Optimizing Glaucoma Care with Data-Driven Solutions: An Analysis of Addressing Social Vulnerability Through Patient-Centered Interventions

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Abstract

Glaucoma, a group of eye diseases, disproportionately affects socially vulnerable groups and underscores significant challenges in treatment accessibility and quality. Our investigation revealed disparities in eye care services in the United States, noting that marginalized populations face obstacles in accessing glaucoma treatment. An evaluation of Social Vulnerability Index (SVI) demographics—age, ethnicity, disability, disease status, and gender—helped develop a targeted intervention strategy. Leveraging machine learning algorithms to analyze data from the National Health and Nutrition Examination Survey, American Community Survey, Behavioral Risk Factor Surveillance System, and anonymized glaucoma records revealed an association between social vulnerability and eye care outcomes. Telemedicine emerged as a promising avenue for enhancing patient satisfaction in specialized eye care and bridging healthcare gaps. Statistical models revealed a significant relationship between marginalized communities and adverse glaucoma outcomes, highlighting disparities in eye care access. These models demonstrated the effectiveness of patient-centered interventions, such as telemedicine and psychological support, in mitigating these disparities by catering to community-specific needs. The findings highlighted the need for comprehensive healthcare interventions targeting the disparities in access to glaucoma care. The research advocated adopting patient-centered solutions to cultivate a more inclusive, sustainable healthcare system.

Introduction

Ensuring access to quality eye care services is pivotal for maintaining a key determinant of health—adequate vision. However, disparities in access persist, influenced by factors such as social vulnerability, geographic distribution of services, and health conditions.[1] The exclusive concentration of glaucoma treatment services in urban areas contributes to inequities, causing delayed diagnoses in underserved communities.[2] Telemedicine advancements, accelerated by the COVID-19 pandemic, present potential solutions for non-urban areas, where access to ophthalmological care is limited.

Social vulnerability is the oppressive forces that define barriers for underserved communities to access resources and are certainly applicable to eye care services. A 2023 neighborhood-level cohort study showed that the higher a patient's level of social vulnerability, represented numerically by the Social Vulnerability Index (SVI), the more significant the association with non-adherence to ophthalmology appointments. SVI "is a rank score of 15 social factors into four themes, including socioeconomic status, household composition/disability, minority status/language, and housing type/transportation."[1] Their work further considers individual characteristics, demonstrating more nuanced factors influence appointment adherence and the importance of targeted interventions to mitigate these discrepancies. Similarly, across Canadian provinces, the skewed optometrist distribution reveals another metric behind SVI in addition to access: utilization. Of the 109 health regions, (HRs), "35 HRs were classified as low utilization, 39 HRs were classified as moderate, and 32 HRs as high utilization"[3] for vision care services. The study proposes better-informed workforce planning to advocate for equitable access to vital eye care services, especially across vulnerable populations under-utilizing existing sparse services. With the multi-level intervention strategies suggested, addressing patients belonging to vulnerable populations' access to eye care services requires appropriate policy interventions.

In the wake of the COVID-19 pandemic, the telecommunications landscape in specialized eye care has evolved to fill the need for a more convenient method for analyzing patient information. A 2022 study demonstrated high satisfaction among participants, despite appointments being longer and increased technical challenges relative to in-person appointments. Particularly among pediatric patients, "99% of parents were comfortable with exam quality, and 97% indicated they would have another telemedicine examination."[4] Due to the concentration of specialized eye care in urban areas, the results suggest that telecommunications could improve access to specialized eye care and further the more collaborative nature of care between eye care providers and their patients. A similar review on the cost-effectiveness of telemedicine in glaucoma screenings found that teleglaucoma "has been shown to reduce the screening time and costs per patient," and that "100% of the patients were either satisfied or very satisfied with the eye screening."[5] While eye care experts initially offered telecommunications as an adaptation to COVID-19 restrictions, its use in glaucoma screenings indicates a more efficient approach that could mitigate healthcare inequities. Focusing on a patient-centered approach to care helps to improve healthcare efficacy in facilitating a closer bond between eye care providers and their patients, which would otherwise be more inaccessible due to sociodemographic barriers.

The barriers to specialized ophthalmologic services and impacts on overall health are not limited to only the North American continent. A cross-sectional Ethiopian glaucoma population study revealed "the prevalence of poor quality of sleep was 82.5% among the glaucoma population,"[6] realizing a significant association between glaucoma and poor sleep quality. The study highlighted that advanced stages of glaucoma are associated with older age, depression, and visual impairment. The impacts of compromised sleep quality extend beyond health and productivity concerns, influencing intersecting societal oppressions and contributing to increased social vulnerability. The researchers ultimately recommended integrating psychiatric counseling into glaucoma follow-up protocols to address poor sleep impacts on patients psychologically. This approach advocates for a more holistic approach to glaucoma management and patient care, resulting in a more sustainable and accessible environment for eye care.

Given persistent challenges in equitable access to ophthalmologic services, targeted interventions addressing social vulnerability and promoting telemedicine emerge as crucial strategies. While acknowledging telemedicine's potential, long-term sustainability in mitigating sociodemographic inequities remains uncertain. My research explored associations between glaucoma, psychological health, and sociodemographic factors to propose tailored interventions, contributing to sustainable and inclusive eye care practices. Such research endeavors may contribute to advancing inclusive and sustainable eye care practices that prioritize and address the needs of vulnerable populations. Specifically, in this study, I examined existing associations between social vulnerability and eye care outcomes, especially for glaucoma, within the United States. I also evaluated the efficacy and sustainability of telemedicine in enhancing access to ophthalmology services, particularly in non-urban and underprivileged communities.

