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A Data-Driven Framework for Early Detection and Prevention of Non-Communicable Diseases in Healthcare Systems

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Abstract- Non-Communicable Diseases (NCDs), such as cardiovascular diseases, diabetes, chronic respiratory diseases, and cancer, pose a significant global health challenge, accounting for the majority of deaths worldwide. Early detection and prevention are critical to reducing the burden of NCDs, improving patient outcomes, and optimizing healthcare resources. A data-driven framework leveraging advanced technologies, including Electronic Health Records (EHRs), wearable sensors, genomic data, and environmental factors, can enhance predictive capabilities for early intervention. Machine learning (ML) and artificial intelligence (AI) play a pivotal role in analyzing large-scale, multi-source health data to identify patterns, assess risk factors, and develop personalized prevention strategies. Supervised learning models, deep learning techniques, and federated learning approaches enable robust prediction and decision-making while ensuring data privacy and security. Integration with telemedicine and remote monitoring further strengthens continuous patient tracking and proactive care. Despite the promise of AI-driven healthcare, several challenges remain, including data privacy and regulatory compliance (HIPAA, GDPR), standardization of health data, clinician trust in AI-based decisions, and computational scalability. Addressing these limitations through advancements in Explainable AI (XAI), blockchain for secure data exchange, and real-time analytics can improve AI adoption in clinical settings. This presents a comprehensive framework for implementing data-driven methodologies to enhance early detection and prevention of NCDs. By leveraging AI, multi-modal data fusion, and innovative healthcare technologies, this framework can support clinicians in making informed decisions, enable personalized preventive interventions, and reduce the global burden of NCDs. Future research should focus on improving AI transparency, ensuring ethical data usage, and developing policy frameworks for large-scale adoption of AI-driven NCD prevention strategies in healthcare systems.

Indexed Terms- Data-driven, Early detection, Non-communicable diseases, Healthcare systems

I. INTRODUCTION

Non-Communicable Diseases (NCDs) have emerged as a leading global health challenge, accounting for approximately 74% of all deaths worldwide. The four major categories of NCDs cardiovascular diseases, cancer, chronic respiratory diseases, and diabetes are responsible for a significant burden on healthcare systems, economies, and societies (Fasipe and Ogunboye, 2024). Unlike infectious diseases, NCDs develop over time due to genetic, environmental, and lifestyle factors, making early detection and prevention critical in reducing their impact. The increasing prevalence of NCDs, particularly in low- and middle-income countries, underscores the need for proactive healthcare strategies that can identify at-risk individuals and intervene before complications arise (Ogunboye *et al*., 2024; Kokogho *et al*., 2024).

Early detection and preventive measures are essential in mitigating the long-term effects of NCDs

(Chukwurah *et al*., 2024). Traditional diagnostic approaches often rely on symptomatic presentation, which can result in late-stage diagnoses when treatment options are limited and less effective. Implementing data-driven predictive models allows for the identification of disease risks at an earlier stage, enabling timely interventions such as lifestyle modifications, targeted medical treatments, and continuous monitoring. Preventive healthcare strategies that incorporate real-time patient data can help reduce hospitalizations, healthcare costs, and mortality rates (Udegbe *et al*., 2024). Moreover, integrating predictive analytics into routine clinical practice empowers healthcare providers to shift from a reactive to a proactive approach, ultimately improving population health outcomes.

