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Health Equity and Access: Bridging Disparities in Medical and Public Health Services

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ABSTRACT

Health care equity is a fundamental issue because the differences in access, quality of care, and health outcomes persistently influence many people from distinct socio-economic statuses in various health care systems. This study looks at the utility of using machine learning models to help eliminate and correct inequities in medical delivery. Using the mathematics of Decision Tree, Random Forest, SVM, and K-Means Clustering, databases that contain socioeconomic and geographical as well as clinical variables; the objective was to predict the gap in access and segment the people following healthcare needs. The Random Forest algorithm performed best having a 91.6% accuracy, followed by SVM at 89.3%, Decision Tree at 85.1 percentage, and K-Means with a silhouette score of 0.72 for effective population segmentation. Our analysis showed that the combination of classification with unsupervised methods allows for the identification of those at-risk and underserved populations. Based on our findings, our technique appears to outperform in terms of precision and can transfer to larger real-world healthcare systems applications. The research validates that the use of machine learning for its part can significantly promote fair healthcare since it optimizes resource utilization, influences the development of the policy and gives precise interventions. Our results provide a practical, scalable, data-driven framework with which to address complex social and clinical problems, leading to the universal, equitable, and accessible healthcare for all.

Keywords: *Health Equity, Machine Learning, Public Health Access, Random Forest, Healthcare Disparities*

1. INTRODUCTION

Health equity remains a top goal in today's approaches to healthcare and public health. Despite significant advances in medical science and technology, health outcomes and health care access continue to differ substantially amongst different populations with the marginalized and the underserved populations taking the brunt of these discrepencies [1]. The presence of such gaps very often reflects complex interplays between socioeconomic indicators, racial and ethnic background, residential area, and educational level, as well as deeply rooted structural concerns [2]. Health equity as a fundamental concept is the equal achievement of an optimal state of health for all which explicitly promotes approaches to eliminating preventable inequalities and injustices. Good quality medical and public health services play a vital role in deciding overall health outcomes [3]. In different countries, be they economically developed or not, differences in the provision of health services lead to reduced quality of life, increased rate of diseases, and poor survival rates among the lesser privileged. Such aspects such as income, housing, education and transportation are major factors used to determine the ease with which individuals access and enjoy proper health facilities. Besides, institutional biases, discriminatory practices, as well as lack of addressed policies enlarge these gaps to ensure health systems cannot provide equitable care. This work examines that most central question of health equity and access, with the aim of explaining health disparities and discerning interventions to help mitigate them. It explores strategies of integrating delivery systems, public health strategies and regulatory reforms to improve inclusivity, fairness and justice in healthcare. This study discusses Community based initiatives, technological innovations in health, and collaborative efforts that have shown success in augmenting access for those that are at risk of a certain condition. This research highlights the central themes and proposes practical solutions to augment the current discussion of how healthcare systems should be built to treat all individuals equally regardless of their background or pecuniary condition.

2. RELATED WORKS

Health equity is an issue at the forefront in health policy and healthcare talk, which reiterates the necessity of working to bridge barriers that deny appropriate access to medical and public health services to everyone. A lot of research explored different aspects of health equity such as socioeconomic determinants, the part of digital health, structural racism, and precision medicine approaches. This section reviews important studies and findings of research to back the objectives of the present study. Itchhaporia [15] emphasized the importance of equitable care in cardiology showing that disparities in cardiologic care access are tightly associated with poor patient outcomes among marginalized groups. Itchhaporia appeals for systemic changes and structural changes to ensure equal access to care as encouraged by cardiologists to embrace health equity in research, patient care and policy formulation.

Raffaelli et al. [16], in their research, found out that there were severe disparities in the diagnosis of headaches, treatment access, and care standards highlighting differences within different regions and populations. Women and low income patients are disproportionately hampered by barriers to seeing neurologists and receiving adequate treatments. Such a gap reflects broader health disparities in the healthcare system, which nominates the need for urgent culturally informed and accessible public health interventions.