Approaches and Methods

Broader Context

My research answered how evidence-based interventions designed to address sociodemographic disparities in ophthalmology care contribute to advancing sustainable eye care practices in the United States. Which interventions show the most promise in effectively addressing sociodemographic disparities in access to ophthalmology care access, and in what ways can the implementation of these interventions be optimized? Professionals in the field of ophthalmology, healthcare policymakers, public health officials, and researchers specializing in healthcare disparities would be interested in sustainable practices in eye care. Additionally, professionals from academic institutions, including UCLA JSEI, government health agencies, and healthcare providers, would benefit from the data-driven decision-making that addresses sociodemographic disparities in ophthalmology care.

Overall Approach

To gauge the effectiveness of healthcare and policy interventions in ophthalmology, I assessed reduced wait times, neighborhood eye care utilization, and patient-reported outcomes in the United States. Therefore, community-level health data, such as that provided in the United States 2020 Census, are the optimal data sources to incorporate a broader understanding of social vulnerability and ophthalmology-related metrics. Following the guidance provided by Dr. Fei Yu of JSEI, I considered the National Health and Nutrition Examination Survey (NHANES by NCHS), the American Community Survey (ACS by the U.S. Census Bureau), and the Behavioral Risk Factor Surveillance System (BRFSS by Centers for Disease Control and Prevention (CDC)). These datasets offer insights into vision impairment by demographic, serving as indicators of social vulnerability factors and eye care service utilization. Through extracting and analyzing these specified data sources, I determined proxy indicators of social vulnerability and their impacts on glaucoma and patient care management.

In evaluating intervention effectiveness, my approach involved developing a machine learning algorithm to predict outcomes and discern influential factors contributing to patient eye care disparities. I aggregated demographic data from NHANES, ACS, and BRFSS, focusing on eye health and social vulnerability variables. After analyzing these factors, my next step matched patients based on criteria such as History of Presenting Illness (HPI) and social vulnerability factors such as age and gender. From this information, I found which interventions are most effective in helping people get the eye care they need based on their background. The core of the analysis was calculating qualified success rates to estimate how interventions impact positive outcomes.[8] My experimental design provided a comprehensive understanding of clinical findings and intervention strategies and offered valuable insights for addressing disparities in patient eye care.

Week	Expected Work
Winter Quarter 2024 Weeks 1-6	Complete: Integrate data derived from diverse surveys, censuses, and patient reports into a unified dataset, categorized according to patient demographics and socioeconomic indicators.
Winter Quarter 2024 Weeks 7-10	Complete: Determine the significance of multicollinear factors and the binary criteria associated with each patient observation.
Spring Quarter 2024 Weeks 1-4	Complete: Investigate existing intervention strategies and their implementation targeted at pertinent demographic segments within the dataset. Document and note findings pertaining to patient outcomes.
Spring Quarter 2024 Weeks 5-10	In progress: Compose a comprehensive research report, adhering to professional standards, for presentation to JSEI Dr. Kouros Nouri-Mahdavi. Conclude the SLAGC course with a summary of the study's outcomes and implications.

Data Cleaning Details

I completed several data processing procedures within the R programming language to ensure the integrity of the dataset for further analysis. I cleaned four datasets: the NHANES, ACS, BRFSS, and NCBI NLM glaucoma clinical notes. First, I changed column names to include precise and informative descriptors, enhancing the data's interpretability. Careful cleaning of numerical values was performed to facilitate conversion into a standard numeric format by removing unnecessary characters like commas and percentage marks. I refined the dataset by handling margin of error indicators, extracting numerical values, and eliminating symbols such as "±". Additionally, I generated confidence interval bounds for population estimations. The percentages of people with and without disabilities were preprocessed similarly, involving cleaning, managing the margin of error, and subsequent calculation of confidence intervals. To focus on the important variables of interest, I selected relevant columns of the percentages of people with and without disabilities along with their corresponding boundaries for further research. These rigorous preprocessing steps, using the R programming language, form the groundwork for robust statistical analysis of the various datasets.

Analysis for Datasets Used for Evaluating Social Vulnerability

I examined three datasets, including ACS, BRFSS by CDC, and NHANES, to explain the social vulnerability determinants underlying health disparities, particularly in access to ophthalmological treatment. ACS collected data from 2022, BRFSS data is from 2016, and NHANES data is a long-term study that began in 1999, with survey years conducted every year since then until 2018. The limitations the Health Insurance Portability and Accountability Act (HIPAA) impose made individual patient-specific information unattainable. As a result, I could not obtain statistics about the distribution of individual patients, especially demographic information. However, I used the NCBI NLM dataset of notes from patients examined for glaucoma by comprehensive or glaucoma ophthalmologists, collected from 480 patients seen between January 1, 2019, to August 31, 2020. This dataset includes a variety of identifiers, including billing codes, provider names, medical record numbers (MRNs), and visit identification numbers. To analyze the text comprehensively, I constructed a text corpus, a container of documents, to generate a term-document matrix that identifies recurring terms across the documents. I then conducted sentiment analysis to assess the emotional connotation associated with common words within the dataset. Each word's sentiment was mapped on a scale from -1 (negative) to 1 (positive), with 0 indicating neutrality. The following are my findings regarding the social vulnerability determinants underlying health disparities in access to ophthalmological treatment.

Results and Discussion

I explored many issues pertaining to differences in the use of eye care services and access to ophthalmological services. My investigation looks at the interaction between employment and disability status, highlighting sociodemographic vulnerabilities that could affect people's capacity to receive eye care services. Next, I analyzed the disparities in gender, age, and vision impairment. I explored the interactions between race, age, and glaucoma detection, and I examined trends in illness prevalence and sentiment extracted from clinical notes related to glaucoma. I arranged these sections in such a way to provide a thorough explanation of the various factors that contribute to variations in the use of eye care. The discussion that follows focuses on intervention strategies that aim to address these variations and promote a more inclusive healthcare system.