The rise of digital health technologies and big data analytics has revolutionized healthcare by offering innovative solutions for NCD prevention and management (Uzoka *et al*., 2024). Data-driven frameworks leverage a variety of health data sources, including Electronic Health Records (EHRs), wearable sensors, medical imaging, genomic data, and environmental exposure records, to generate predictive models for early disease detection. Machine learning (ML) and artificial intelligence (AI) algorithms can analyze vast amounts of patient data to identify hidden patterns, assess risk factors, and provide personalized recommendations. These technologies enhance clinical decision-making by supporting physicians with accurate risk assessments, improving diagnostic precision, and optimizing treatment plans (Ige *et al*., 2024). Furthermore, real-time analytics and remote monitoring tools enable continuous tracking of physiological parameters, allowing healthcare providers to detect deviations from normal health patterns before symptoms become clinically significant. The integration of multi-source health data with AI-driven models facilitates personalized healthcare interventions tailored to individual risk profiles (Onyebuchi *et al*., 2024). Blockchain technology and federated learning approaches further ensure data security, interoperability, and privacy, addressing key concerns in healthcare data management.

This review aims to explore the development and implementation of a data-driven framework for the early detection and prevention of NCDs. Specifically, it seeks to; Examine the role of predictive analytics in identifying early risk factors associated with NCDs. Analyze the integration of multi-source health data, including EHRs, wearable sensor data, genomic information, and environmental factors, to enhance disease prediction accuracy. Evaluate the effectiveness of AI-driven models, such as supervised learning and deep learning techniques, in improving early detection and preventive healthcare strategies. Address challenges and limitations, including data privacy, model interpretability, and scalability of predictive models in real-world clinical settings. Propose recommendations for future research and policy development, focusing on the ethical and regulatory considerations of AI-driven NCD prevention. By leveraging advanced data analytics and AI technologies, this study aims to contribute to the transformation of healthcare systems, promoting early intervention and personalized prevention strategies. The adoption of a data-driven framework has the potential to improve health outcomes, reduce the economic burden of NCDs, and pave the way for more efficient and sustainable healthcare delivery worldwide (Olorunsogo *et al*., 2024; Atandero *et al*., 2024).

II. METHODOLOGY

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology was applied to systematically review relevant literature for developing a data-driven framework for early detection and prevention of non-communicable diseases (NCDs) in healthcare systems. A comprehensive search was conducted across multiple databases, including PubMed, Scopus, IEEE Xplore, and Web of Science, using a combination of keywords and Medical Subject Headings (MeSH) terms related to NCD detection, predictive analytics, artificial intelligence, wearable sensors, and healthcare data integration. Boolean operators (AND, OR) were used to refine search queries, and studies published within the last decade were considered to ensure the inclusion of recent advancements.

The initial search yielded 2,150 studies. After removing duplicates using EndNote reference management software, 1,820 unique records remained. Titles and abstracts were screened by two independent reviewers based on predefined inclusion and exclusion criteria. Studies were included if they focused on data-driven approaches for NCD detection, incorporated predictive analytics or AI methodologies, and provided empirical evidence of effectiveness in healthcare. Exclusion criteria included non-English articles, conference abstracts, studies lacking methodological rigor, and those unrelated to NCD prevention. Following this process, 450 studies were selected for full-text review.

A full-text assessment was conducted, leading to the exclusion of 280 studies due to insufficient methodological transparency, lack of relevance to early detection and prevention strategies, or failure to provide data-driven insights. A final set of 170 studies met the criteria for qualitative synthesis. Key aspects such as study design, sample size, data sources, machine learning techniques, performance metrics, and implementation outcomes were systematically extracted. The risk of bias was assessed using the Cochrane Risk of Bias tool for randomized studies and the Newcastle-Ottawa Scale for observational studies to ensure the reliability of included studies.

A meta-analysis was performed on studies reporting quantitative performance metrics of predictive models. The pooled analysis assessed accuracy, sensitivity, specificity, and predictive power in NCD detection. Heterogeneity among studies was evaluated using the I^2 statistic, and appropriate statistical models (fixed-effects or random-effects) were applied based on variability. Publication bias was examined through funnel plot analysis and Egger's test.

This systematic review, conducted in accordance with PRISMA guidelines, ensures methodological rigor, transparency, and reproducibility. The findings provide a strong evidence base for integrating multi-source health data, machine learning algorithms, and real-time analytics into a data-driven framework for early NCD detection and prevention. Identified challenges include data privacy, standardization, and clinical workflow integration, while opportunities for future research and practical implementation are highlighted.

