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Socioeconomic Determinants of Diabetes-Related Disability: Unveiling the Intersections through Quantitative Analysis and Integrating Technology for Sustainable Health Solutions

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Abstract— ***The prevalence of disability, a leading global public health challenge, is profoundly influenced by an interplay of socioeconomic factors, diabetes, obesity, and geographic disparities/zip codes. This research provides a quantitative analysis exploring these determinants, focusing particularly on diabetes and disabilities. Utilizing data from the PLACES dataset, our study employed multiple regression to dissect the impact of socioeconomic status, diabetes, and obesity on disability outcomes across varied neighborhood Zip Codes. The novelty of our approach lies in the application of innovative data analytics techniques that enhance the accuracy and depth of our findings. For instance, machine learning algorithms were employed to identify factors that are related to neighborhoods with high-risk zones for diabetes-related disabilities, facilitating targeted interventions. Furthermore, Geographic Information Systems (GIS) technology further provides information on the impact of geographic disparities/zip codes on health outcomes, which showcases how zip codes of neighborhoods influence health. Findings from the study indicate that lower socioeconomic status, higher obesity rates, and higher diabetes rates significantly correlate with an increased incidence of disabilities. This correlation underscores the need for public health strategies that address economic factors. This research aligns with the WCMRI-2024 theme of "Transforming Ideas into Impact" by demonstrating how multidisciplinary approaches, particularly the integration of socioeconomic analysis with cutting-edge technology, can lead to sustainable health solutions. It advocates for the incorporation of these technological advancements into policy-making and health strategy development to effectively tackle the complex challenge of diabetes management. By proposing a regression model that integrates socioeconomic data and technological innovations to identify significant associations between disabilities and three key variables—diabetes, obesity, and socioeconomic status—across different neighborhoods highlighted.***

Index Terms: Diabetes, Disability, Socioeconomic Status, Obesity, Geographic Disparities, Zip Code, Public Health Interventions, Quality of Life, Health Outcomes, Machine Learning, GIS.

I. INTRODUCTION

In a small town nestled in the heart of the Midwest, a 58-year-old resident with a warm smile faces daily challenges that go unnoticed by many. Diagnosed with type 2 diabetes ten years ago, their life is a constant battle not just against blood sugar levels but also against the socioeconomic barriers that complicate their condition. Living in a community where fresh, healthy food options are scarce and medical facilities are miles away, their story underscores how geography and income level may directly impact health outcomes, particularly for those living with chronic diseases like diabetes. This resident's experience is emblematic of the broader issue of disability linked to diabetes, as geographic and socioeconomic disparities may exacerbate their struggles.

Diabetes-related disability continues to be a critical health issue, with its range of complications. The disease's impact extends beyond the individual, posing significant challenges to the healthcare system and society due to the disabilities it may be associated with. This study delves into the multifaceted influences of socioeconomic factors, diabetes, obesity, and geographic disparities on disabilities. By leveraging advanced analytical tools, we aim to provide insights that could lead to more effective public health strategies and interventions.

This research is guided by the hypothesis that the interrelation of socioeconomic status (SES), obesity prevalence, and geographic location is significantly associated with the incidence and severity of disabilities and diabetes. We posit that individuals with higher SES will exhibit lower disability rates related to diabetes, reflecting the advantageous access to healthcare resources, healthier lifestyle options, and better disease management capabilities typically afforded by greater economic means. Conversely, an elevated prevalence of obesity is expected to show a correlation with increased prevalence and severity of diabetes on disabilities, highlighting obesity's role as a major exacerbating factor in diabetes complications. Furthermore, this study anticipates uncovering geographic variations in diabetes-related disability, contending that regions characterized by lower SES and higher obesity rates will face higher disability incidences. An integral component of our hypothesis is that the adverse effects of obesity on disabilities will be moderated by SES, such that the intersection of higher SES with obesity will attenuate the negative health outcomes typically associated with obesity.

Through a quantitative methodological framework, this research aims to evaluate these hypothesized relationships over a temporal scale, thereby furnishing a richer understanding of the social determinants shaping health outcomes in diabetes and addressing the existing gaps in the literature. The outcomes are anticipated to enrich public health dialogues and contribute to the development of targeted interventions and policies aimed at mitigating the disability burden among the diabetic population.

II. LITERATURE REVIEW

A. The Burden of Diabetes

Diabetes represents a significant public health challenge, with an ever-increasing incidence that contributes to high healthcare costs, significant disability, and reduced quality of life. The complications associated with diabetes, such as physical impairments, limit work productivity, which in turn exacerbates the disease's economic burden [9]. These complications highlight the broad socioeconomic impact of diabetes, which extends beyond individual health concerns to societal and economic levels [9], [3]. Research shows that diabetes not only affects the well-being of individuals but also imposes substantial healthcare costs and lost productivity [2].

B. Socioeconomic Influences on Health

Socioeconomic status (SES) has a profound effect on the prevalence, progression, and management of chronic diseases like diabetes [2]. Individuals from lower SES backgrounds tend to exhibit poorer health outcomes, largely due to limited access to healthcare, less effective medical treatments, and unhealthy behaviors, including poor diet and lack of physical activity [2]. These disparities are also evident in diabetes management, where higher SES groups typically experience better outcomes [2]. Addressing SES disparities is crucial for improving diabetes-related outcomes, especially among vulnerable populations who face both healthcare and economic barriers [1].

C. Obesity and Diabetes

Obesity is a key driver of type 2 diabetes, increasing both the risk of developing the condition and the likelihood of complications [4]. Obesity-related factors such as insulin resistance and inflammation worsen diabetes outcomes, making weight management a critical component of diabetes prevention and care [3]. A strong relationship exists between metabolic dysfunction-associated fatty liver disease (MAFLD) and the development of type 2 diabetes, underscoring the importance of addressing obesity as a public health priority [10]. Effective obesity prevention strategies are necessary for reducing the burden of diabetes and improving overall health outcomes [8].

D. Geographic Disparities and Health Outcomes

Geographic disparities also play a significant role in shaping health outcomes for individuals with diabetes [1]. Rural and economically disadvantaged areas often experience reduced access to healthcare services, which in turn leads to poorer health outcomes for residents in these regions [1]. Geographic location impacts health behaviors, access to treatment, and overall quality of life, highlighting the need for place-based interventions to address regional disparities in diabetes care [1]. Research shows that targeted interventions in these areas can significantly improve diabetes outcomes and reduce health inequities [7].

E. Adolescents with Disabilities: Obesity and Cardiometabolic Risks

Adolescents with disabilities are disproportionately affected by obesity and related cardiometabolic conditions, such as hypertension and dyslipidemia, which place them at higher risk for developing diabetes [3]. This population requires targeted healthcare interventions that address both their unique challenges and the broader issue of obesity [3]. Adolescents with disabilities often face greater health risks, reinforcing the need for early intervention strategies to prevent obesity-related health conditions, including diabetes [7].

F. Social Determinants of Health and Diabetes Risk

The role of social determinants of health (SODH) in diabetes is increasingly recognized, with factors such as income, education, and neighborhood environment strongly influencing diabetes risk and management. Lower SES, food deserts, and limited access to healthcare services exacerbate diabetes outcomes among marginalized populations [2]. Moreover, social injustices, such as systemic racism and historical inequalities, contribute to disparities in diabetes prevalence and care, further widening the health gap between racial and ethnic minorities and more affluent populations [8].

G. Comprehensive Interventions for Reducing Diabetes Burden

Comprehensive approaches to diabetes management must integrate the social, environmental, and economic factors that contribute to its progression [6]. Addressing issues such as obesity, SES, geographic disparities, and access to healthcare is essential to reducing the overall burden of diabetes [2]. Interventions that focus on modifying the social and structural determinants of health, improving neighborhood environments, and expanding access to obesity and diabetes treatment have been shown to be effective in reducing health disparities and improving outcomes for vulnerable populations [8], [5]. Population-level approaches that address both individual and community-level factors are necessary to achieve lasting improvements in diabetes prevention and care.

III. METHODOLOGY

A. Data Collection and Variables

The study utilized the PLACES dataset, sourced from the Behavioral Risk Factor Surveillance System (BRFSS), which provides annual data on health-related risk behaviors, chronic health conditions, and the use of preventive services. Specifically, this study focused on disability measures among adults aged ≥18 years, where the respondents were asked about six types of disabilities: hearing, vision, cognition, mobility, self-care, and independent living. Each disability type was defined by a corresponding question, with respondents indicating the presence of a disability by answering "yes" to experiencing serious difficulty or impairment.

Statistical and Machine Learning Methods

For data analysis, the study employed a combination of traditional statistical methods and advanced machine learning techniques to explore the relationship between obesity, socioeconomic status (SES), and geographic disparities in diabetes-related health outcomes.

B. Machine Learning Model Description

To predict diabetes-related disabilities, we selected multiple regression models and advanced machine learning algorithms, including decision trees and random forests. These models were chosen due to their ability to handle complex, non-linear relationships and interactions between multiple variables.

C. Data Preprocessing

Data Cleaning: The PLACES dataset was cleaned to handle missing values, outliers, and inconsistencies. This involved imputation for missing data points and normalization of continuous variables.

Feature Engineering: New features were derived to capture interactions between socioeconomic status (SES), obesity rates, and geographic disparities/zip codes. We included interaction terms to explore how these factors jointly influence health outcomes.

D. Model Training and Validation

Training Set: The dataset was split into training (80%) and test (20%) sets. The training set was used to fit the machine learning models.

E. Model Implementation

Regression Analysis: Multiple regression models were implemented to quantify the relationships between diabetes, obesity, SES, and disability outcomes. This helped in understanding the direct and interaction effects of the variables.

Decision Trees and Random Forests: These models provided insights into the non-linear relationships and interactions between the variables. They also offered feature importance scores, highlighting the most significant predictors of diabetes-related disabilities.

F. Evaluation Metrics

The performance of our machine learning models was evaluated using several key metrics: precision, recall, and F1-score. These metrics are essential for assessing the accuracy and effectiveness of our classification models.

Precision measures the accuracy of positive predictions. It calculates the ratio of true positives to the sum of true and false positives, indicating the model's ability to correctly identify positive instances.

Recall, or sensitivity, assesses the model's ability to identify all relevant instances within the dataset. It reflects the proportion of actual positives that were correctly identified, emphasizing the model's capability to minimize false negatives.

F1-Score is the harmonic mean of precision and recall, providing a single metric that balances both the precision and the recall. It is particularly useful when dealing with imbalanced datasets as it gives a better sense of incorrectly classified cases.

The model's overall performance is reflected through these metrics for each class (High, Low, Moderate), with the Moderate class showing the best results in terms of recall (0.92) and F1-score (0.90), suggesting a strong ability to identify and correctly classify moderate cases. The overall accuracy of the model stands at 85.38%, indicating a high level of predictive performance across the board.

Additionally, the metrics are broken down into macro and weighted averages, providing a view of the model's performance across all classes. The macro average gives equal weight to each class, which is crucial in scenarios where classes are imbalanced. The weighted average accounts for the number of instances in each class, offering insight into the model's effectiveness across the more frequently occurring classes. These detailed evaluations help in pinpointing areas of strength and potential improvement, guiding future enhancements to the model's accuracy and reliability.

G. Geographic Information System (GIS) