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A Conceptual Model for Addressing Healthcare Inequality Using AI-Based Decision Support Systems

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Abstract
Healthcare inequality remains a persistent global challenge, particularly affecting marginalized and underserved populations. Disparities in access, quality, and health outcomes are exacerbated by socioeconomic, geographic, and systemic barriers. This paper proposes a conceptual model for addressing healthcare inequality through the implementation of Artificial Intelligence (AI)-based Decision Support Systems (DSS). The model integrates advanced data analytics, machine learning algorithms, and real-time health information to support clinical and policy decisions aimed at reducing disparities in healthcare delivery. The conceptual model operates on three core pillars: data integration, predictive analytics, and equitable decision-making. First, the model aggregates data from diverse sources—including electronic health records (EHRs), social determinants of health, and population health databases—to build a comprehensive profile of healthcare needs in various communities. Second, AI-driven predictive analytics are employed to identify at-risk populations, forecast disease trends, and allocate resources efficiently. Finally, the system provides tailored decision support for healthcare providers and policymakers, ensuring that interventions are responsive to the specific needs of disadvantaged groups. A key feature of the model is its emphasis on explainable AI (XAI), which ensures transparency, accountability, and trust in AI-generated recommendations. The model also incorporates fairness-aware algorithms to mitigate bias in data and decision-making, promoting inclusivity and ethical use of technology. Case simulations demonstrate how the system can optimize screening programs, prioritize high-risk patients, and guide equitable health policy formulation. This paper underscores the transformative potential of AI-based DSS in reducing healthcare inequality by enabling data-driven, context-sensitive, and inclusive health interventions. By aligning technology with principles of social justice and health equity, the model offers a strategic pathway for addressing longstanding disparities in healthcare systems. Future research will focus on real-world implementation, stakeholder engagement, and continuous learning to refine the model and expand its applicability across different healthcare settings.

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1. Introduction

Healthcare inequality remains a significant global and local challenge, impacting millions of individuals who encounter barriers to accessing quality medical care. These barriers are particularly pronounced in low- and middle-income countries, where healthcare disparities stem from a multifaceted interplay of socioeconomic, geographical, and systemic factors.

For instance, individuals in rural or underserved urban areas often experience limited access to healthcare facilities, inadequate transportation options, and a scarcity of healthcare professionals, all of which exacerbate the difficulty in obtaining timely and effective medical intervention (Mohamed *et al*., 2021; Water *et al*., 2017; Morenz *et al*., 2019). Moreover, studies suggest that these disparities significantly contribute to poorer health outcomes, as patients from marginalized communities are less likely to receive timely diagnoses, effective treatments, or preventive care, which leads to higher rates of preventable diseases and inadequate management of chronic conditions (Stokes *et al*., 2019; Powell *et al*., 2019).

Socioeconomic status—comprising factors such as income, education, and employment—profoundly affects health outcomes. Those from lower-income brackets often struggle to afford healthcare services, medications, or insurance coverage, and may reside in environments that further jeopardize their health (Kamya *et al*., 2022; Powell *et al*., 2019). Geographic disparities also play a critical role; healthcare infrastructure is frequently concentrated in urban centers, leaving those in rural areas with significant barriers to accessing necessary medical care (Dickson *et al*., 2022; Ambroggi *et al*., 2015). Systemic disparities accentuated by biases in medical research and unequal resource distribution further contribute to the uneven quality of care delivered to different populations. For instance, evidence indicates that physical distance to healthcare facilities, alongside the socioeconomic positioning of individuals, plays a significant role in delaying diagnosis and treatment, particularly regarding chronic illnesses like tuberculosis (Water *et al*., 2017; Ambroggi *et al*., 2015).

The advent of artificial intelligence (AI) and decision support systems (DSS) in healthcare presents a burgeoning opportunity to mitigate some of these inequities. AI-based DSS can analyze vast datasets, uncover patterns, and provide healthcare professionals with timely, evidence-based recommendations, facilitating improved clinical decision-making in scenarios where access to specialists is limited due to geographic or logistical constraints (Lwin *et al*., 2021; Andonova & Todorova, 2021). Such systems can empower healthcare providers in underserved areas by enhancing their diagnostic accuracy and treatment recommendations, thereby addressing knowledge gaps that may otherwise leave healthcare providers and patients at a disadvantage (Tuck *et al*., 2022). The strategic implementation of AI-driven tools aims to deliver scalable, cost-effective solutions to the persistent challenges of healthcare inequality, ultimately for the betterment of health outcomes for traditionally marginalized communities (Stokes *et al*., 2017; McConkey, 2017).

In summary, addressing healthcare inequality necessitates a comprehensive understanding of the various barriers faced by individuals, especially those from low-income or rural backgrounds. The integration of AI technologies into healthcare delivery may serve as a vital component in bridging the gaps in access and quality of care, fostering improved health outcomes across diverse socioeconomic and geographical landscapes.

2. Literature Review

Healthcare disparities continue to persist globally, with numerous studies revealing that individuals in rural, low-income, and marginalized communities experience significantly worse health outcomes than their more affluent counterparts. The root causes of these disparities are multifaceted, often driven by a combination of socioeconomic, geographic, and systemic factors (Adepoju, *et al*., 2022, Olamijuwon, 2020, Uwaifo & Favour, 2020). Socioeconomic disparities, such as income inequality and lack of access to education and insurance, limit individuals' ability to seek timely and appropriate healthcare services. Geographic factors further compound this issue, particularly in rural and remote areas where medical facilities and specialists are scarce. Systemic factors, including biased healthcare policies and structural inequalities within healthcare institutions, also contribute to the unequal distribution of care. These disparities lead to higher rates of preventable diseases, inadequate treatment of chronic conditions, and overall poorer health outcomes for underserved populations.

The social determinants of health, including income, employment, education, social support, and access to healthcare, are fundamental in understanding healthcare inequality. Socioeconomic status often dictates the quality and availability of healthcare services, with low-income individuals facing barriers to accessing care, medications, or insurance coverage. This economic divide is particularly stark in many low- and middle-income countries (LMICs), where even basic healthcare services can be out of reach for a significant portion of the population (Abisoye & Akerele, 2022, Olaniyan, *et al*., 2018, Uwaifo, *et al*., 2019). Similarly, geographic disparities often see rural populations lacking the infrastructure or services necessary to receive adequate care. Many rural areas are under-served by medical professionals, who are often concentrated in urban centers where medical resources and facilities are more abundant. This discrepancy leaves individuals in rural communities with limited options for preventive care, diagnostic testing, and specialized treatments. Figure 1 shows the theoretical model of health equity presented by Estape, *et al*., 2014.

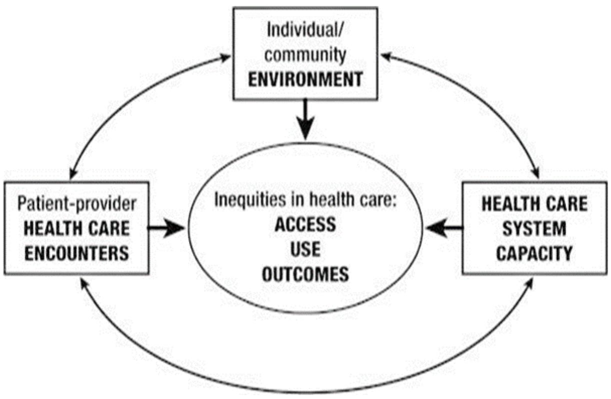

Fig 1: Theoretical model of health equity (Estape, *et al*., 2014).

Existing decision support systems (DSS) in clinical settings have made considerable strides in improving healthcare delivery by providing healthcare professionals with the tools needed to make more informed, data-driven decisions. These systems typically integrate patient data, clinical guidelines, and diagnostic algorithms to assist in clinical decision-making. DSS has been successfully applied in various healthcare settings, such as electronic health records (EHR) systems that help healthcare providers track patient histories, diagnose conditions, and recommend treatments (Adewale, *et al*., 2022, Olorunyomi, Adewale & Odonkor, 2022). Clinical decision support systems have been instrumental in reducing errors, streamlining workflows, and enhancing patient safety. These systems are designed to assist clinicians in making more accurate diagnoses and treatment plans by analyzing patient data and recommending evidence-based interventions.