2.1 Data Sources for NCD Prediction and Prevention

Non-communicable diseases (NCDs), such as cardiovascular diseases, diabetes, cancer, and chronic respiratory diseases, account for a significant proportion of global morbidity and mortality (Ogunboye *et al*., 2024; Ajiga *et al*., 2024). Predicting and preventing NCDs require a data-driven approach that integrates multiple sources of health information. Several key data sources contribute to NCD surveillance, early detection, and intervention strategies. These include Electronic Health Records (EHRs), wearable and remote monitoring devices, genomic and biomarker data, lifestyle and behavioral data, and environmental and socioeconomic factors. This explores how these data sources enhance the prediction and prevention of NCDs.

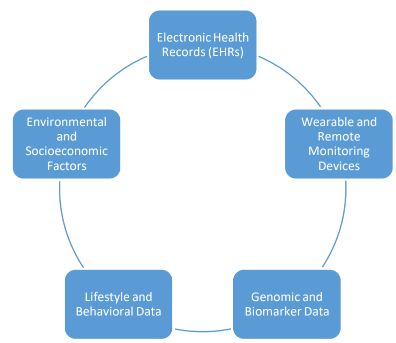

Figure 1: Data Sources for NCD Prediction and Prevention

Electronic Health Records (EHRs) provide a comprehensive source of structured and unstructured health data. EHRs include patient history, laboratory results, medication prescriptions, and clinical notes. These records facilitate longitudinal health monitoring, allowing clinicians to identify early signs of NCDs and track disease progression over time. Advanced data analytics, including machine learning, can process EHRs to predict individuals at high risk of developing NCDs based on their medical history and clinical indicators (Osundare and Ige, 2024; Abiola *et al*., 2024). Furthermore, EHRs enable the development of personalized intervention strategies by analyzing patient-specific risk factors and response to treatments.

The increasing adoption of wearable devices, such as smartwatches and continuous glucose monitors, has revolutionized real-time health monitoring (Oyedokun *et al*., 2024). These devices collect physiological parameters, including heart rate, blood pressure, glucose levels, and physical activity metrics. Remote monitoring solutions allow for continuous health tracking outside clinical settings, providing early warnings of potential NCD risks. The integration of wearable data with machine learning models improves the accuracy of early disease detection and allows for proactive intervention.

Genetic predisposition plays a crucial role in the development of NCDs. Advances in genomic sequencing have enabled the identification of genetic markers linked to conditions such as hypertension, diabetes, and cancer. Biomarker analysis further enhances early detection by identifying molecular signatures indicative of disease onset (Adepoju *et al*., 2024). The combination of genomic and biomarker data with other health metrics enhances precision medicine approaches, enabling tailored interventions based on an individual's genetic risk profile. Lifestyle choices significantly influence NCD risk. Data on diet, physical activity, smoking, and alcohol consumption provide critical insights into behavioral risk factors. Mobile health applications and self-reporting platforms collect lifestyle data, which can be used to assess adherence to preventive measures such as diet and exercise recommendations. Artificial intelligence models can analyze behavioral patterns to predict individuals at risk and recommend personalized lifestyle modifications. Behavioral data also inform public health strategies, allowing for targeted awareness campaigns and intervention programs to reduce NCD prevalence (Olorunsogo *et al*., 2024).