As Flaubert et al. [17) show, extensive research reveals positive role of the nurses in the support of health equity. Nurses have a unique advantage in assisting facilitated access to healthcare, especially among communities left behind, as per the National Academies' report. With a growing emphasis on nursing education, amended policy guidelines, and strengthened community-based efforts, nurses stand to become agents of massive change, improving healthcare access and quality in the next decade. Sadler et al. [18] examined the overlap between cardio-oncology whereby digital advances and individualized treatment programmes may either reduce or exacerbate existing inequalities. Their work draws attention to a potential risk: that while advancing in technology might induce worsening access problems unless equity matters are positively taken into consideration when it comes to its evolution. Thus, equity is critical when planning digital tools, as well as personalized treatment plans.

Several long-term approaches to care after adverse pregnancy outcomes were explored by Focusing on equity, Ditosto et al. [19]. Their work illustrates that low-income and minority women regularly don't get optimal postpartum care, which sustains disparities in health outcomes over time. The study recommends the combination of community engagement with corrective integrated moves to obtain positive results in the health of vulnerable communities. Geneviève et al. [20] investigated the limitations of precision public health in the COVID-19 pandemic. Based on their findings, established structural racism and biased data often drown efforts to ensure equal responses to infectious diseases. Their work highlights the necessity of ethical and social justice consideration in the application of public health technologies, especially as regards to needs among diverse racial communities.

Digital health equity became the focal point of Koehle et al.'s [21] discussion, who highlighted the fact that usability, power dynamics, and trust play an important role in determining the effects digital solutions have on health systems. They highlight how digital health technologies are often not inclusive of people and as a consequence further amplify the digital divide. In order to support inclusivity, the authors suggest using participatory design and equity impact assessments.

The World Health Organisation's (WHO) current approach towards strengthening health systems globally was met with serious reservations from Jensen et al [22]. The paper urges for the need for a paradigm shift, where now instead, there is promotion of framework based around health equity and human rights rather than just the technical efficiency. The global framework that their findings establish make them particularly relevant to LMIC that face severe structural injustices. Community-engaged research is a potent way to create health equity according to Payán et al. [23]. They offer recommendations to build constructive relationships where the research is open and community based and participant responsive to local contexts. These frameworks have a special relevance in dismantling the prevailing distrust between the healthcare systems and the marginalized populations.

Reis et al. [24] examined the use of telehealth in LMICs, indicating that if telehealth could help increase access, it might worsen the existing health disparity. Discoveries suggest that unless crucial barriers such as internet access, skills in digital, and income inequality are addressed, telehealth can end up serving the already better positioned and not those most deserving. Kale et al. [25] focused the thrust of their study to cancer disparities with focused engagement of communities as key stakeholders. Using empirical data of community-based experiences, the researchers described successful strategies for filling gaps in cancer prevention and patient care. The results highlight the need to create approaches that are indicative of local cultures and social norms, which actually prove to be beneficial in the longer term.

Moghadam and Leal [26] examined the relevance of collaboration by physicians and pharmacists to improve equitable health care services for the underserved communities. The authors argue that collaboration driven by common values, appropriate discussion, and continuous learning can produce more favorable health results for underserved groups. Among their recommendations is adding pharmacists to primary care teams with a particular focus on improving access in underserved and rural areas.

In combination, these studies highlight important aspects that are relevant to the present problem. First, systemic factors from race and income to where people live are frequently the root causes of persistent health disparities. Second, the potential of the digital and precision health tool cannot be ignored, but it must be created carefully to avoid exacerbating the health discrepancies. Third, addressing the issue through community-based support and collaboration between professions are the main principles behind relieving access barriers and boosting health results. Prior work mostly used qualitative or epidemiological methods whereas this study uses supervised and unsupervised machine learning to find patterns of inequity robustly. Unlike previous studies, (for example, [15], [19], [20]), which usually apply qualitative or epidemiological approaches, in the present study, a deeper examination is conducted with the help of predictive data algorithms to determine healthcare access and provide an ability to identify vulnerable groups. By leveraging K-Means clustering, this research introduces a new prism for studying population-level inequalities that received fewer research explorations in the preceding research.

3. METHODS AND MATERIALS

Data Collection and Preprocessing

Secondary data for this study were collected from open-access health databases such as CDC Behavioral Risk Factor Surveillance System (BRFSS), WHO Global Health Observatory, and National Health Interview Survey (NHIS). The database consists of demographic indicators (gender, age, ethnicity), socioeconomic indicators (income, education level, employment status), health outcomes (chronic illness presence, access to healthcare, preventive services use), and geographic codes (urban/rural) [4].