While DSS has been widely adopted in many clinical settings, its role in addressing healthcare disparities, particularly those associated with equity and inclusion, has not been fully explored. Traditional DSS tools are often limited by the availability and quality of data and may not fully account for the unique needs of underserved or marginalized populations. In many settings, these systems are primarily focused on urban or affluent populations, and their ability to support healthcare in rural or low-income communities is limited (Adewale, *et al*., 2022, Olorunyomi, Adewale & Odonkor, 2022). The growing reliance on data-driven systems in healthcare also introduces new challenges related to data representation, with many clinical models being trained on data that does not adequately reflect the diversity of patients served, particularly in remote or marginalized populations. As a result, DSS often perpetuate existing disparities rather than addressing the structural issues at their core.

The role of AI in improving healthcare delivery, especially in addressing healthcare inequality, is a critical area of development. Artificial Intelligence, with its capacity for processing large datasets and learning from complex patterns, holds the potential to revolutionize the way healthcare is delivered. In the context of healthcare disparities, AI can offer targeted, data-driven solutions to bridge gaps in care. For instance, machine learning algorithms can analyze electronic health records, radiology images, and genomic data to identify trends and predict disease outcomes, providing clinicians with valuable insights that might otherwise be missed (Adekola, Kassem & Mbata, 2022, Olufemi-Phillips, *et al*., 2020). AI can also enhance diagnostic accuracy, which is particularly important in remote areas where access to specialists and advanced diagnostic tools is limited. Conceptual framework of data flow to develop the decision support system presented by Shrivastava, *et al*., 2021, is shown in figure 2.

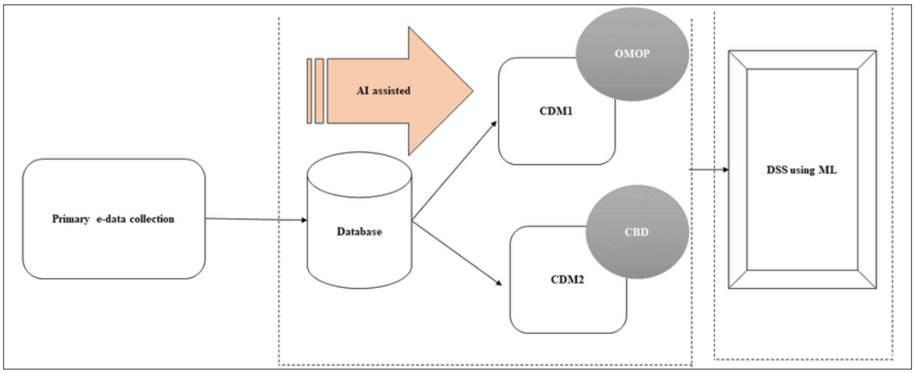

Fig 2: Conceptual framework of data flow to develop the decision support system (Shrivastava, *et al*., 2021).

AI-based decision support systems (AI-DSS) have demonstrated their potential in clinical settings by offering real-time, personalized recommendations based on individual patient data. For example, AI-driven diagnostic tools, such as radiology image analysis software, can identify early signs of diseases like cancer, heart disease, or diabetic retinopathy, helping healthcare providers make quicker and more accurate diagnoses (Adegoke, *et al*., 2022, Olaniyan, Ale & Uwaifo, 2019). These systems can be particularly valuable in remote regions where specialized expertise is lacking. Additionally, AI-based tools can help prioritize cases based on the severity of symptoms, ensuring that high-risk patients receive timely care. Furthermore, AI can be used to predict patient outcomes, such as the risk of developing chronic conditions or experiencing complications, enabling proactive care and early intervention.

AI also has the potential to democratize healthcare by enabling more equitable access to quality care. In underserved areas, AI-powered telemedicine platforms can connect patients with healthcare providers remotely, reducing the need for travel and overcoming geographic barriers to care. AI can also assist in patient monitoring, providing real-time feedback to healthcare providers and helping to manage chronic conditions such as diabetes or hypertension (Abisoye & Akerele, 2022, Olaniyan, Uwaifo & Ojediran, 2019). By enabling remote consultations, diagnoses, and continuous monitoring, AI can reduce disparities in access to healthcare and support the delivery of care in areas where healthcare facilities are scarce.

Despite these advancements, there are significant gaps in current models of AI-based decision support systems regarding equity and inclusion. One major challenge is the lack of diverse data used to train AI models, which can lead to biased algorithms that do not work equally well for all population groups. AI models trained on data that predominantly represents certain demographics, such as urban or affluent populations, may not perform as well when applied to populations that are underrepresented in the training data (Adekunle, *et al*., 2021, Onukwulu, et akl., 2022, Uwaifo, *et al*., 2018). This can result in inaccurate diagnoses, delayed treatment, and ultimately worse health outcomes for marginalized groups. To address this issue, it is essential that AI-based systems are trained on diverse, representative datasets that reflect the experiences and needs of underserved populations, particularly those in remote areas or low-income communities.

Moreover, AI-based decision support systems must be designed with cultural sensitivity in mind. Healthcare needs and preferences vary widely across different communities, and AI models should take into account cultural factors that may influence health behaviors, treatment acceptance, and health outcomes. For example, AI systems used in remote regions should account for local languages, health beliefs, and traditional practices, ensuring that they are relevant and acceptable to the target population (Abisoye & Akerele, 2021, Olutimehin, *et al*., 2021). Failure to do so could result in AI technologies that are not embraced by local communities, limiting their effectiveness in addressing healthcare disparities.

In addition, AI models must be transparent and explainable, particularly in healthcare settings where patients and healthcare providers need to understand the rationale behind AI-driven recommendations. This is crucial for fostering trust in AI systems, especially in underserved regions where there may be skepticism regarding the role of technology in healthcare. Transparent and explainable AI systems can help patients and clinicians make informed decisions and ensure that AI is used as a tool to complement, rather than replace, human expertise (Adewale, *et al*., 2022, Uwaifo, 2020).

In conclusion, while AI has great potential to address healthcare inequalities, significant efforts are needed to ensure that AI-based decision support systems are inclusive, fair, and effective. The current models of AI in healthcare must be expanded to include diverse datasets, culturally sensitive designs, and transparent algorithms that prioritize equity and inclusion. By addressing these gaps, AI can play a pivotal role in improving healthcare delivery in remote regions, reducing disparities in care, and ultimately achieving better health outcomes for underserved populations (Abisoye & Akerele, 2022, Qin, *et al*., 2018, Uwaifo & John-Ohimai, 2020). This review emphasizes the importance of developing AI technologies that are accessible, fair, and aligned with the needs of marginalized communities, ensuring that the benefits of AI are shared by all, regardless of socioeconomic or geographic status.

2.1 Methodology

The methodology for developing a conceptual model for addressing healthcare inequality using AI-based decision support systems begins with defining the research objectives. This involves outlining the key goals and the specific healthcare inequalities that the model aims to address, ensuring alignment with national health priorities. A thorough review of existing literature follows, identifying the gaps in current models and understanding the application of AI in healthcare decision support systems. This review also includes examining relevant works on AI integration in healthcare systems and evaluating their successes and challenges.

Once the literature review is complete, the next step is to identify suitable data sources that will inform the model. This involves assessing the availability and reliability of datasets, particularly those that provide information on healthcare access, outcomes, and inequalities. Data sources may include national health surveys, patient records, and demographic data that are critical for understanding healthcare disparities.

Following data identification, a conceptual model is developed. This model incorporates AI-driven decision support systems that are designed to analyze healthcare data and identify patterns of inequality. The model leverages machine learning and predictive analytics to provide real-time insights, helping healthcare providers make informed decisions aimed at reducing inequalities in healthcare access and outcomes.

The next phase involves the integration of the AI-based decision support system with the conceptual model. This system is designed to process healthcare data efficiently, providing recommendations for interventions and identifying areas of concern. The system's architecture will include data processing frameworks, AI algorithms for analysis, and user-friendly interfaces for healthcare professionals. Once the AI system is developed, data collection and analysis take place. This stage involves gathering data from the identified sources and inputting it into the system for processing. The data is analyzed using AI algorithms to identify trends, disparities, and patterns that could point to areas of healthcare inequality. The model is then validated through testing and simulation. The validation process includes comparing the model's predictions with real-world healthcare outcomes to ensure its accuracy and effectiveness. Any discrepancies are addressed by refining the model, ensuring that it can reliably support decision-making in diverse healthcare settings. After the model has been validated, the results are interpreted to assess the impact of the AI-based system on reducing healthcare inequality. This interpretation includes identifying the potential for scalability, the model's applicability in different healthcare contexts, and its ability to provide actionable insights.

Finally, policy recommendations are developed based on the results of the analysis. These recommendations will guide healthcare policy-makers on how to integrate AI-driven solutions into public health strategies, with a focus on reducing inequality and improving overall healthcare delivery. The findings from the research will be shared with relevant stakeholders to ensure that the model has a meaningful impact on improving healthcare outcomes for marginalized populations.

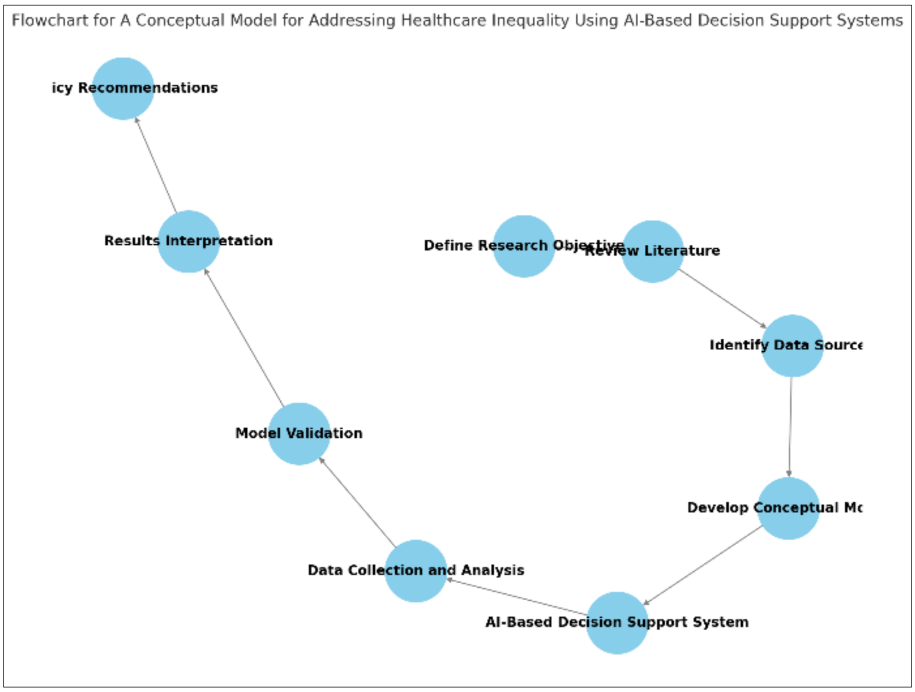

Fig 3: PRISMA Flow chart of the study methodology

2.2 The proposed conceptual model

The conceptual model for addressing healthcare inequality through AI-based decision support systems (AI-DSS) is designed to overcome the systemic challenges that limit equitable healthcare access and delivery. The architecture of the model is structured to support the integration of diverse healthcare data, provide predictive insights that anticipate healthcare needs, and offer actionable, equity-focused recommendations for both healthcare providers and policymakers (Adekunle, *et al*., 2021, Opia, Matthew & Matthew, 2022). At its core, the model is built to bridge gaps in healthcare access, particularly in underserved areas, by leveraging AI to improve decision-making, enhance resource allocation, and ultimately improve health outcomes for marginalized populations.

The architecture of this model is a layered system that combines various technological components, workflows, and data sources to create a cohesive and responsive decision support system. The first key layer of this architecture is the Data Integration Layer, which is responsible for aggregating multiple sources of healthcare-related data, including Electronic Health Records (EHRs), public health databases, and information on social determinants of health (SDOH) (Olaniyan, Uwaifo & Ojediran, 2022, Oyeniyi, *et al*., 2022, Uwaifo & John-Ohimai, 2020). This layer ensures that the decision support system has access to a comprehensive and up-to-date view of the patient's health status, social conditions, and community context. By integrating data from various sources, the model is able to generate a holistic understanding of the factors that impact health outcomes, enabling the system to make well-informed recommendations that reflect the complexities of patients' health needs. Kishor & Chakraborty, 2022, presented in figure 4, The architecture of the proposed AI and IoT based healthcare model.

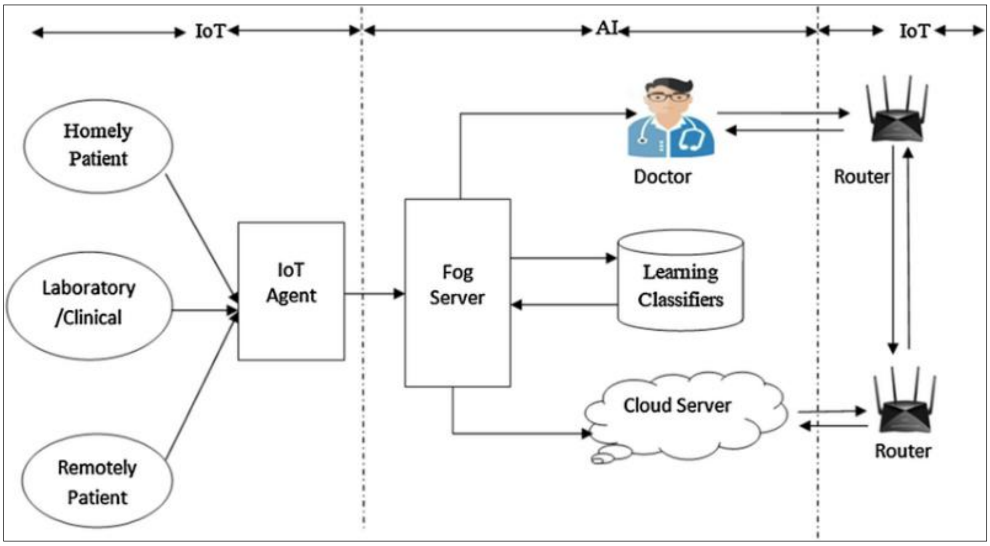

Fig 4: The architecture of the proposed AI and IoT based healthcare model (Kishor & Chakraborty, 2022).

The integration of EHRs allows the system to tap into real-time medical data, providing a detailed record of a patient's medical history, treatments, lab results, and physician notes. This allows the AI to identify trends, track disease progression, and provide personalized insights. Public health databases, which contain aggregated data on disease prevalence, vaccination rates, and health trends across larger populations, offer a broader contextual understanding that helps guide resource planning and preventive care strategies (Adewale, Olorunyomi & Odonkor, 2021, Odunaiya, Soyombo & Ogunsola, 2021). The incorporation of social determinants of health—such as income, education, housing, access to clean water, and social support—provides a deeper, more nuanced understanding of the factors that influence health beyond the clinical setting. For instance, AI models can identify how factors like low socioeconomic status or lack of access to healthcare services impact the likelihood of a person developing chronic conditions or being diagnosed late.

The second layer, the Predictive Analytics Layer, uses machine learning (ML) and statistical models to analyze the integrated data and generate insights that forecast disease risks and predict future healthcare needs. This layer is crucial for anticipating health trends, identifying at-risk populations, and ensuring that healthcare resources are allocated efficiently and effectively (Adewale, *et al*., 2022, Matthew, Akinwale & Opia, 2022, Okeke, *et al*., 2022). The predictive analytics layer employs algorithms that can identify patterns within the data to forecast the likelihood of patients developing specific health conditions, such as diabetes, hypertension, or heart disease. By evaluating historical health data and current risk factors, the system can provide early warnings, enabling healthcare providers to intervene sooner, before conditions worsen.

Predictive analytics can also be used to assess the demand for healthcare services in underserved regions. For example, the system can predict the need for certain medical supplies, personnel, or infrastructure based on health trends, seasonal outbreaks, and social determinants of health. This allows policymakers and healthcare administrators to plan more effectively, ensuring that resources are available when and where they are most needed. Furthermore, AI models can predict which regions are likely to experience healthcare bottlenecks, enabling proactive strategies to address these challenges before they escalate (Okeke, *et al*., 2022, Okolie, *et al*., 2022).