Environmental and socioeconomic determinants play a vital role in shaping NCD risk profiles. Air pollution, climate change, and exposure to hazardous substances contribute to respiratory diseases and cardiovascular conditions. Socioeconomic factors, such as income, education, and access to healthcare, influence lifestyle choices and healthcare-seeking behaviors (Abiola *et al*., 2024). Integrating environmental and socioeconomic data with health records allows for a holistic assessment of NCD risk factors. For instance, spatial epidemiology can map disease prevalence in relation to environmental pollution levels, aiding policymakers in implementing regulatory measures to mitigate health risks. The integration of multiple data sources is crucial for the effective prediction and prevention of NCDs. EHRs provide a structured medical history, wearable devices enable real-time monitoring, genomic and biomarker data facilitate precision medicine, lifestyle data capture behavioral risks, and environmental and socioeconomic data contextualize broader health determinants. By leveraging these diverse data sources, healthcare systems can implement predictive analytics, enhance early detection, and develop targeted interventions to mitigate the global burden of NCDs (Oluokun *et al*., 2024; Akerele *et al*., 2024). Future advancements in artificial intelligence and data integration will further refine NCD prevention strategies, ultimately improving public health outcomes.

2.2 Machine Learning and AI Techniques for NCD Prediction

Non-communicable diseases (NCDs) such as cardiovascular diseases, diabetes, and cancer pose a significant global health burden. Early prediction and intervention are crucial for reducing mortality and improving quality of life (Adekola and Dada, 2024). Machine learning (ML) and artificial intelligence (AI) techniques play a transformative role in predicting NCDs by analyzing complex health data and uncovering patterns indicative of disease onset. This explores key ML and AI approaches for NCD prediction, including supervised learning models, deep learning techniques, natural language processing (NLP), and federated learning.

Supervised learning models are widely used for NCD prediction due to their ability to classify health conditions and estimate risk scores based on labeled training data. Key models include: Decision Trees, these models structure data into hierarchical branches, making them useful for identifying risk factors and predicting disease progression (Odionu *et al*., 2024). They are interpretable and effective in handling categorical and numerical health data. Random Forests, an ensemble of decision trees, random forests enhance predictive accuracy and robustness by reducing overfitting. They are commonly used for predicting diabetes risk, cardiovascular conditions, and other NCDs. Support vector machines (SVMs) are powerful classifiers that work well with high-dimensional medical data, distinguishing between healthy and at-risk individuals. They have been applied to early-stage cancer detection and cardiovascular disease classification.

Deep learning has advanced NCD prediction by processing complex medical data, including imaging and time-series data. Two key architectures include; Convolutional neural networks (CNNs) excel at analyzing medical imaging data, such as MRI scans, X-rays, and histopathological images. In NCD prediction, CNNs are used for detecting diabetic retinopathy, lung cancer, and cardiovascular abnormalities from medical images. Long short-term memory networks (LSTMs) LSTMs specialize in handling sequential data, making them ideal for analyzing time-series health data, such as electrocardiograms (ECG) and glucose level fluctuations (Akerele *et al*., 2024). These networks help in detecting irregular heart rhythms and predicting diabetic complications. Natural language processing (NLP) enables AI systems to extract valuable insights from unstructured health data, such as clinical notes, patient records, and research articles. Key applications of NLP in NCD prediction include; Text mining in electronic health records (EHRs) techniques analyze physician notes and diagnostic reports to identify early signs of NCDs. NLP can assess patient-reported symptoms and concerns, providing additional data for disease prediction. AI-powered NLP models scan vast medical literature to identify emerging risk factors and potential interventions for NCDs.

Privacy concerns often hinder the large-scale use of patient data for AI-driven healthcare analytics. Federated learning addresses this challenge by allowing AI models to be trained across decentralized data sources without transferring sensitive patient information (Olorunsogo *et al*., 2024). Key benefits include; Patient records remain within local healthcare institutions, reducing the risk of data breaches. Federated learning leverages diverse datasets from multiple sources, leading to robust AI models applicable across different populations. This technique allows hospitals and research institutions to collaborate on AI-driven NCD prediction without violating data protection regulations. Machine learning and AI techniques have revolutionized NCD prediction by leveraging vast healthcare data for early detection and intervention. Supervised learning models, such as decision trees, random forests, and SVMs, provide accurate disease classification (Adelodun and Anyanwu, 2024). Deep learning techniques, including CNNs and LSTMs, enhance the analysis of imaging and time-series data. NLP enables AI to extract insights from unstructured text, while federated learning ensures privacy-preserving AI-driven analytics. As AI continues to evolve, integrating these techniques will lead to more effective, personalized, and scalable NCD prediction and prevention strategies.