Disability Status and Employment

Based on the ACS 1-year estimates for 2022, the majority of working individuals aged 16 and older did not have disabilities (Figure 1). However, the most significant gap in employment status between disabled and non-disabled individuals above the age of 16 was noted among unpaid family workers, who are more likely to have a disability (Figure 2). This discrepancy reflects a type of social vulnerability, disability status, and unpaid labor, that may affect their use of social services like glaucoma treatment.[9]

As people with higher incomes and educational levels had lower rates of disability (Figure 3), the correlation between socioeconomic status and disability emphasizes how critical it is to mitigate accessibility obstacles to available resources.[9] People *without* a disability are marginally more likely to work from home and drive alone, so differences in work schedules and transportation options by disability status highlighted the need for tailored treatments to guarantee fair access to eye care.[10] As such, my analysis emphasized the significance of considering socio-economic factors and employment dynamics in understanding and addressing disparities in glaucoma service prevalence and utilization within the context of disability prevalence among the working-age population.

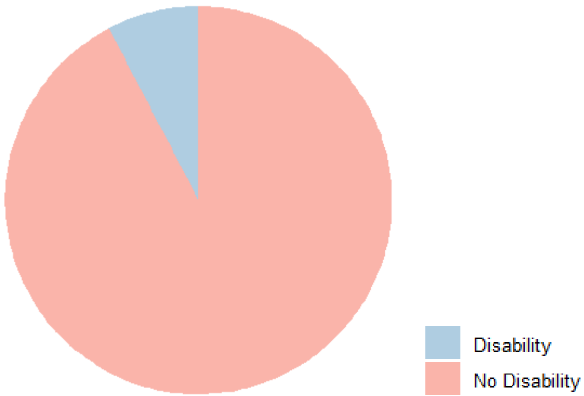

Figure 1: Employment Status of Individuals Aged 16 and Over, Stratified by Disability Status, Derived from ACS 2022 Data.

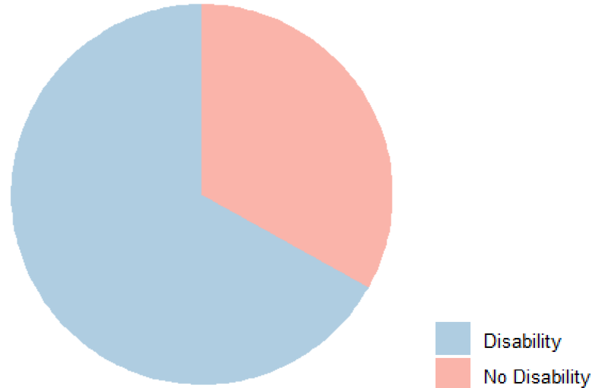

Figure 2: Proportion of Unpaid Family Workers among Individuals Aged 16 and Over, Stratified by Disability Status, Derived from ACS 2022 Data.

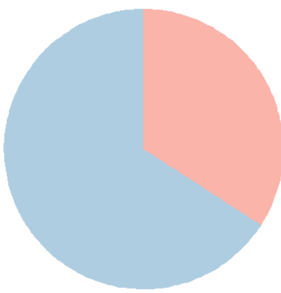

Figure 3a: Education Status of Individuals Less than High School Graduate Equivalency. Derived from ACS 2022 Data.

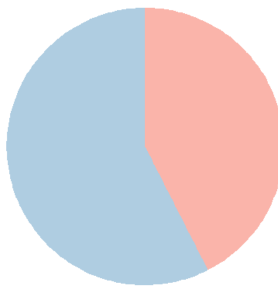

Figure 3b: Education Status of Individuals At High School Graduate Equivalency. Derived from ACS 2022 Data.

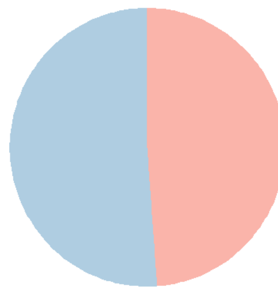

Figure 3c: Education Status of Individuals At Some College/Associate's Degree. Derived from ACS 2022 Data.

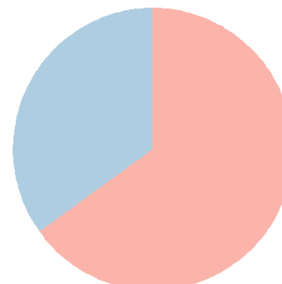

Figure 3d: Education Status of Individuals At Bachelor's Degree or Higher. Derived from ACS 2022 Data.

Gender, Age, and Vision Impairment

Further exploring the intersections of social vulnerabilities, ACS data from 2022 highlighted gender differences in visual impairment prevalence among older populations. Data on visual impairment in people 75 years and older revealed an association between gender differences in visual health. Compared to males, females in this age bracket were proportionally more prone to visual impairment (Figure 4a). This disparity raised concerns regarding possible gender-specific health or lifestyle factors that could lead to older age-related visual impairment[11]. Females may be diagnosed with visual impairment at a higher prevalence or more frequently, which underscored the necessity for gender-sensitive practices in the provision of visual health care[12] (Figure 4b). Yet, there was a counterintuitive pattern; in every age group, females are more likely than males to *lack* visual impairment (Figure 4c). This paradox presented fascinating possibilities about how lifestyle choices, biological conditions, or healthcare access could influence visual health outcomes. There was a gender-neutral distribution of the lack of visual impairment in all age groups (Figure 4d). While there may be gender differences in the reasons causing vision impairment, other universal variables may affect its absence. This comprehensive analysis of gender, aging, and visual health revealed the imperative for additional research endeavors to further explore the social determinants of visual health disparities.