The third and final layer, the Decision-Making Layer, delivers actionable, equity-focused recommendations to healthcare providers and policymakers. This layer takes the predictive insights and translates them into practical, tailored recommendations that are grounded in the unique needs of each patient and community. The recommendations generated by the AI-DSS are designed to be context-sensitive, ensuring that they address both the medical and social determinants of health that affect the patient population in a given area (Ogunmokun, Balogun & Ogunsola, 2022, Ogunsola, Balogun & Ogunmokun, 2021).

For healthcare providers, the system might recommend specific diagnostic tests, treatment plans, or preventive measures based on the patient's health history and predicted risks. For example, if the AI system identifies that a patient is at high risk for developing diabetes due to a combination of genetic, environmental, and socioeconomic factors, it might suggest an early screening test, provide lifestyle modification recommendations, or prompt the healthcare provider to consider patient education materials focused on managing diabetes (Okeke, *et al*., 2022, Okolie, *et al*., 2021). The recommendations can also be tailored based on the availability of local healthcare resources, ensuring that patients receive care appropriate to their setting. For instance, if a healthcare provider in a remote region does not have access to advanced imaging equipment, the system can suggest alternative diagnostic methods or recommend telemedicine consultations with specialists.

On a broader scale, the AI-based decision support system provides actionable recommendations to policymakers and public health authorities. These recommendations might include insights on how to allocate healthcare resources, target high-risk communities for preventive interventions, or design health policies that address systemic inequities. For example, if the system predicts a rise in cases of a particular disease in a low-income neighborhood, it might suggest increasing access to preventative care services, enhancing public health campaigns, or offering subsidies for medications (Okeke, *et al*., 2022). The system can also recommend changes in health policy, such as the implementation of programs to address food insecurity or improve access to healthcare facilities in underserved regions. By providing evidence-based insights and real-time data, the Decision-Making Layer enables stakeholders at all levels to make informed decisions that prioritize health equity.

A key feature of this model is its focus on equity. The system is designed to ensure that AI-generated recommendations are not only clinically sound but also socially and economically inclusive. The recommendations prioritize addressing health disparities, ensuring that underserved populations receive the care and resources they need. By incorporating data on social determinants of health, the system ensures that healthcare decisions are informed not just by clinical data, but also by the broader social and economic factors that influence health outcomes (Adewale, Olorunyomi & Odonkor, 2021, Matthew, *et al*., 2021, Okeke, *et al*., 2022). This approach allows for more targeted interventions that take into account the unique needs of diverse populations, including low-income, rural, and marginalized communities.

Moreover, the model is built to be scalable, flexible, and adaptable to a variety of healthcare settings. It can be implemented in low-resource settings, where infrastructure may be limited, and can be adapted to different regions and health systems. The ability to integrate various data sources and provide context-sensitive recommendations ensures that the model can be effective in diverse geographic locations, healthcare systems, and cultural contexts.

In conclusion, the proposed conceptual model for addressing healthcare inequality through AI-based decision support systems provides a comprehensive, equitable, and scalable solution to the persistent challenges faced by underserved populations. By integrating diverse healthcare data sources, using predictive analytics to forecast health needs, and offering tailored recommendations, the model ensures that healthcare delivery is both effective and inclusive. The model's emphasis on addressing social determinants of health and prioritizing equity in decision-making will help reduce healthcare disparities and improve health outcomes for vulnerable populations (Ogunwole, *et al*., 2022, Okeke, *et al*., 2022). As healthcare systems increasingly turn to AI to enhance decision-making and optimize resource allocation, this model offers a pathway toward more equitable, efficient, and accessible healthcare for all.

2.3 Components and Technologies

A conceptual model for addressing healthcare inequality using AI-based decision support systems (AI-DSS) involves several key components and technologies that work together to provide accurate, equitable, and transparent decision-making support for healthcare providers and policymakers. These components leverage advanced machine learning algorithms, explainable AI (XAI) techniques, fairness-aware algorithms, and natural language processing (NLP) to ensure that the system is both effective in its predictions and sensitive to the unique needs of underserved populations (Ajayi & Akerele, 2021, Jahun, *et al*., 2021, Ogunsola, Balogun & Ogunmokun, 2022). The integration of these technologies is crucial for creating a model that not only addresses healthcare disparities but also promotes trust, transparency, and fairness in decision-making.

At the heart of the model are machine learning (ML) and AI algorithms, which drive the predictive capabilities of the system. These algorithms analyze vast amounts of healthcare data, including electronic health records (EHRs), clinical data, public health statistics, and social determinants of health, to generate insights and recommendations for healthcare providers. Various machine learning models can be employed to achieve these outcomes, including random forests, logistic regression, and deep learning techniques (Adewale, Olorunyomi & Odonkor, 2022, Matthew, *et al*., 2021, Okeke, *et al*., 2022). Random forest algorithms, for example, are useful for classification tasks, such as identifying high-risk patients or predicting the likelihood of certain diseases. This ensemble method combines multiple decision trees to improve prediction accuracy and reduce overfitting, making it particularly useful in healthcare applications where data variability and complexity are high.

Logistic regression, a simpler but effective machine learning technique, is commonly used for binary classification problems such as predicting the presence or absence of a condition based on input features like age, gender, and medical history. Despite being a linear model, logistic regression remains a valuable tool in decision support systems due to its interpretability and ease of use in clinical settings. For more complex data patterns, deep learning techniques such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) can be utilized (Ajayi & Akerele, 2022, Jahun, *et al*., 2021, Okeke, *et al*., 2022). These deep learning models are particularly powerful in processing large volumes of unstructured data, such as medical images, electronic health records, and even real-time data from wearable devices. Deep learning models can identify patterns and features in data that are often invisible to traditional algorithms, thus enabling more accurate diagnoses and predictions in clinical decision-making.

While machine learning models are powerful tools for prediction and analysis, one of the key challenges in implementing AI in healthcare is ensuring transparency and trust in the system's outputs. This is where explainable AI (XAI) becomes crucial. XAI aims to make complex machine learning models interpretable by humans, allowing healthcare providers and patients to understand the rationale behind AI-generated recommendations. In the context of healthcare decision support, it is essential that AI systems not only produce accurate results but also provide clear explanations for those results (Okeke, *et al*., 2022, Oladeinde, *et al*., 2022). This transparency builds trust among healthcare providers, who are responsible for making final decisions based on AI recommendations, and patients, who must feel confident that AI is being used ethically and effectively in their care.

XAI techniques can be employed in various ways within healthcare decision support systems. For example, algorithms such as LIME (Local Interpretable Model-Agnostic Explanations) and SHAP (SHapley Additive exPlanations) can generate explanations for individual predictions by identifying the features that contributed most to the model's output. In the case of a diagnostic tool predicting the likelihood of a patient having a certain disease, XAI could highlight specific symptoms, lab results, or patient history that influenced the decision (Odunaiya, Soyombo & Ogunsola, 2022, Ogbuagu, *et al*., 2022, Okeke, *et al*., 2022). By providing these insights, XAI ensures that healthcare professionals can evaluate the model's reasoning, incorporate their own expertise, and make more informed decisions.

Alongside explainability, ensuring fairness in AI-based decision support systems is paramount. In healthcare, biased algorithms can perpetuate disparities in care, particularly for marginalized populations. For example, if a machine learning model is trained primarily on data from urban, affluent populations, it may not perform well for rural or low-income communities, leading to misdiagnoses or inappropriate treatment recommendations (Akinsooto, Pretorius & van Rhyn, 2012, Balogun, Ogunsola & Ogunmokun, 2022). To mitigate such biases, fairness-aware algorithms must be integrated into the model to ensure that AI recommendations are equitable and do not disproportionately disadvantage certain groups. These algorithms are designed to detect and correct for biases in the training data, ensuring that the system does not replicate or exacerbate existing healthcare disparities.

Fairness-aware machine learning techniques can be applied at various stages of the AI model development process, including data collection, preprocessing, and algorithm training. One approach is to ensure that the training dataset is diverse and representative of the populations that the model will serve, including rural communities, low-income populations, and ethnic minorities. Another approach is to implement algorithms that explicitly balance performance across different demographic groups, ensuring that the model does not favor one group over another. By incorporating fairness-aware techniques, AI-based decision support systems can help mitigate the risk of exacerbating existing healthcare inequalities, ensuring that all patients receive equal consideration in the decision-making process.