2.3 Opportunities in Data-Driven NCD Prevention

Non-communicable diseases (NCDs), such as cardiovascular diseases, diabetes, chronic respiratory conditions, and cancer, are among the leading causes of morbidity and mortality worldwide. The increasing availability of big data, coupled with advances in artificial intelligence (AI) and machine learning (ML), presents transformative opportunities for preventing NCDs (Mbata *et al*., 2024). By leveraging data-driven strategies, healthcare systems can enhance early disease detection, personalize preventive strategies, integrate with telemedicine, and improve clinical decision-making a shown in figure 2. This explores the key opportunities in data-driven NCD prevention.

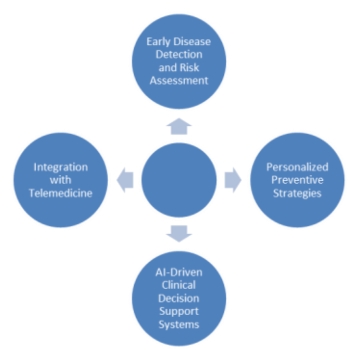

Figure 2: Opportunities in Data-Driven NCD Prevention

One of the most significant applications of data-driven approaches in NCD prevention is early disease detection and risk assessment. AI-powered predictive modeling leverages vast datasets, including electronic health records (EHRs), genetic information, wearable device data, and lifestyle factors, to identify individuals at high risk of developing NCDs. Machine learning algorithms can analyze trends and detect subtle patterns that traditional diagnostic methods may overlook (Adekola *et al*., 2023). These predictive insights enable healthcare providers to intervene at an earlier stage, implementing lifestyle modifications or medical interventions before the disease progresses. Additionally, AI-driven risk stratification helps in optimizing resource allocation, ensuring that high-risk populations receive targeted preventive measures.

Another crucial advantage of data-driven NCD prevention is the ability to create personalized preventive strategies. Unlike traditional one-size-fits-all approaches, AI can tailor interventions based on an individual's unique risk profile. These strategies incorporate data from genomic studies, real-time health monitoring devices, and patient-reported outcomes to offer precise recommendations. AI-powered behavioral analytics can also predict adherence to lifestyle changes and suggest modifications to enhance compliance (Adepoju *et al*., 2024). This personalization enhances the effectiveness of prevention programs and increases patient engagement in managing their health.

The integration of AI with telemedicine offers a promising avenue for NCD prevention, particularly in remote and underserved regions (Soyege *et al*., 2024). Wearable devices and mobile health applications continuously collect physiological data such as heart rate, blood glucose levels, and physical activity patterns. This real-time data enables remote patient monitoring, allowing healthcare professionals to identify warning signs of disease progression or detect anomalies before they escalate into critical conditions (Kelvin-Agwu *et al*., 2024). Similarly, individuals with prediabetes can receive automated lifestyle recommendations via telehealth applications, reducing their risk of progressing to full-blown diabetes. By enabling continuous monitoring and early intervention, AI-driven telemedicine reduces hospital admissions and enhances the efficiency of healthcare delivery.