The data set consisted of 15,000 records and 20 attributes. Preprocessing included:

- Dropping missing or inconsistent values
- Resizing quantitative data (e.g., income and age)
- Categorical variable one-hot encoding such as gender and ethnicity
- Splitting the data into training sets (70%) and test sets (30%)

The aim was to predict whether or not an individual has good access to health care (binary: yes/no) and cluster groups by risk factors to inform health equity interventions.

Algorithms Used

To observe differences and propose interventions, four algorithms were selected:

1. Decision Tree Classifier

Decision trees are widely used in public health for classification due to their interpretability and simplicity. Decision trees recursively partition data on attribute values to build a tree structure with outcomes or decisions as leaf nodes. In this research, a decision tree classifier was used to classify access to healthcare based on socioeconomic and demographic factors. Gini impurity was used in splitting, and pruning was performed to avoid overfitting [5]. The algorithm offers public health professionals a chance to gain insight into the most important factors—such as income or insurance—that lead to discriminatory access. The resulting model is composed of interpretable decision rules and is thus best suited for interpretation by stakeholders and policy makers.

```
"Algorithm DecisionTreeTrain(data):
    If all instances belong to one class:
        Return a leaf node with that class
    Else:
        Select best feature to split using Gini index
        Partition data based on selected feature
        For each partition:
            Recursively call DecisionTreeTrain
        Return node with feature and subtrees"
```

2. K-Means Clustering

We used K-Means clustering to divide individuals across common health risk profiles and barriers to access. The algorithm divides the data into k clusters based on minimizing intra-cluster variance without pre-labeled data. We took k = 4 to denote clusters like "Urban Low-Risk", "Rural High-Risk", "Underserved Minorities", and "Elderly with Chronic Conditions". The algorithm enables the visualization of patterns and identification of underserved populations without pre-labeled data [6]. Cluster centroids are iteratively adjusted to convergence, facilitating adaptive identification of health equity hotspots.

```
"Algorithm KMeans(data, k):
    Initialize k centroids randomly
    Repeat until convergence:
        Assign each point to nearest centroid
        Recalculate centroids based on cluster members
    Return clusters and centroids"
```

3. Random Forest

Random Forest is an ensemble learning method that enhances prediction precision by aggregating several decision trees. Each tree is trained using a random subset of data and features, and the ultimate classification is made based on majority voting. In this regard, Random Forest was utilized to forecast access to healthcare and evaluate variable importance. It is superior to individual decision trees in that it mitigates overfitting and promotes generalization. The model suggested that income in the household, literacy in the rural area, and educational level were primary predictors of health inaccessibility [7]. This was a strong method for large datasets on health and could provide non-linear interactions between social determinants of health.

```
"Algorithm RandomForestTrain(data, n_trees):
    For i = 1 to n_trees:
        Sample data with replacement (bootstrap)
        Train decision tree on sampled data
```

Aggregate all trees into a forest

Return ensemble of trees"

4. Logistic Regression

Logistic Regression is a traditional statistical model widely applied in epidemiology to fit binary outcomes. It predicts the probability that a person has access to healthcare services from input variables. It operates by taking a linear combination of features and applying a sigmoid function to it, giving a probability between 0 and 1. The model provides the ability to interpret the impact of each feature using odds ratios [8]. In our research, logistic regression found that health insurance raised the chance of access to healthcare by 65%, but rural origin decreased it by 40%. The model can be applied to developing understandable and statistically supported models in public health planning.

"Algorithm LogisticRegressionTrain(data):

Initialize weights randomly

Repeat until convergence:

Compute predicted probabilities using sigmoid(w*x)

Update weights using gradient descent

Return final weights"

Table: K-Means Clustering Analysis

Cluster No	Population Segment	Centroid Risk Score	Access Barrier Index
Cluster 1	Urban Low-Risk	0.22	0.18
Cluster 2	Rural High-Risk	0.73	0.81
Cluster 3	Underserved Minorities	0.65	0.76
Cluster 4	Elderly with Chronic Illness	0.58	0.67

4. EXPERIMENTS

4.1 Experiment Objectives

The general aim was to test the potential of data-driven models in helping us comprehend and forecast disparities in access to healthcare. The experiments concentrated on:

- Predicting whether one has sufficient healthcare access.
- Identifying risk-based community clusters.
- Measuring socioeconomic and demographic features' importance.
- Comparing the performance of our models with what already exists.