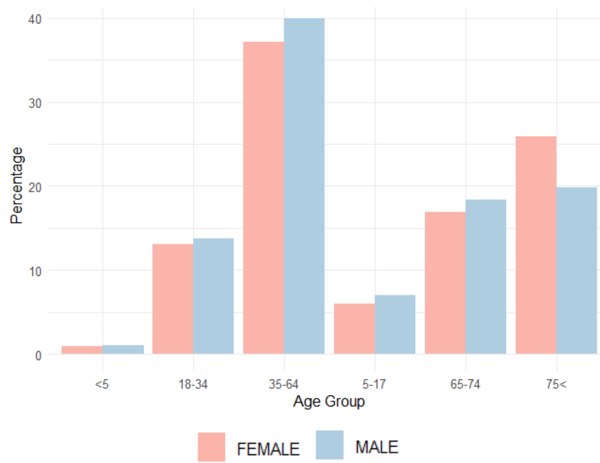

Figure 4a: Percentage of Individuals with Visual Difficulty, Stratified by Gender and Age Group, Derived from ACS 2022 Data.

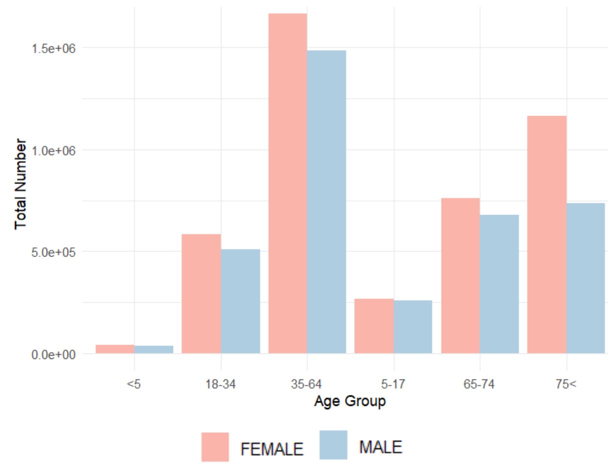

Figure 4b: Total Number of Individuals with Visual Difficulty, Stratified by Gender and Age Group, Derived from ACS 2022 Data.

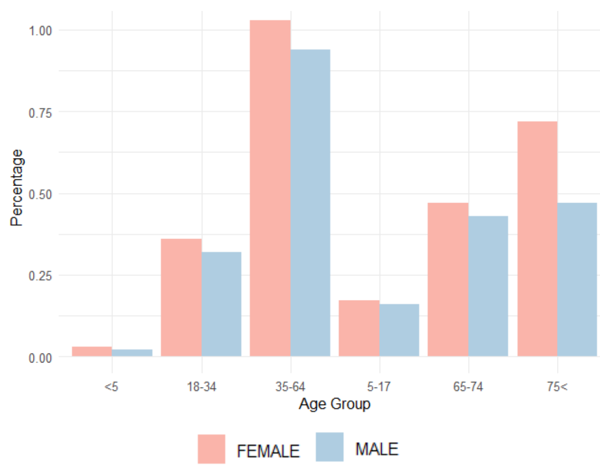

Figure 4c: Percentage of Individuals without Visual Difficulty, Stratified by Gender and Age Group, Derived from ACS 2022 Data.

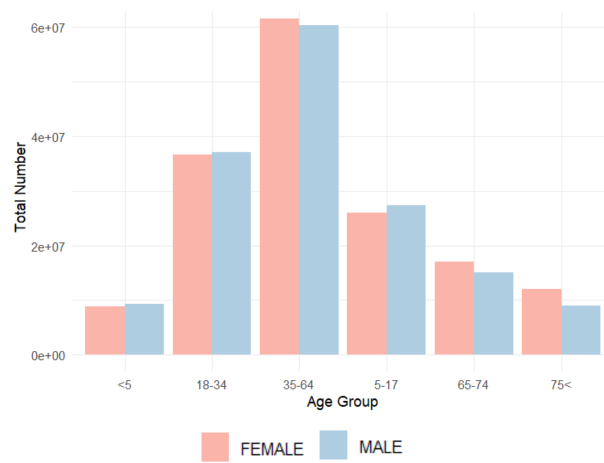

Figure 4d: Total Number of Individuals without Visual Difficulty, Stratified by Gender and Age Group, Derived from ACS 2022 Data.

Race, Age, and Glaucoma Detection

Analyzing specific glaucoma types data from the 2016 BRFSS by the CDC provided insight into the distribution of glaucoma across different demographic parameters. Although glaucoma may affect anyone of any age, ophthalmologists frequently detect it in those between 40 and 64, emphasizing the importance of detection efforts throughout one's lifetime (Figure 5). The limited variation in frequency between racial groups indicated that glaucoma's impact is universal. However, there were gaps in data collecting for several racial categories such as "Other" and "North American Native" (Figure 6), which would warrant improved reporting procedures[14]. A higher frequency of response rate regarding glaucoma from California and New York and lowest response rates from Utah, Alabama, and Alaska, demonstrated differences in data collection and informed targeted strategies to improve eye care services in underrepresented regions (Figure 7). There may also be an unrepresented trend in differences in population size, healthcare utilization patterns, and insurance coverage rates.[13] Ultimately, the higher annual presence of certain conditions among glaucoma patients highlighted the need for tailored interventions to address the unique challenges posed by these diseases in affected individuals.

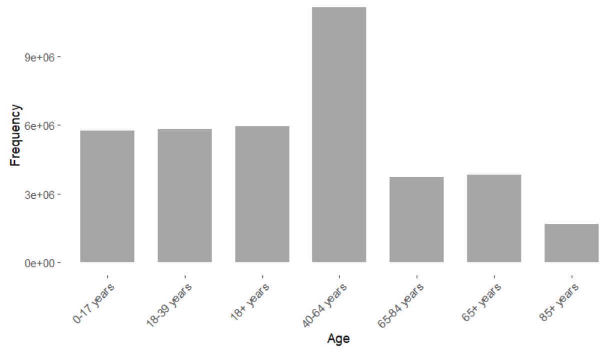

Figure 5: Glaucoma Detection by Type of Detection and Age Group, Derived from BRFSS by CDC 2016 Data.