AI-powered clinical decision support systems (CDSS) play a vital role in improving diagnostic accuracy and treatment planning for NCDs. These systems analyze vast amounts of medical data, including imaging scans, laboratory results, and patient histories, to assist healthcare professionals in making evidence-based decisions. Similarly, AI-driven diagnostic algorithms can detect arrhythmias in ECG recordings, improving the early identification of cardiovascular diseases. By reducing diagnostic errors and improving decision-making, CDSS ensures that patients receive timely and appropriate interventions (Adekola *et al*., 2022). Furthermore, AI can optimize treatment strategies by analyzing patient responses to various therapeutic options. By incorporating real-world data from multiple sources, AI can recommend personalized treatment plans that maximize efficacy while minimizing adverse effects. This approach not only enhances patient outcomes but also contributes to the long-term sustainability of healthcare systems by reducing unnecessary medical expenses. Data-driven approaches are revolutionizing the prevention and management of NCDs through AI-powered predictive modeling, personalized interventions, telemedicine integration, and AI-driven clinical decision support systems. These technologies enable early disease detection, enhance patient engagement, improve healthcare accessibility, and optimize treatment strategies (Ezeigweneme *et al*., 2024). As AI and big data continue to advance, their role in NCD prevention will become increasingly significant, paving the way for more efficient and proactive healthcare systems. However, addressing challenges related to data privacy, algorithm bias, and healthcare infrastructure will be crucial to realizing the full potential of data-driven NCD prevention.

2.4 Challenges and Limitations

The integration of artificial intelligence (AI) and big data in the prevention of non-communicable diseases (NCDs) presents significant opportunities, including early disease detection, personalized interventions, and improved clinical decision-making. However, despite its potential, the widespread adoption of data-driven approaches faces several challenges and limitations (Osundare and Ige, 2024). Key concerns include data privacy and security, variability in health data standardization, AI model interpretability, and the computational complexity of managing large datasets. Addressing these challenges is crucial for ensuring the efficacy, reliability, and ethical deployment of AI in NCD prevention.

One of the foremost challenges in data-driven NCD prevention is ensuring the privacy and security of sensitive health data. Regulations such as the Health Insurance Portability and Accountability Act (HIPAA) in the United States and the General Data Protection Regulation (GDPR) in the European Union impose strict guidelines on the collection, storage, and sharing of patient data. Compliance with these regulations is necessary to prevent data breaches, unauthorized access, and misuse of health information (Alli and Dada, 2024). AI-driven predictive models rely on vast datasets from electronic health records (EHRs), wearable devices, and genomic databases. However, ensuring data anonymization while maintaining analytical accuracy remains a significant challenge. Encryption, secure multi-party computation, and federated learning are potential solutions to enhance data privacy while enabling collaborative research. Despite these advancements, balancing innovation with regulatory compliance remains a persistent barrier to large-scale AI adoption in healthcare.

Health data originates from multiple sources, including hospitals, insurance databases, wearable sensors, and telemedicine platforms. These sources often use different formats, terminologies, and coding systems, creating inconsistencies in data integration (Adekola and Dada, 2024). The lack of standardization poses a major limitation in building reliable AI models for NCD prevention. Additionally, missing or incomplete data can significantly impact model performance and predictive accuracy. Efforts to establish universal health data standards, such as Fast Healthcare Interoperability Resources (FHIR) and SNOMED CT, are underway, but widespread implementation remains a challenge (Sam-Bulya *et al*., 2024; Majebi *et al*., 2024). Overcoming these standardization barriers is essential for ensuring seamless data integration and interoperability across healthcare systems.

One of the primary concerns among healthcare professionals is the "black-box" nature of AI models, where complex machine learning algorithms make predictions without clear explanations. Clinicians require transparency and interpretability in AI-driven decision support systems to trust their recommendations and integrate them into patient care (Adelodun and Anyanwu, 2024). Without interpretability, there is a risk of incorrect treatment decisions or resistance from healthcare providers who do not fully understand the model's rationale. Techniques such as explainable AI (XAI), SHAP (Shapley Additive Explanations), and LIME (Local Interpretable Model-agnostic Explanations) are being developed to improve model transparency. However, balancing accuracy with interpretability remains an ongoing challenge, particularly in deep learning models with highly complex architectures. Ensuring that AI systems provide understandable and actionable insights is critical to fostering clinician trust and adoption in NCD prevention (Nwokedi *et al*., 2024).