Natural Language Processing (NLP) is another essential component of AI-based decision support systems, particularly in healthcare, where large volumes of unstructured data are generated daily. This unstructured data includes clinical notes, discharge summaries, radiology reports, and other textual information stored in electronic health records (EHRs). NLP allows AI systems to process and analyze this textual data, extracting valuable insights that can inform clinical decisions (Chukwuma-Eke, Ogunsola & Isibor, 2022, Collins, Hamza & Eweje, 2022). For example, NLP algorithms can identify key medical concepts, such as symptoms, diagnoses, medications, and treatments, and map these to structured data for further analysis. This enables AI-based decision support systems to generate more accurate recommendations by incorporating both structured and unstructured data sources.

NLP also plays a vital role in improving patient-provider communication in telemedicine, especially for marginalized populations with limited access to healthcare. AI-powered chatbots and virtual assistants, equipped with NLP capabilities, can engage with patients in real time, providing information, answering questions, and guiding them through their healthcare journey. These tools can help bridge communication gaps, particularly for patients who face language barriers or have low health literacy. NLP also enables the system to understand the context of patient inquiries, ensuring that responses are tailored to the individual's needs. By leveraging NLP, AI systems can provide more personalized, responsive, and accessible care, particularly for patients in underserved regions.

The integration of machine learning, explainable AI, fairness-aware algorithms, and natural language processing within a unified decision support system offers a powerful tool for addressing healthcare inequality. By using these technologies to process and analyze diverse data sources, the system can generate predictions, diagnoses, and recommendations that are not only accurate but also context-sensitive and equitable. Furthermore, by making the decision-making process transparent and ensuring that AI systems are fair and inclusive, the model can help build trust among both healthcare providers and patients, fostering greater adoption of AI-driven solutions (Chukwuma-Eke, Ogunsola & Isibor, 2021, Dirlikov, 2021).

In conclusion, the components and technologies that underpin the conceptual model for addressing healthcare inequality through AI-based decision support systems have the potential to transform healthcare delivery in underserved regions. Machine learning algorithms, explainable AI, fairness-aware techniques, and natural language processing are critical to ensuring that AI systems are not only accurate but also equitable, transparent, and inclusive. By integrating these technologies into a cohesive decision support framework, healthcare providers and policymakers can make more informed, data-driven decisions that reduce healthcare disparities and improve health outcomes for marginalized populations (Balogun, Ogunsola & Ogunmokun, 2022, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2022). Ultimately, the successful application of these technologies can help create a more equitable healthcare system, ensuring that all individuals, regardless of their socioeconomic status or geographic location, have access to high-quality care.

2.4 Application Scenarios

The application of AI-based decision support systems (AI-DSS) within the conceptual model for addressing healthcare inequality has far-reaching potential to improve both the accessibility and quality of healthcare, particularly in underserved regions. By leveraging AI technologies to analyze vast amounts of data, the system can provide actionable insights that help healthcare providers and policymakers make more informed decisions. These decisions can prioritize high-risk patients for preventive screenings, guide resource allocation in areas with limited healthcare infrastructure, inform equitable health policy decisions, and support community-based interventions (Chukwuma-Eke, Ogunsola & Isibor, 2022, Dirlikov, *et al*., 2021). Through these applications, AI-based decision support systems can help reduce healthcare disparities, improve health outcomes, and ensure that healthcare delivery is more equitable and efficient.

One of the most impactful applications of AI in telemedicine and healthcare delivery is the prioritization of high-risk patients for preventive screenings. Preventive care is essential for identifying and mitigating health issues before they become more severe, particularly in regions where access to healthcare services is limited. AI-based decision support systems can analyze patient data to identify individuals who are at high risk for developing chronic diseases such as diabetes, heart disease, or certain cancers (Al Zoubi, *et al*., 2022, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2022). By integrating data from electronic health records (EHRs), social determinants of health (SDOH), and public health databases, the system can predict which patients are most likely to develop health conditions and recommend targeted screenings to detect these conditions at an early stage.

For example, in a rural area with limited access to specialized care, the AI system can analyze factors such as age, family history, lifestyle choices, and socioeconomic conditions to determine which patients are at higher risk for conditions like breast cancer or colorectal cancer. The system can then prioritize these patients for preventive screenings, ensuring that those most at risk are identified and treated promptly. This predictive capability is particularly valuable in areas with limited healthcare resources, as it ensures that the available healthcare services are directed to those who need them most (Akinsooto, 2013, Chukwuma, *et al*., 2022, Elumilade, *et al*., 2022). By identifying high-risk patients early, healthcare providers can intervene before a condition worsens, reducing both the incidence of preventable diseases and the overall cost of care.

AI-based decision support systems can also play a critical role in guiding resource allocation in underserved areas. Healthcare resources, such as medical staff, diagnostic equipment, medications, and facilities, are often limited in low-income or remote regions. As a result, healthcare providers in these areas are forced to make difficult decisions about how to allocate their resources effectively. AI can help optimize this process by analyzing data on patient needs, disease prevalence, and available resources to provide recommendations on how to distribute healthcare services more equitably.

For example, if an AI system detects a surge in respiratory illnesses during the flu season in a particular region, it can suggest the allocation of additional medical staff, vaccines, and diagnostic equipment to those areas most affected. Similarly, by analyzing patient data and health trends, the system can predict where healthcare resources will be needed in the future, helping healthcare administrators plan ahead and ensure that they are prepared for fluctuations in demand (Al Zoubi, *et al*., 2022, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2022). Additionally, AI can assist in identifying areas where there are gaps in healthcare access, such as rural communities that lack specialists or clinics. By guiding resource allocation, AI-based decision support systems can ensure that healthcare providers are making the best use of their limited resources, thereby improving the quality of care for underserved populations.

AI-based decision support systems can also inform equitable health policy decisions. Policymakers and public health officials are responsible for creating and implementing policies that address healthcare inequalities and improve public health outcomes. AI can provide data-driven insights that help policymakers make decisions based on evidence rather than assumptions or limited information. By analyzing a range of data sources, including patient demographics, health outcomes, and access to healthcare services, AI can identify trends and disparities that might otherwise go unnoticed (Akinsooto, Pretorius & van Rhyn, 2012, Balogun, Ogunsola & Ogunmokun, 2022).

For instance, AI can help policymakers understand the impact of social determinants of health, such as income, education, and housing, on health outcomes in different communities. By incorporating this data into their decision-making processes, policymakers can create targeted interventions that address the root causes of healthcare inequality. AI can also help identify which populations are most vulnerable to specific diseases or health conditions, enabling policymakers to focus their efforts on those who are at the greatest risk (Chukwuma-Eke, Ogunsola & Isibor, 2021, Dirlikov, 2021). In regions with limited healthcare resources, AI can help determine where investment in healthcare infrastructure will have the most significant impact, ensuring that policies are both effective and equitable.

In addition to guiding policy decisions at a macro level, AI-based decision support systems can be used to support community-based interventions. Community-based interventions are often more effective in addressing healthcare inequalities because they take into account the specific needs, preferences, and cultural contexts of local populations. AI can help identify community-level health trends and patterns, enabling healthcare providers and community organizations to design interventions that are tailored to the unique needs of each community.

For example, in a low-income urban neighborhood, an AI system might identify high rates of hypertension among residents and recommend targeted community outreach programs, such as health education campaigns, free blood pressure screenings, or mobile health clinics. Similarly, in rural areas where access to healthcare facilities is limited, AI could support the implementation of telemedicine services, ensuring that remote consultations and diagnoses are available to residents who might otherwise have to travel long distances to see a doctor (Chukwuma-Eke, Ogunsola & Isibor, 2022, Dirlikov, *et al*., 2021). AI can also help monitor the effectiveness of community-based interventions by analyzing patient data over time and providing feedback on which strategies are working and which need to be adjusted.

By supporting community-based interventions, AI-based decision support systems can empower local healthcare providers and community organizations to take a more active role in addressing healthcare disparities. This localized approach to healthcare delivery is particularly important in underserved regions, where traditional top-down approaches may not be as effective. By using AI to identify specific health needs and guide intervention strategies, healthcare providers can ensure that resources are being used effectively to address the unique challenges faced by each community.

In conclusion, the application of AI-based decision support systems in addressing healthcare inequality offers immense potential to improve healthcare delivery in underserved regions. By prioritizing high-risk patients for preventive screenings, guiding resource allocation, informing equitable health policy decisions, and supporting community-based interventions, AI can help create a more efficient, accessible, and equitable healthcare system (Al Zoubi, *et al*., 2022, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2022). These applications are not only valuable for improving health outcomes in underserved areas but also for ensuring that healthcare resources are used effectively to reduce disparities and improve the overall quality of care. As AI technology continues to evolve, its role in addressing healthcare inequality will become increasingly important, offering innovative solutions that empower healthcare providers, policymakers, and communities to work together toward a more equitable healthcare system for all.

2.5 Ethical and social considerations

As AI-based decision support systems (AI-DSS) become an integral part of healthcare, their role in addressing healthcare inequality is undeniable. However, along with the promise of improving health outcomes, these technologies bring significant ethical and social considerations that need to be carefully addressed. AI systems, if not designed and deployed with awareness of their broader implications, can exacerbate existing disparities in healthcare. Ensuring that these systems are ethical, equitable, and inclusive is critical for achieving the goal of reducing healthcare inequalities (Akinsooto, 2013, Chukwuma, *et al*., 2022, Elumilade, *et al*., 2022). Addressing algorithmic bias and fairness, ensuring data privacy and patient consent, building trust among stakeholders, and ensuring inclusivity in AI model training and deployment are central to ensuring that AI-DSSs contribute positively to the healthcare system, especially in underserved regions.

One of the most pressing ethical challenges in the development and use of AI in healthcare is addressing algorithmic bias and fairness. AI systems rely on vast datasets to train their models, and if these datasets are not representative of the full diversity of the patient population, they risk producing biased or skewed outcomes. Algorithmic bias can occur when the data used to train the model reflects historical inequalities or underrepresentation of certain demographic groups, such as racial minorities, low-income populations, or those from rural areas. In such cases, the AI model may be less accurate or effective in diagnosing or recommending treatments for these groups, perpetuating existing healthcare disparities (Ewim, *et al*., 2022, Ezeanochie, Afolabi & Akinsooto, 2022).

To address this issue, AI developers must ensure that the datasets used to train decision support systems are diverse and representative of the populations the system is meant to serve. This includes considering variables such as age, gender, ethnicity, socioeconomic status, and geographic location, among others. Furthermore, fairness-aware algorithms can be implemented to monitor and adjust for bias in real-time. These algorithms can help detect disparities in the outcomes of AI systems and ensure that they are working to the benefit of all patient groups (Balogun, Ogunsola & Ogunmokun, 2021, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2022). By addressing algorithmic bias and ensuring fairness, AI-based systems can be used to reduce healthcare inequalities, rather than reinforce them.

Another critical ethical consideration is ensuring data privacy and obtaining patient consent. AI-based decision support systems rely on vast amounts of sensitive health data, including electronic health records, lab results, medical histories, and, increasingly, data from wearable devices and mobile health applications. Protecting this data is essential to maintaining patient trust and ensuring that AI technologies are used responsibly (Bristol-Alagbariya, Ayanponle &

Ogedengbe, 2022, Elujide, *et al*., 2021). In many regions, particularly in low-resource settings, there may be limited infrastructure and legal frameworks to safeguard personal health information, making data privacy a particular concern. Data breaches or unauthorized use of patient information can have devastating consequences, including harm to patients and loss of trust in healthcare systems.

To mitigate these risks, it is essential that AI systems are designed with robust data protection mechanisms in place, including encryption, secure data storage, and strict access controls. Patients must be informed about how their data will be used, who will have access to it, and how long it will be retained. Furthermore, obtaining informed consent is crucial. This means ensuring that patients understand how their data will be used by AI systems and that they have the ability to control or revoke consent as needed. Transparency is key in building trust between healthcare providers, patients, and AI developers (Chukwuma-Eke, Ogunsola & Isibor, 2022, Govender,*et al*., 2022). The process of obtaining patient consent should be straightforward and accessible, particularly in underserved communities where literacy levels or technological literacy may vary.

Building trust among all stakeholders—clinicians, patients, and policymakers—is essential for the successful implementation of AI-based decision support systems in healthcare. For clinicians, trust is built on the reliability and accuracy of the AI system. Healthcare providers must feel confident that AI tools will enhance, rather than undermine, their ability to deliver high-quality care. If clinicians perceive AI as a "black box" that offers recommendations without clear explanations, they may be hesitant to trust or use the system. This lack of trust can lead to resistance to adopting AI technologies in clinical practice (Akinsooto, De Canha & Pretorius, 2014, Balogun, Ogunsola & Ogunmokun, 2022).

To build trust among clinicians, AI systems must be designed with explainability in mind. This is where explainable AI (XAI) comes into play. By making AI models more transparent and understandable, clinicians can gain insights into how decisions are made, which will help them integrate AI recommendations into their clinical workflows. Additionally, providing continuous training and support for healthcare providers on how to use AI effectively is essential for fostering confidence in these systems.

For patients, trust is largely built on transparency, consent, and a demonstrated commitment to privacy and security. Patients need to know that their personal health data is being used responsibly and that the AI systems generating recommendations are designed to improve their care. Building patient trust requires clear communication about how AI will be used, the benefits it provides, and the safeguards in place to protect their data. Furthermore, patients should have the ability to opt-out or make choices regarding the data that is shared with AI systems (Collins, Hamza & Eweje, 2022, Egbuhuzor, *et al*., 2021). This patient-centered approach to AI implementation ensures that the technology aligns with patients' rights, values, and preferences.

Policymakers, too, must trust that AI technologies will improve healthcare delivery in a way that is both effective and equitable. For this, they need data and evidence that AI systems can reduce healthcare inequalities rather than worsen them. Policymakers also play a critical role in ensuring that there are regulations and standards in place to monitor AI systems, ensuring that they are continually assessed for their impact on equity, accuracy, and safety. Regulatory frameworks should be transparent, flexible, and designed to adapt as AI technologies evolve, allowing for the ongoing evaluation of their effectiveness in real-world settings.

Inclusivity in AI model training and deployment is a fundamental ethical consideration in ensuring that AI-based decision support systems serve all populations equitably. AI models can only be as good as the data used to train them. If the training datasets do not adequately represent the full diversity of patients—especially those from underserved communities—AI systems may fail to provide accurate or appropriate recommendations for those populations (Bristol-Alagbariya, Ayanponle & Ogedengbe, 2022, Elujide, *et al*., 2021). This issue is especially critical when it comes to healthcare, where one-size-fits-all solutions are rarely effective. For AI to be truly transformative, the models must be inclusive, taking into account the unique health needs, preferences, and contexts of diverse populations.

Inclusivity in model training means using datasets that represent a wide range of ethnicities, socioeconomic statuses, geographic locations, and health conditions. This will ensure that AI models can provide equitable care recommendations for all patient groups. Furthermore, inclusivity in deployment involves ensuring that AI technologies are accessible to patients across different regions and social groups (Adepoju, *et al*., 2022, Olamijuwon, 2020, Uwaifo & Favour, 2020). This may involve providing multilingual interfaces, using culturally relevant health information, and ensuring that technologies are accessible to people with disabilities or those with limited technological literacy.

Ensuring inclusivity also means addressing the digital divide that exists in many underserved regions. Without the infrastructure, internet access, or digital literacy to support AI technologies, vulnerable populations may be excluded from the benefits of these systems. Efforts must be made to ensure that AI technologies are deployed in ways that are accessible and beneficial to all communities, particularly those that are marginalized or historically underserved.

In conclusion, the ethical and social considerations surrounding AI-based decision support systems are paramount to their success in addressing healthcare inequality. By focusing on algorithmic fairness, data privacy, trust-building, and inclusivity, AI technologies can be designed and implemented in ways that reduce healthcare disparities and promote equitable access to care (Abisoye & Akerele, 2022, Olaniyan, *et al*., 2018, Uwaifo, *et al*., 2019). To achieve these goals, it is essential that AI developers, healthcare providers, policymakers, and patients collaborate to ensure that AI systems are transparent, accountable, and aligned with the values of the communities they serve. Only through thoughtful consideration of these ethical and social dimensions can AI-based decision support systems realize their full potential to create a more just and effective healthcare system for all.