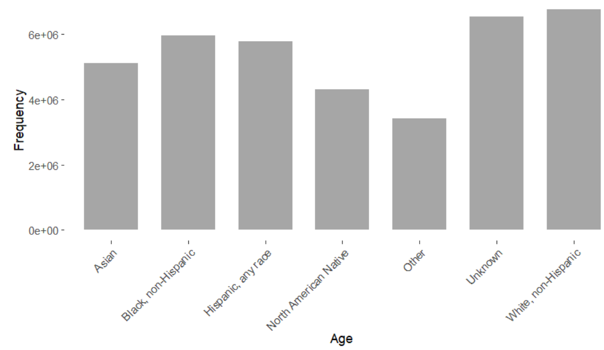

Figure 6: Glaucoma Detection by Type of Detection and Race, Derived from BRFSS by CDC 2016 Data.

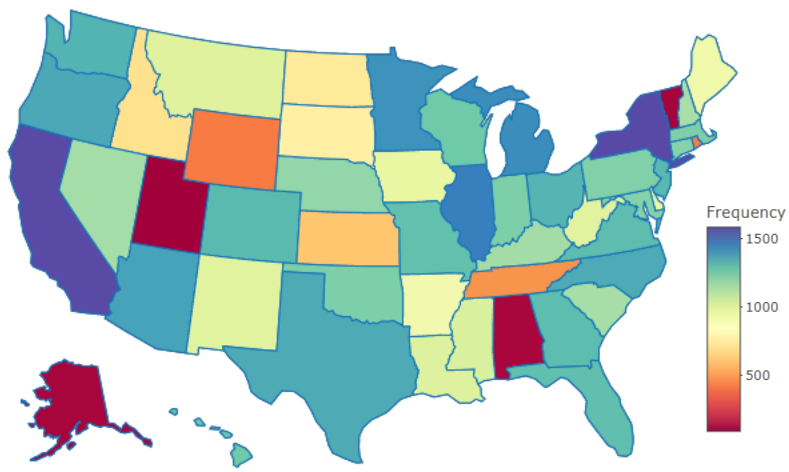

Figure 7: U.S. Map depicting Frequency of Glaucoma Insurance Responses, Derived from BRFSS by CDC 2016 Data.

Disease Prevalence

The NHANES data offered significant insights into the prevalence and interrelationships of various health conditions within the surveyed population from various 1-year long surveys from 1999 to 2018. There was a range in confidence levels for oral, chronic, and acute diseases, illustrating variability and uncertainty in prevalence estimates (Figure 8), underscoring the necessity for a comprehensive analysis of the presented data.[14] With acute diseases accounting for 35 percent of participants and confidence levels as high as 80 percent, the population's acute health disorders represented a significant burden that informs healthcare planning and resource allocation tactics. The observed difference in median prevalence between chronic and acute diseases for the survey year 1-year period from 2017 to 2018 (Figure 9) demonstrated the dynamic shift in disease patterns that observations reveal over time, highlighting the need for ongoing monitoring and strategy adaptation in the healthcare industry. These findings offered valuable insights into the prevalence and interrelationships of health conditions within the surveyed population, facilitating targeted healthcare interventions and resource allocation efforts. Collectively, these datasets provided a thorough understanding of health disparities and their complex causes based on social vulnerability.

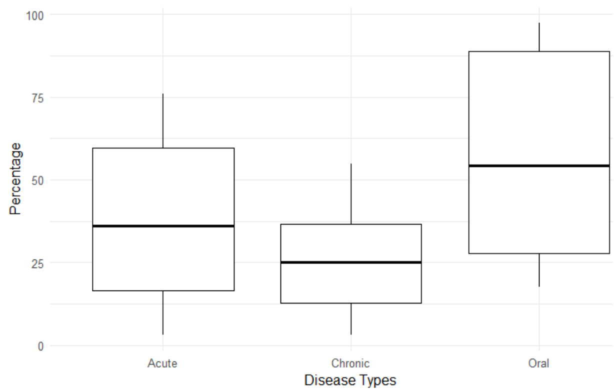

Figure 8: Percentage of Individuals with Oral, Chronic, and Acute Diseases and Confidence Intervals, Derived from NHANES.

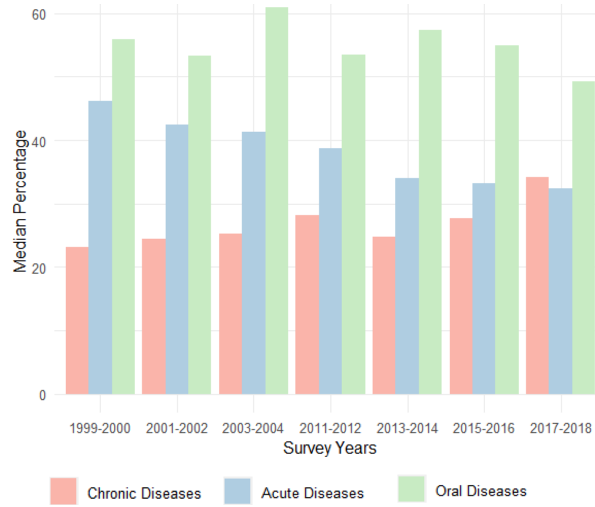

Figure 9: Median Percentage of Individuals with Diseases, Derived from NHANES.