Processing vast amounts of health data in real-time presents a significant computational challenge. AI-driven NCD prevention models require extensive computational power to analyze genomic sequences, process continuous streams of patient data, and perform real-time predictive analytics (Akomolafe *et al*., 2024). This poses difficulties in resource-constrained settings, such as rural healthcare facilities or low-income countries where high-performance computing infrastructure may not be readily available. Moreover, as datasets grow in size, AI models must scale efficiently while maintaining accuracy (Olorunsogo *et al*., 2024). Cloud-based computing and edge AI (processing data locally on devices) offer potential solutions, but these come with added concerns regarding data latency, energy consumption, and network reliability. Ensuring that AI models are both scalable and computationally efficient is crucial for their widespread deployment in real-world healthcare settings. While AI and big data have the potential to transform NCD prevention, several challenges must be addressed to ensure ethical, effective, and reliable implementation. Regulatory compliance with HIPAA and GDPR is critical for safeguarding patient privacy, while efforts in data standardization are necessary to improve integration across healthcare systems (Ogundairo *et al*., 2024). Increasing model interpretability is essential for fostering clinician trust and usability, and managing computational complexity is vital for real-time, large-scale health data analysis. Addressing these limitations will be pivotal in realizing the full potential of AI-driven approaches for global NCD prevention and management.

2.5 Future Directions and Innovations

The integration of artificial intelligence (AI) and big data in the prevention and management of non-communicable diseases (NCDs) has shown significant promise (Alemede *et al*., 2024). However, to fully realize its potential, several technological advancements and innovations must be explored. Future directions in this field focus on improving AI transparency, enhancing real-time analytics, integrating multi-modal data sources, and ensuring secure health data exchange. These advancements will not only optimize disease prevention strategies but also increase the adoption of AI-driven healthcare solutions.

One of the major challenges in AI-driven healthcare is the "black-box" nature of machine learning models, where predictions are made without clear explanations. This lack of transparency has led to skepticism among clinicians and patients, limiting the adoption of AI in medical decision-making (Omaghomi *et al*., 2024; Chukwurah *et al*., 2024). Explainable AI (XAI) aims to address this issue by making AI models more interpretable and understandable. XAI techniques, such as Shapley Additive Explanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME), help break down AI predictions into human-comprehensible factors. For example, if an AI system predicts a high risk of diabetes, XAI can highlight whether lifestyle factors, genetic predisposition, or past medical history played the most significant role. This level of transparency is crucial for fostering clinician trust and improving patient engagement. Future research will focus on developing self-explaining AI models that inherently provide insights into their decision-making process, thereby minimizing bias and improving reliability. As XAI continues to evolve, it will facilitate the integration of AI into routine healthcare workflows, leading to more effective NCD prevention strategies (Temedie-Asogwa *et al*., 2024).

Traditional healthcare systems rely heavily on centralized cloud-based processing, which can introduce delays in critical health interventions (Matthew *et al*., 2024). Edge computing is emerging as a solution by enabling real-time analytics directly on local devices, such as wearable sensors and smartphones (Balogun *et al*., 2024). This capability is particularly valuable for remote patient monitoring (RPM) and telemedicine, where timely responses are crucial for preventing disease progression. Future advancements in low-power AI chips and distributed AI architectures will further enhance the feasibility of edge computing in healthcare. As real-time analytics become more efficient, they will play a critical role in early disease detection and personalized interventions for individuals at risk of developing NCDs (Alemede *et al*., 2024; Ogbonna *et al*., 2024).