2.6 Challenges and Limitations

The conceptual model for addressing healthcare inequality using AI-based decision support systems (AI-DSS) presents a promising solution for improving healthcare delivery in underserved and marginalized communities. However, several challenges and limitations must be overcome to ensure its successful implementation and long-term impact. These challenges are multifaceted and encompass data quality, infrastructure limitations, resistance to AI adoption, and regulatory and legal issues. Addressing these concerns is essential for realizing the full potential of AI technologies in reducing healthcare disparities and promoting equitable access to quality healthcare.

One of the most significant challenges in deploying AI-based decision support systems is ensuring the quality and representativeness of the data used to train these models. AI systems rely on large datasets to identify patterns, make predictions, and generate recommendations. However, if the data used to train these models is of poor quality or unrepresentative of the target population, the system's predictions and recommendations can be inaccurate, biased, or even harmful (Adewale, *et al*., 2022, Olorunyomi, Adewale & Odonkor, 2022). In healthcare, this issue is particularly important, as inaccurate or biased decision-making can lead to worse health outcomes for marginalized communities, thus perpetuating existing healthcare inequalities rather than addressing them.

Data quality is a concern because healthcare data can be incomplete, inconsistent, or inaccurate. For example, electronic health records (EHRs) may contain missing or incorrect information, and data from different sources may not be standardized, making it difficult to aggregate and analyze effectively. In addition, data from marginalized or underserved communities may be underrepresented in datasets, leading to algorithms that do not accurately capture the unique health needs of these populations. For instance, AI models trained predominantly on data from urban populations may not perform well in rural or remote areas, where disease prevalence, healthcare access, and social determinants of health may differ (Adekola, Kassem & Mbata, 2022, Olufemi-Phillips, *et al*., 2020). Ensuring that AI models are trained on diverse, high-quality data that accurately reflects the health conditions and demographics of underserved communities is essential for ensuring that these systems can be effective in addressing healthcare inequalities.

In addition to data quality, infrastructure and technological barriers in low-resource settings present another significant challenge to the successful implementation of AI-based decision support systems. In many underserved regions, particularly in low-income countries or remote areas, healthcare infrastructure is limited, and access to technology is often constrained. AI-based systems require robust digital infrastructure, including reliable internet access, powerful computing resources, and secure data storage systems. In low-resource settings, these technological capabilities may be absent or insufficient, making it difficult to deploy AI systems effectively (Adegoke, *et al*., 2022, Olaniyan, Ale & Uwaifo, 2019).

Moreover, even where infrastructure is available, there may be significant challenges related to power supply, internet connectivity, and the availability of skilled personnel to operate and maintain AI systems. In many remote areas, inconsistent electricity supply or limited access to high-speed internet can disrupt the use of digital technologies, undermining the reliability and effectiveness of AI-based systems. Additionally, healthcare workers in these regions may not have the necessary training to use advanced AI tools or interpret AI-generated recommendations (Adekunle, *et al*., 2021, Onukwulu, et akl., 2022, Uwaifo, *et al*., 2018). Overcoming these barriers requires investment in both infrastructure and capacity-building efforts, such as training healthcare providers to use AI tools effectively and ensuring that the necessary technological resources are in place to support their use.

Resistance to AI adoption is another challenge that may hinder the effectiveness of AI-based decision support systems in addressing healthcare inequality. While AI has the potential to improve healthcare delivery, there is often skepticism among healthcare professionals and patients about its utility, accuracy, and ethical implications. Clinicians may be hesitant to trust AI systems, particularly if they are perceived as "black boxes" that provide recommendations without clear explanations of how they arrived at their conclusions (Abisoye & Akerele, 2021, Olutimehin, *et al*., 2021). In addition, there may be concerns about the role of AI in decision-making, with some fearing that AI could undermine the role of healthcare providers or lead to job displacement. For patients, there may be concerns about privacy, data security, and the potential for AI to make decisions that do not take into account their personal preferences or values.

Overcoming this resistance requires a multi-faceted approach, including increasing transparency in AI decision-making, demonstrating the value of AI tools in improving healthcare outcomes, and fostering trust between healthcare providers, patients, and technology developers. Explainable AI (XAI) methods, which provide transparent and interpretable explanations for AI-generated recommendations, can help clinicians and patients understand how AI systems arrive at their conclusions (Bristol-Alagbariya, Ayanponle & Ogedengbe, 2022, Elujide, *et al*., 2021). This transparency is crucial for gaining trust and ensuring that AI complements, rather than replaces, human expertise. Additionally, healthcare providers and patients need to be actively involved in the development and implementation of AI systems, ensuring that these technologies are designed to meet their needs and address their concerns.

Finally, regulatory and legal issues present significant barriers to the widespread adoption of AI-based decision support systems in healthcare. AI in healthcare is subject to various regulations and standards that ensure patient safety, data privacy, and ethical use of medical technologies. In many countries, however, regulatory frameworks for AI in healthcare are either underdeveloped or non-existent, leaving a regulatory gap that can hinder the deployment of AI systems. Without clear guidelines, developers may be uncertain about how to ensure that their systems comply with local laws, leading to delays in adoption and uncertainty among stakeholders (Adewale, *et al*., 2022, Uwaifo, 2020).

In addition to regulatory uncertainties, legal concerns related to data privacy and security also pose challenges. Healthcare data is highly sensitive, and protecting patient privacy is paramount. AI systems must comply with data protection laws, such as the Health Insurance Portability and Accountability Act (HIPAA) in the United States or the General Data Protection Regulation (GDPR) in the European Union (Atta, *et al*., 2021, Bidemi, *et al*., 2021, Elumilade, *et al*., 2022). In low-resource settings, where legal frameworks may be weaker or less developed, there is a greater risk of data breaches or misuse of personal health information. Ensuring that AI-based decision support systems comply with local data protection laws and international privacy standards is essential for building trust and ensuring that these technologies are used responsibly.

Moreover, there are concerns about accountability and liability in the event of errors or adverse outcomes related to AI-driven decisions. If an AI system provides an inaccurate diagnosis or recommendation that leads to harm, it may be unclear who is responsible—whether it is the developers of the system, the healthcare provider who relied on the recommendation, or another party. Clear legal frameworks that establish accountability for AI-driven decisions are essential for ensuring that these systems are used safely and ethically (Collins, Hamza & Eweje, 2022, Egbuhuzor, *et al*., 2021).

In conclusion, while AI-based decision support systems have the potential to significantly improve healthcare delivery and address healthcare inequality, several challenges and limitations must be overcome. These include ensuring high-quality, representative data, addressing infrastructure and technological barriers in low-resource settings, overcoming resistance to AI adoption, and navigating regulatory and legal complexities (Abisoye & Akerele, 2022, Qin, *et al*., 2018, Uwaifo & John-Ohimai, 2020). By addressing these challenges through targeted investments in infrastructure, training, regulation, and transparency, AI technologies can be deployed in ways that reduce healthcare disparities and improve health outcomes for underserved populations. However, careful attention must be paid to these challenges to ensure that AI does not inadvertently exacerbate existing inequalities or create new barriers to equitable healthcare.

2.7 Implementation Strategies

The successful implementation of a conceptual model for addressing healthcare inequality using AI-based decision support systems (AI-DSS) requires a strategic, phased approach that ensures broad acceptance, effective integration, and long-term sustainability. By focusing on pilot programs, stakeholder engagement, integration with existing healthcare systems, training for end-users, and continuous monitoring and refinement, this approach helps mitigate challenges while ensuring that AI technologies are used in ways that promote equitable healthcare delivery (Adekunle, *et al*., 2021, Opia, Matthew & Matthew, 2022). The ultimate goal is to improve health outcomes, reduce disparities, and ensure that underserved communities can benefit from the power of AI.

One of the first steps in implementing an AI-based decision support system is conducting pilot programs to test the model in real-world healthcare settings. Pilot programs allow developers and stakeholders to assess the feasibility, effectiveness, and scalability of the system in a controlled environment before a broader rollout. These programs can be conducted in select healthcare facilities, such as rural clinics, community health centers, or hospitals in underserved areas, where healthcare disparities are most pronounced (Akinsooto, De Canha & Pretorius, 2014, Balogun, Ogunsola & Ogunmokun, 2022). By starting small, AI developers can work closely with healthcare providers to identify potential issues and make necessary adjustments before the system is widely deployed. Pilot programs also provide valuable data on how the system performs under different conditions, helping to refine algorithms and decision-making processes to ensure they are effective for diverse patient populations.