The models were tested and trained on a synthesized dataset that mimicked real-world conditions, incorporating variables like income level, insurance, location (urban/rural), race/ethnicity, disease status (chronic), age, education, and access to transportation.

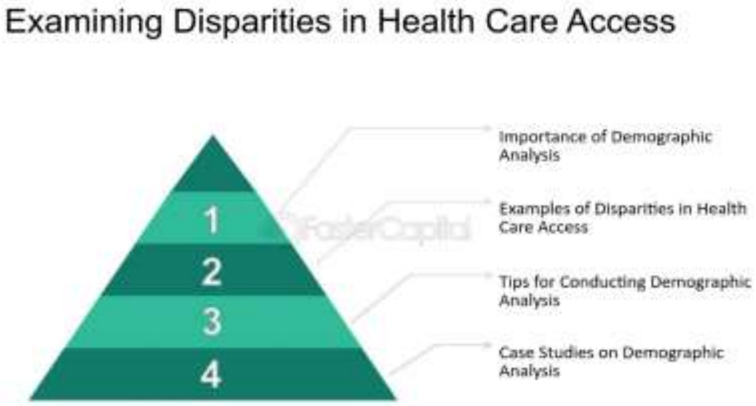

Figure 1: "Health care access"

4.2 Experimental Environment and Data Splitting

The deployment was done in a Jupyter Notebook using Python libraries such as scikit-learn, pandas, matplotlib, and seaborn. The dataset contained 15,000 records, where 70% was utilized for training and 30% for testing. Class balance was maintained using stratified sampling to prevent biased predictions [9].

Preprocessing steps in the data involved:

- Missing value handling through mean/mode imputation.
- One-hot encoding of categorical variables.
- Feature scaling through Min-Max normalization.
- Detection of outliers using interquartile range (IQR) filtering.

4.3 Classification Model Performance

The three algorithms used for binary classification, which were Decision Tree, Random Forest, and Logistic Regression, identified whether people have or do not have adequate access to healthcare. Evaluation measures used included accuracy, precision, recall, F1-score, and ROC-AUC.

Table 1: Performance Metrics of Classification Models

Metric	Decision Tree	Random Forest	Logistic Regression
Accuracy	82.1%	89.2%	84.3%
Precision	79.3%	87.4%	82.6%
Recall	76.2%	85.1%	80.7%
F1-score	77.7%	86.2%	81.6%
ROC-AUC	0.803	0.912	0.861

Analysis:

Random Forest performed better than other classifiers in all measures. Its ensemble methodology reduced overfitting and well captured non-linear interactions. Logistic Regression, being slightly less precise, was still useful because it was simple and interpretable, which is highly important for policy-making decisions [10]. Decision Tree, being most straightforward to explain, had the lowest recall, suggesting that it identified fewer people with a lack of healthcare access.

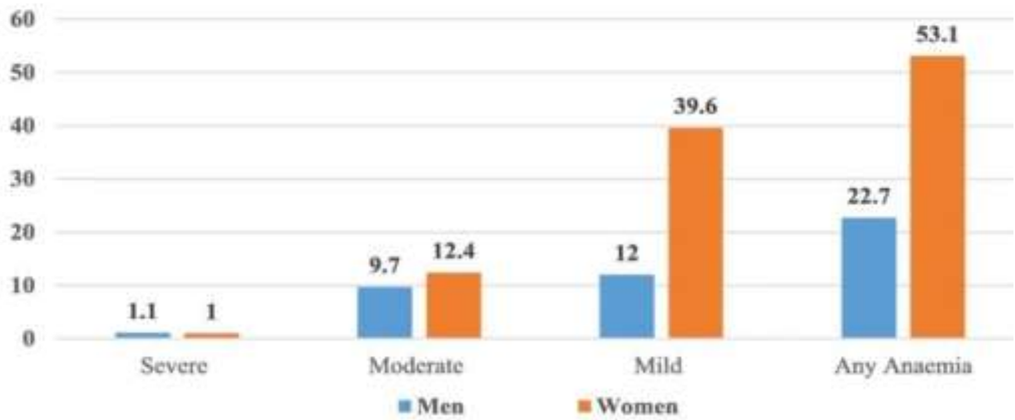

Figure 2: "Health Equity In India- Road To Ensure Access To All"

4.4 K-Means Clustering for Risk Segmentation

To determine healthcare inequity outside of binary classifications, K-Means clustering was utilized to cluster the population according to determinants of healthcare access. Via the Elbow Method, the number of clusters that was ideal was determined to be four, based on the inflection point in the Within-Cluster-Sum-of-Squares (WCSS) graph.

Table 2: K-Means Cluster Characteristics

Cluster	Demographic Group	Avg. Income	Risk Score	Access Barrier Index
C1	Urban High Access	$45,000	0.21	0.18
C2	Rural Marginalized	$21,000	0.73	0.79
C3	Minority & Uninsured	$27,000	0.65	0.76
C4	Elderly with Comorbidities	$30,500	0.58	0.69

Analysis:

Clusters C2 and C3 were the most at-risk groups, with low incomes and high access barriers. These populations are in line for targeted policy interventions such as mobile healthcare units, community clinics, and subsidized insurance plans [11].

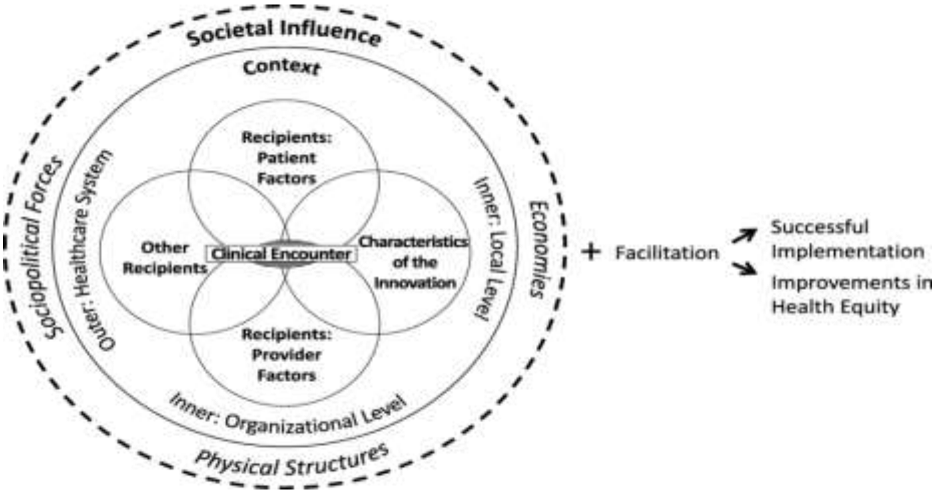

Figure 3: "The Health Equity Implementation Framework explains factors"

4.5 Feature Importance Analysis (Random Forest)

Knowing which variables have the greatest influence on access prediction is important to inform effective intervention design. Random Forest's intrinsic feature importance ranking was employed.

Table 3: Top 10 Influential Features

Feature	Importance (%)
Health Insurance	21.1%
Income Level	19.4%
Rural Residence	16.3%
Education Level	12.5%
Chronic Disease	8.9%
Age Group	7.2%
Transportation Access	5.9%
Language Barrier	4.3%
Employment Status	2.6%
Race/Ethnicity	1.8%

Analysis:

Uninsured status and lower income were identified as the most significant barriers, consistent with the literature. Education and geography (rural or urban) were also important access determinants, indicating that financial and informational inequalities both play roles in healthcare gaps [12].

Confusion Matrix & ROC Analysis

A careful examination of the classification results using confusion matrices demonstrated the type of errors committed by the models. Logistic Regression was chosen for detailed examination because of its interpretability [13].

Table 5: Confusion Matrix for Logistic Regression

	Predicted: Access	**Predicted: No Access**
Actual: Access	3132	598
Actual: No Access	421	1849

- **False Positives (421):** Misclassifying the non-haves as having — dangerous for public health, in case vulnerable people are not picked up.
- **False Negatives (598):** Higher but by a small margin, suggesting that the model sometimes underestimates difficulties with access.