Glaucoma Clinical Notes

Out of the 2,245 matched words from the 2022 NCBI NLM dataset of 480 clinical notes, the majority were categorized as neutral[15]. Specifically, less than 20% displayed either a negative or positive sentiment, with a higher proportion falling into the negative category (Figure 10). To identify the most common words excluding stop words (common prepositions and filler words), I parsed each clinical note into strings and tallied the frequency of each word, and this approach yielded 2,352 unique words. Notably, the abbreviation "OU," meaning "oculus uterque" or "each eye," emerged as the most frequently occurring term (782 counts). This was followed by "eye" (422 counts) and "HPI" (History of Presenting Illness) (384 counts). The most common non-neutral words were "vision" (358 counts), "patient" (201 counts), and "female" (178 counts), all positively scored terms of 0.5, 0.5, and 0.4, respectively. Upon subjecting these 2,352 words to sentiment analysis, the distribution of neutral, negative, and positive sentiments remained consistent with previous findings, reaffirming the robustness of the results (Figure 11).

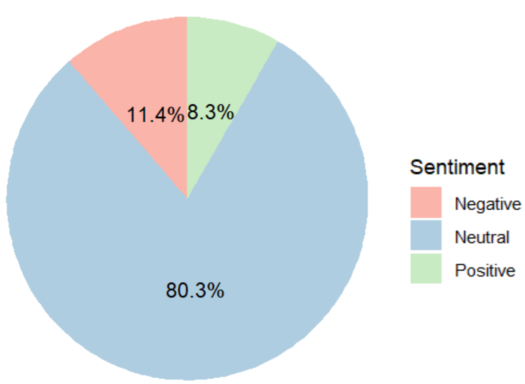

Figure 10: Sentiment breakdown by individual words in the text document matrix, Derived from NCBI NLM 2019-2020.

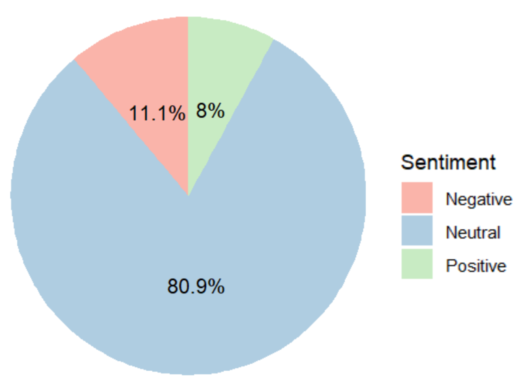

Figure 11: Sentiment breakdown by individual tokenized words, Derived from NCBI NLM 2019-2020.

I defined the major intervention categories as medications, family history-based interventions, progress checks, and further medical and psychological assessments and planned interventions (Figure 12). The data indicated a predominant reliance on medication-based interventions in glaucoma management. Using sentiment analysis alongside intervention data sheds light on the effectiveness and medical neutrality of various treatment approaches conducted by glaucoma specialists.[16] By examining the distribution and contextual subtleties of these interventions, it became possible to identify regions in glaucoma interventions that can benefit from optimization, which would improve the general standard of patient ophthalmological treatment.

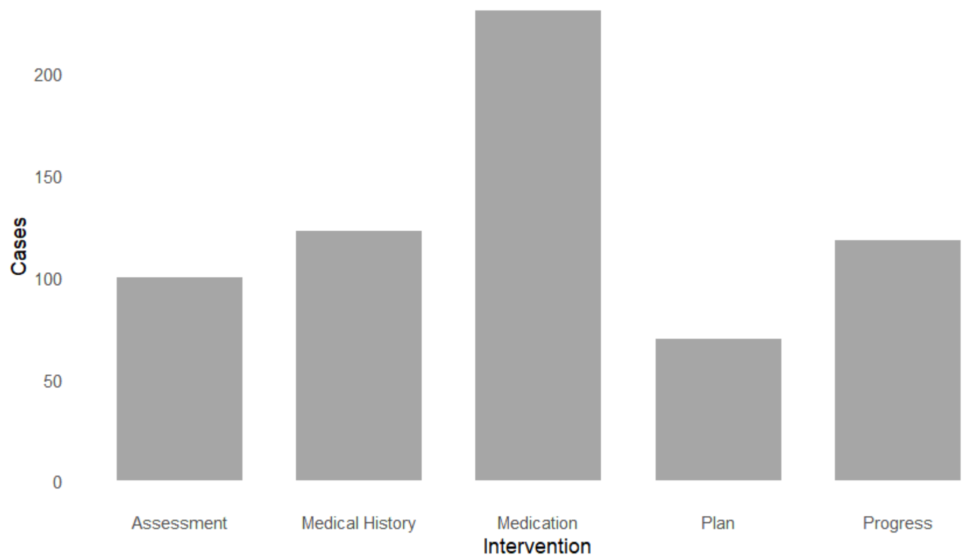

Figure 12: Distribution of Cases by Intervention Category Before Criteria Matching. Derived from NCBI NLM 2019-2020.

Intervention Criteria Matching

Understanding the distribution of glaucoma interventions stratified by race and ethnicity, particularly among minority populations like those of African or Hispanic/Latino descent and disabled individuals, is a persisting knowledge gap in the field of glaucoma research. The lack of diversity in research populations results in the findings being statistically insignificant and limiting their generalizability to the intended populations.[17] The FDA, NIH, and NLM do not yet provide enough updated and detailed data on the prevalence of glaucoma or specific interventions for these populations. These discrepancies in reporting may be caused in part by minority groups' reluctance to engage in clinical trials as well as their current disproportionate underrepresentation in the U.S. population data collection.[18] Even though this study did not explore social vulnerability-specific interventions because of access barriers to JSEI patient information, it is important to address inequities in glaucoma interventions through future customized interventions in studies.

Previous studies have presented conflicting findings regarding factors associated with the progression and distribution of glaucoma. Specifically, some research has failed to establish a association between visual field loss in glaucoma patients and factors such as age, gender, race/ethnicity, or systemic diseases, while others have reported significant associations.[19] This inconsistency contributes to confusion and may lead to inaccurate conclusions. I used criteria matching and machine learning algorithms to determine the most effective intervention strategies for facilitating access to necessary eye care among individuals from diverse socioeconomic backgrounds given the information that is currently publicly available.[20] I extracted age, gender, and HPI information from the 2022 NCBI NLM 480 clinical notes and assigned a proxy patient ID based on the matching criteria.

Figure 12 shows the deidentified intervention strategies; however, there was a distinct change in the distribution of intervention strategies when I matched patients according to sociodemographic vulnerability characteristics. I identified 213 of 480 patients from whom I extracted sociodemographic information, including age, gender, and HPI. I then cataloged 79 of those 213 patients with unique intervention strategies: Assessments, Medical History, Medication, Plan, and Progress. Assessments are suggested or completed medical examinations ordered by the physician and recorded in the notes, such as intraocular pressure, visual acuity, and psychological tests. Medications are prescriptions like Latanoprost, eye drops that decrease pressure inside the eye. Assessments overtook medications as the most common approach (Figure 13), indicating that a more comprehensive and individualized intervention involves both medication and assessments.

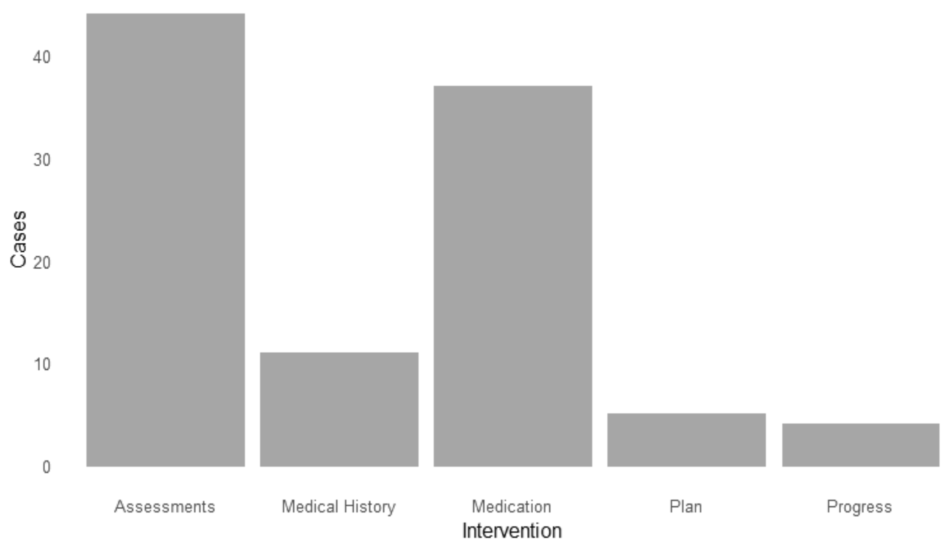

Figure 13: Distribution of Cases by Intervention Category After Criteria Matching. Derived from NCBI NLM 2019-2020.

Among the 79 patients receiving identified intervention treatment, the average age surpassed 60 years for criteria-matched glaucoma patients (Figure 14). Notably, patients with only ophthalmologist comments on any glaucoma progress or an intake on medical history had the lowest mean age. Compared to older patients, who typically have planned interventions, younger patients generally have access to a broader range of treatment alternatives, encouraging a more proactive rather than reactive approach. Customizing interventions based on age to slow glaucoma progression may maintain a higher quality of life for a longer period. There is also a trend that a marginal majority of patients receiving intervention treatment are female (Figure 15). This conclusion is consistent with earlier findings that show women in all age groups are more likely than men to experience visual impairments. The variations in intervention strategies based on specific criteria underscore the importance of sociodemographic factors in addressing the unique challenges communities face in eye care.

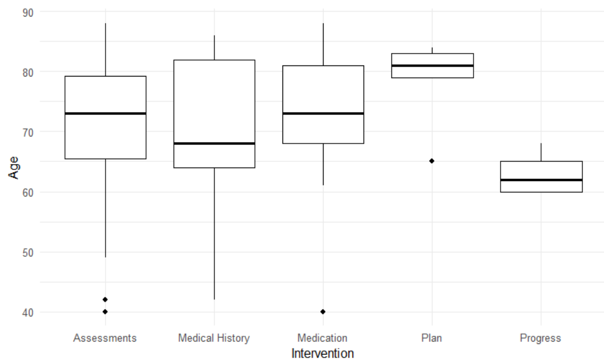

Figure 14: Distribution of Ages by Intervention Category After Criteria Matching. Derived from NCBI NLM 2019-2020.

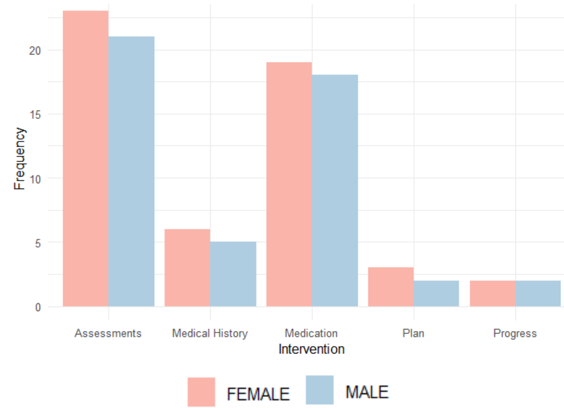

Figure 15: Distribution of Genders by Intervention Category After Criteria Matching. Derived from NCBI NLM 2019-2020.