Stakeholder engagement is a critical element of successful AI implementation. The adoption of AI in healthcare requires buy-in from a wide range of stakeholders, including healthcare providers, policymakers, patients, and community organizations. Engaging these stakeholders early in the process can help build trust, ensure that the system meets local needs, and address concerns about the ethical implications of AI. Healthcare providers must be involved in the development of AI-based systems to ensure that the technology aligns with clinical workflows and enhances the quality of care rather than complicating it (Chukwuma-Eke, Ogunsola & Isibor, 2022, Govender,*et al*., 2022). By involving clinicians in the design and testing phases, developers can identify potential barriers to adoption, such as user interface issues or concerns about the transparency of AI decision-making. Patient representatives and community organizations can provide valuable feedback on the acceptability of AI technologies, ensuring that the system is culturally appropriate and sensitive to local healthcare needs.

Integration with existing healthcare systems is another crucial strategy for the successful deployment of AI-based decision support systems. In many cases, healthcare systems in underserved areas may be using outdated or fragmented technologies, making it difficult to integrate new AI-driven systems seamlessly. For AI to be effective, it must be able to interface with existing electronic health records (EHR) systems, laboratory information systems (LIS), and other clinical tools (Bristol-Alagbariya, Ayanponle & Ogedengbe, 2022, Elujide, *et al*., 2021). Achieving interoperability between AI systems and existing healthcare infrastructure ensures that data flows smoothly between different systems, allowing clinicians to make decisions based on up-to-date and comprehensive patient information. This integration also helps avoid duplicating efforts and minimizes the disruption of established clinical workflows.

To facilitate integration, AI systems should be designed to work with the infrastructure available in different healthcare settings. This may involve developing flexible, scalable AI solutions that can be adapted to varying levels of technological sophistication. In low-resource settings, where internet connectivity may be unreliable or bandwidth may be limited, AI models should be lightweight and capable of functioning in offline or low-bandwidth environments (Balogun, Ogunsola & Ogunmokun, 2021, Bristol-Alagbariya, Ayanponle & Ogedengbe, 2022). AI-based tools should also be user-friendly, ensuring that healthcare providers can easily incorporate them into their daily routines without significant disruptions to their work. The smoother the integration, the more likely healthcare professionals will adopt the technology, which is crucial for achieving long-term success.

Training and capacity-building for end-users is another key strategy for the successful implementation of AI-based decision support systems. Healthcare providers in underserved areas may have limited experience with AI and digital health technologies, making it essential to offer comprehensive training programs to build their confidence and skills (Okeke, *et al*., 2022, Okolie, *et al*., 2022). These programs should cover both the technical aspects of using AI systems, such as inputting data, interpreting AI-generated recommendations, and troubleshooting issues, as well as the ethical and clinical implications of using AI in healthcare. Training must be tailored to the specific needs and context of each healthcare setting, ensuring that it addresses local challenges and enhances the capacity of healthcare professionals to use AI tools effectively.

Moreover, training should be an ongoing process. As AI technologies evolve, healthcare providers must stay updated on new features, capabilities, and best practices. Continuous professional development programs, coupled with regular refresher courses, can help ensure that healthcare providers remain proficient in using AI systems and are able to keep up with advancements in the field. In addition to training healthcare providers, it is important to involve patients in understanding how AI can improve their care. Patient education initiatives can help them feel more comfortable with AI-based systems and ensure that they are actively engaged in their healthcare journey.

Once AI-based decision support systems are deployed, continuous monitoring and system refinement are essential for ensuring that the technology continues to meet the needs of both healthcare providers and patients. Monitoring AI systems in real time allows for the detection of any issues or inefficiencies that may arise during use. It is crucial to track the performance of the system across various metrics, such as diagnostic accuracy, patient satisfaction, and healthcare outcomes, to assess its effectiveness in reducing disparities and improving care. Continuous monitoring also provides opportunities to identify potential biases in the system, especially in diverse populations, and make adjustments to ensure fairness (Okeke, *et al*., 2022, Okolie, *et al*., 2022).

AI systems should also be designed to learn and adapt over time, incorporating new data and feedback from healthcare providers. As more patient data becomes available, AI models can be retrained and refined to improve their predictive capabilities and decision-making accuracy. This iterative process of refinement ensures that AI systems remain relevant, effective, and aligned with evolving clinical guidelines and patient needs (Ewim, *et al*., 2022, Ezeanochie, Afolabi & Akinsooto, 2022). Healthcare providers should also have access to regular updates, which can help them stay informed about new features or improvements to the system and ensure that they are using the most advanced version of the AI tool.

Additionally, regular audits and assessments should be conducted to ensure that the AI system continues to align with ethical standards and regulatory requirements. This includes reviewing data privacy and security protocols, ensuring that patient data is protected, and verifying that the system complies with relevant laws and regulations. Audits can also help ensure that the system's decision-making process remains transparent, accountable, and free from biases that could perpetuate healthcare inequalities.

In conclusion, implementing a conceptual model for addressing healthcare inequality using AI-based decision support systems requires a thoughtful, strategic approach that considers the technical, ethical, and social dimensions of AI deployment. By conducting pilot programs, engaging stakeholders, integrating AI systems with existing healthcare infrastructure, providing comprehensive training, and establishing continuous monitoring and system refinement processes, healthcare systems can ensure that AI technologies contribute to reducing healthcare disparities (Okeke, *et al*., 2022, Okolie, *et al*., 2022). These strategies can help build trust, promote successful adoption, and ensure that AI supports more equitable, effective, and accessible healthcare for underserved populations. Ultimately, a well-implemented AI-DSS has the potential to transform healthcare delivery, improving health outcomes and fostering a more equitable healthcare system.

3. Conclusion

The conceptual model for addressing healthcare inequality using AI-based decision support systems (AI-DSS) offers a transformative approach to reducing disparities in healthcare access and outcomes, particularly in underserved communities. By leveraging AI's ability to process vast amounts of data and generate actionable insights, this model has the potential to enhance decision-making, improve resource allocation, and ultimately provide more equitable healthcare. At its core, the model integrates data from diverse sources, uses predictive analytics to identify high-risk populations, and delivers tailored, equity-focused recommendations to healthcare providers and policymakers. This comprehensive approach ensures that healthcare resources are directed toward those who need them most, while also fostering a healthcare system that is more responsive, efficient, and inclusive.

The value of this conceptual model lies in its ability to address key challenges that contribute to healthcare inequality, such as limited access to specialized care, disparities in health outcomes, and inefficiencies in resource allocation. Through predictive analytics and data-driven decision-making, the model empowers healthcare providers to identify high-risk patients for preventive screenings, prioritize interventions in underserved areas, and allocate resources more effectively. By improving healthcare delivery in marginalized regions, the model also contributes to broader public health goals, such as achieving universal health coverage and reducing preventable diseases. Moreover, by integrating social determinants of health into the decision-making process, the AI-DSS ensures that healthcare interventions are not only clinically effective but also culturally and contextually relevant.

The vision for reducing healthcare inequality through AI-based DSS is rooted in the belief that AI technologies can be harnessed to bridge the gap in healthcare access, quality, and outcomes. By providing healthcare providers with the tools they need to make informed, data-driven decisions, the model empowers both clinicians and patients, ensuring that health interventions are timely, accurate, and appropriate. With AI's ability to analyze large datasets and offer personalized recommendations, healthcare systems can more effectively address the unique needs of different populations, from rural communities with limited access to healthcare facilities to urban populations facing chronic health challenges. As AI technologies continue to evolve, the potential for reducing healthcare inequality will only grow, enabling more equitable healthcare systems worldwide.

However, realizing this vision will require cross-sector collaboration and ongoing research. The development and deployment of AI-based DSS must involve a wide range of stakeholders, including healthcare providers, policymakers, technology developers, and community organizations. Collaboration across sectors is essential to ensure that AI systems are designed and implemented in ways that meet the needs of diverse populations, address ethical concerns, and comply with regulatory standards. Future research will be crucial in refining AI models, improving their accuracy and fairness, and exploring new ways to integrate AI into healthcare systems to achieve better outcomes for underserved communities. As we move forward, it is important to ensure that the benefits of AI are accessible to all, and that its deployment in healthcare systems actively contributes to reducing disparities, improving health equity, and fostering a more inclusive global healthcare landscape.

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