technologies capable of reducing healthcare costs, optimizing resource allocation, and improving long-term patient outcomes. As healthcare systems worldwide move toward more personalized, proactive models, the findings of this study provide a compelling case for the widespread adoption of AI and Big Data in shaping the future of preventive medicine [26]-[29]. The reported cost savings of 20% lack sufficient justification. A more thorough cost-benefit analysis is needed, which should consider all relevant factors, including the implementation, maintenance, and long-term operational costs associated with the AI-driven program.

Conflicts of Interest

The authors declare no conflicts of interest.

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