Intervention Modeling

I developed several machine learning models to predict the success of interventions in glaucoma progression and evaluate their efficacy in slowing or improving it. For clarity and interpretability, I excluded neutral terms from the patient notes, and I based the analysis solely on the "positive" and "negative" sentiments. I used random forest, logistic regression, decision trees, and gradient-boosting machine (GBM) classification models[21], considering the variables of age, gender, and the intervention strategies implemented (Table 1). Out of the 213 unique patients analyzed, sentiment data was available for 207 patients, with 41 experiencing a negative outcome and 166 showing a positive outcome. I set the random seed to 100 and conducted an 80/20 train-test split for the data. The evaluation metrics for the four classification models were calculated using the following equations.

Abbreviations: TP true positive, TN true negative, FP false positive, FN false negative.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \qquad \text{Precision} = \frac{TP}{TP+FP} \qquad \text{Recall} = \frac{TP}{TP+FN}$$

$$\text{Specificity} = \frac{TN}{TN+FP} \qquad \text{F1 Score} = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

	Accuracy	Precision	Recall	Specificity	F1 Score	AUC
Random Forest	0.7561	0.9118	0.8158	0.00	0.8615	0.5170
Logistic Regression	0.7073	0.8529	0.8056	0.00	0.8284	0.5019
Decision Tree	0.7073	0.8529	0.8056	0.00	0.8284	0.5019
GBM	0.7073	0.8529	0.8056	0.00	0.8284	0.5019

Table 1: Performance Metrics Comparison of Machine Learning Models for Glaucoma Intervention Effectiveness Prediction. Derived from NCBI NLM 2019-2020.

Through running multiple iterations with different random seeds for training and testing data splits, random forest consistently outperformed the other models, while logistic regression and GBM showed similar performance levels. Decision trees, lacking an ensemble approach, demonstrated poorer performance across multiple iterations. I further validated these findings using 5-fold cross-validation to mitigate overfitting risks. The weakness across all four models lies in their specificity: the ability to accurately predict negative intervention outcomes. This shortfall could be due to the dataset's imbalance favoring positive results or the sentiment analysis's limited representation of what defines a positive intervention outcome.[22] The AUC values for all four models are only slightly above 0.5, indicating that these models are barely better than random assignment and are poor at distinguishing whether a patient's outcome will be positive or negative based on sociodemographic factors like age, gender, and intervention strategy.

I undersampled to address the imbalance in the distribution of positive and negative outcomes.[23] This technique involves reducing the number of instances in the majority positive class from 166 to 41 observations to achieve a more balanced representation of both classes. The classification models' performances were assessed after randomly sampling 166 instances down to 41 without replacement (Table 2). The classification algorithms remained constant, where settings like learning rate, regularization strength, and batch size are unchanged.

	Accuracy	Precision	Recall	Specificity	F1 Score	AUC
Random Forest	0.5625	0.6250	0.5556	0.5714	0.5882	0.5625
Logistic Regression	0.6250	0.7500	0.6000	0.6667	0.6667	0.6250
Decision Tree	0.4375	0.5000	0.4444	0.4286	0.4688	0.5625
GBM	0.2500	0.2500	0.2500	0.2500	0.2500	0.7500

Table 2: Performance Metrics Comparison of Machine Learning Models for Glaucoma Intervention Effectiveness Prediction Using Undersampled Data. Derived from NCBI NLM 2019-2020.

All models exhibited improved specificity and declining accuracy in the balanced undersampled dataset. One possible explanation for this decline in accuracy is the loss of data related to positive outcome prediction. Logistic regression surpassed random forest as the most effective model for predicting the effects of interventions, and this is consistent with the stability of logistic regression on smaller datasets in contrast to other models that are more complex that are more prone to overfitting.[24] GBM's high AUC in this situation can be attributed to its capacity for ensemble learning that improves upon weak learners. While GBM may excel at distinguishing between positive and negative outcomes, it may not perform as well when it comes to correctly classifying outcomes and incorrectly misclassifying outcomes due to overfitting on the small dataset.[25] Researchers and clinicians can improve the reliability of glaucoma prediction models and improve patient outcomes by understanding the subtleties of model performance in the context of imbalanced and undersampled datasets.

Undertaking comprehensive research on glaucoma prevalence and developing tailored therapies for sociodemographically vulnerable populations is currently hindered by the absence of current, accessible, and comprehensive data. However, the predictive powers of machine learning models, like random forest, show promise for predicting the effectiveness of interventions for patients matched according to sociodemographic parameters. While machine learning has its advantages, its ability to effectively identify negative outcomes for personalized interventions is still limited in addressing disparities in eye care.

Success Rates Calculations and Modeling

By calculating success rate, my analysis concludes its exploration of glaucoma intervention strategies to address disparities in patient eye care. I calculated success rates based on gender and named intervention strategy for the previous 79 criteria-matched patients who had intervention strategy information available (Table 3). I defined success as a positive outcome corresponding to the patient's intervention strategy's sentiment. Gender-specific success rates differed, with assessments indicating the highest success rate at 88.46% for females and 60% for males. Assessments and medications were the two best intervention strategies at an average success rate of 74.23% and 68.16% respectively, and these findings are consistent with previous analysis on the incidence of glaucoma in women. What made assessments successful was its customized approach because it considered the patient's particular sociodemographic vulnerability factors, specifically gender. This analysis highlighted the significance of providing successful interventions customized to unique populations' health priorities when making judgments about healthcare interventions.

Intervention Strategy	Gender	Total Number of Patients	Positive Outcome (Success)	Success Rate
Assessments	Female	26	23	88.46%
Assessments	Male	5	3	60.00%
Medical History	Female	11	6	54.55%
Medical History	Male	2	1	50.00%
Medications	Female	24	19	79.17%
Medications	Male	7	4	57.14%
Plan	Female	5	3	60.00%
Plan	Male	1	0	0.00%
Progress	Female	3	2	66.67%
Progress	Male	0	0	N/A

Table 3: Success Rates by Gender for Intervention Strategies. Derived from NCBI NLM 2019-2020.

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