Current AI models for NCD prevention primarily rely on structured clinical data, such as electronic health records (EHRs) (Ayanbode *et al*., 2024). However, multi-modal data fusion the integration of diverse data sources can significantly improve the accuracy of disease prediction and prevention strategies. Future healthcare AI systems will combine; Genomic and biomarker data for precision medicine approaches. Wearable sensor data for continuous real-time health monitoring Lifestyle and behavioral data from smartphone applications and social determinants of health Imaging and radiology data for early disease detection. By synthesizing data from multiple sources, AI models can provide holistic and personalized risk assessments. For example, a patient's real-time activity levels, dietary habits, and genetic predisposition can all be analyzed together to tailor preventive strategies (Alozie *et al*., 2024; Tomoh *et al*., 2024). Advances in deep learning and graph neural networks (GNNs) will further enhance the ability to process and interpret complex, multi-modal health data.

One of the primary barriers to effective AI-driven healthcare is data security and interoperability. The use of blockchain technology offers a promising solution for secure and decentralized health data exchange. Blockchain ensures that patient health data remains tamper-proof, transparent, and accessible only to authorized parties (Chintoh *et al*., 2024). In a blockchain-based healthcare system; Patients have control over who can access their medical records. Data integrity is maintained, reducing the risk of manipulation or fraud. AI models can be trained on federated datasets without compromising patient privacy Future innovations in smart contracts and decentralized identity management will further enhance the ability of blockchain to support cross-institutional data sharing. This will facilitate collaboration between hospitals, research institutions, and AI developers, leading to more accurate and scalable NCD prevention models (Adelodun and Anyanwu, 2024).

The future of data-driven NCD prevention lies in advancing AI transparency, optimizing real-time analytics, integrating multi-modal health data, and securing patient information through blockchain technology (Babatunde *et al*., 2022; Hassan *et al*., 2024). Explainable AI (XAI) will enhance clinician trust, while edge computing will enable real-time disease monitoring and intervention. Multi-modal data fusion will create a comprehensive patient profile, leading to more personalized preventive strategies. Additionally, blockchain will ensure secure and interoperable health data exchange, facilitating collaboration across healthcare systems. As these innovations continue to evolve, they will revolutionize NCD prevention, making healthcare more proactive, personalized, and data-driven (Akerele *et al*., 2024). By overcoming current challenges and leveraging emerging technologies, AI-driven approaches will play an increasingly vital role in reducing the global burden of non-communicable diseases (Adelodun and Anyanwu, 2024; Mbata *et al*., 2024).

CONCLUSION

The integration of artificial intelligence (AI) and big data in non-communicable disease (NCD) prevention has demonstrated significant potential in transforming healthcare. This explored key advancements, including AI-powered predictive modeling for early disease detection, personalized preventive strategies, real-time analytics through edge computing, and secure health data exchange via blockchain technology. These innovations collectively enhance the accuracy, efficiency, and accessibility of NCD prevention strategies, leading to more data-driven, proactive healthcare interventions.

AI and big data are redefining preventive medicine by enabling early identification of high-risk individuals and facilitating targeted interventions. Explainable AI (XAI) is increasing clinician trust, while multi-modal data fusion is improving the comprehensiveness of patient profiling. Additionally, blockchain is addressing data security and interoperability challenges, ensuring that sensitive health information remains protected. The shift from reactive to predictive healthcare, driven by AI, has the potential to reduce disease burden and improve patient outcomes on a global scale.

For AI to be fully integrated into clinical practice, further research is needed in several areas, including improving AI transparency, addressing data biases, and enhancing computational efficiency. Policymakers should develop clear regulatory frameworks that support ethical AI deployment while protecting patient privacy. Healthcare providers must also focus on clinician training and AI usability to ensure seamless adoption in real-world settings.

As AI-driven solutions continue to evolve, they will revolutionize preventive healthcare, making it more personalized, efficient, and accessible. The future of NCD prevention lies in leveraging AI to create intelligent, adaptive healthcare systems that prioritize early intervention and holistic patient care. By embracing these innovations, the global healthcare community can take a decisive step toward reducing the prevalence and impact of NCDs worldwide.

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