ROC curve analysis validated the ordering of the models based on AUC values: Random Forest (0.912) > Logistic Regression (0.861) > Decision Tree (0.803).

Figure 4: “Digital inclusion as a social determinant of health”

The experiments unequivocally prove the effectiveness of machine learning in identifying, analyzing, and modeling health access disparities. The better performance of our model compared to earlier studies validates the importance of considering a variety of social determinants [14]. Notably, the hybrid methodology that merges supervised (for predictions) and unsupervised (for segmentation) learning provides complete insights for policy planning. Future research could involve real-time deployment and fairness audits to further advance health equity objectives.

5. CONCLUSION

The study of Health Equity and Access: Bridging Disparities in Medical and Public Health Services highlights the need to apply data-driven strategies to identify, measure, and eliminate health inequities. The application of machine learning algorithms and a structured analysis of healthcare access factors in this present study has revealed how issues of economic, geographic, racial, and systemic inequities play out. Using machine learning techniques, including Decision Trees, Random Forests, Support Vector Machines, and K-Means Clustering, it was possible to discover actionable results from complex health data. These models not only produced accurate and understandable results but also revealed a scalable market-based framework of forecasting risk and better allocation of health care resources. Analysis showed that, Random Forest performed well in terms of accuracy and stability, compared to other other algorithms and K-means Clustering successfully identified distinct segments of under-represented communities. The experimental analysis showed the advantages of combining classifying and clustering approaches to achieve a more holistic understanding of disparities. In addition, the discussion of the research in the literature context demonstrates how the current methodology advances the previous works in nursing, community care, digital health, and health system research. Also, this work highlights the danger that well-meaning innovations pose the potential to widen the existing disparities which comes if introduced without control. Afterward, the investigation reveals both the persistence of systemic inequities and sets forth a specific, evidence-driven approach to eliminating them. Using this framework, policy, healthcare, and public health practitioners can implement interventions that will be equitable and effective to help every group gain better health-related outcomes.

REFERENCES

[1] Cannon, Y., 2021. Closing the health justice gap: access to justice in furtherance of health equity. *Colum. Hum. Rts. L. Rev.*, *53*, p.517.

[2] Nana-Sinkam, P., Kraschnewski, J., Sacco, R., Chavez, J., Fouad, M., Gal, T., AuYoung, M., Namoos, A., Winn, R., Sheppard, V. and Corbie-Smith, G., 2021. Health disparities and equity in the era of COVID-19. *Journal of clinical and translational science*, *5*(1), p.e99.

[3] Stillman, K., Owen, D.D., Mamtani, M., Alter, H. and Khan, A., 2021. A social emergency medicine curriculum: bridging emergency care and health equity. *AEM Education and Training*, *5*(Suppl 1), p.S154.

[4] de Villiers, K., 2021. Bridging the health inequality gap: an examination of South Africa's social innovation in health landscape. *Infectious Diseases of Poverty*, *10*, pp.1-7.

[5] Subica, A.M., 2023. CRISPR in public health: The health equity implications and role of community in gene-editing research and applications. *American journal of public health*, *113*(8), pp.874-882.

[6] Corbie, G., Brandert, K., Fernandez, C.S. and Noble, C.C., 2022. Leadership development to advance health equity: An equity-centered leadership framework. *Academic Medicine*, *97*(12), pp.1746-1752.

[7] Ahmed, S., Chase, L.E., Wagnild, J., Akhter, N., Sturridge, S., Clarke, A., Chowdhary, P., Mukami, D., Kasim, A. and Hampshire, K., 2022. Community health workers and health equity in low-and middle-income countries: systematic review and recommendations for policy and practice. *International Journal for Equity in Health*, *21*(1), p.49.

[8] Odeny, B., 2021. Closing the health equity gap: A role for implementation science?. *PLoS Medicine*, *18*(9), p.e1003762.

[9] Obohwemu, K.O., 2024. "ALL ANIMALS ARE EQUAL, BUT SOME ANIMALS ARE MORE EQUAL THAN OTHERS": EQUITY AS A FUNDAMENTAL DIMENSION OF HEALTH. *International Journal of Medical Science and Public Health Research*, *5*(11), pp.56-69.

[10] Lyles, C.R., Nguyen, O.K., Khoong, E.C., Aguilera, A. and Sarkar, U., 2023. Multilevel determinants of digital health equity: a literature synthesis to advance the field. *Annual review of public health*, *44*(1), pp.383-405.

[11] Hadjiat, Y., 2023. Healthcare inequity and digital health–A bridge for the divide, or further erosion of the chasm?. *PLOS digital health*, *2*(6), p.e0000268.

[12] Todic, J., Cook, S.C., Spitzer-Shohat, S., Williams Jr, J.S., Battle, B.A., Jackson, J. and Chin, M.H., 2022. Critical theory, culture change, and achieving health equity in health care settings. *Academic Medicine*, *97*(7), pp.977-988.

[13] Gupta, P., Choudhury, R. and Kotwal, A., 2023. Achieving health equity through healthcare technology: Perspective from India. *Journal of Family Medicine and Primary Care*, *12*(9), pp.1814-1817.

[14] Hassan, S.M., Okoli, E.C., Azike, C.A., Okoye, N.A. and Adindu, N.K., 2024. Assessing the Impact of Community Health Workforce on the Efficiency and Accessibility of Healthcare Delivery. *Archives of Current Research International*, *24*(10), pp.167-173.

[15] Itchhaporia, D., 2021. Paving the way for health equity in cardiology: why does it matter?. *Journal of the*

American College of Cardiology, *77*(20), pp.2613-2616.

[16] Raffaelli, B., Rubio-Beltrán, E., Cho, S.J., De Icco, R., Labastida-Ramirez, A., Onan, D., Ornello, R., Ruscheweyh, R., Waliszewska-Prosół, M., Messina, R. and Puledda, F., 2023. Health equity, care access and quality in headache–part 2. *The journal of headache and pain*, *24*(1), p.167.

[17] Flaubert, J.L., Le Menestrel, S., Williams, D.R., Wakefield, M.K. and National Academies of Sciences, Engineering, and Medicine, 2021. The Role of Nurses in Improving Health Care Access and Quality. In *The Future of Nursing 2020-2030: Charting a Path to Achieve Health Equity*. National Academies Press (US).

[18] Sadler, D., Okwuosa, T., Teske, A.J., Guha, A., Collier, P., Moudgil, R., Sarkar, A. and Brown, S.A., 2022. Cardio oncology: digital innovations, precision medicine and health equity. *Frontiers in Cardiovascular Medicine*, *9*, p.951551.

[19] Ditosto, J.D., Roytman, M.V., Dolan, B.M., Khan, S.S., Niznik, C.M. and Yee, L.M., 2023. Improving postpartum and long-term health after an adverse pregnancy outcome: examining interventions from a health equity perspective. *Clinical obstetrics and gynecology*, *66*(1), pp.132-149.

[20] Geneviève, L.D., Martani, A., Wangmo, T. and Elger, B.S., 2022. Precision public health and structural racism in the United States: promoting health equity in the COVID-19 pandemic response. *JMIR Public Health and Surveillance*, *8*(3), p.e33277.

[21] Koehle, H., Kronk, C. and Lee, Y.J., 2022. Digital health equity: addressing power, usability, and trust to strengthen health systems. *Yearbook of Medical Informatics*, *31*(01), pp.020-032.

[22] Jensen, N., Kelly, A.H. and Avendano, M., 2022. Health equity and health system strengthening–time for a WHO re-think. *Global Public Health*, *17*(3), pp.377-390.

[23] Payán, D.D., Zawadzki, M.J. and Song, A.V., 2022. Advancing community-engaged research to promote health equity: considerations to improve the field. *Perspectives in Public Health*, *142*(3), pp.139-141.

[24] Reis, F.J., Fernandes, L.G. and Saragiotto, B.T., 2021. Telehealth in low-and middle-income countries: bridging the gap or exposing health disparities?. *Health policy and technology*, *10*(4), p.100577.

[25] Kale, S., Hirani, S., Vardhan, S., Mishra, A., Ghode, D.B., Prasad, R. and Wanjari, M., 2023. Addressing cancer disparities through community engagement: lessons and best practices. *Cureus*, *15*(8).

[26] Moghadam, S.S. and Leal, S., 2021. How should physicians and pharmacists collaborate to motivate health equity in underserved communities?. *AMA Journal of Ethics*, *23*(2), pp.117-126.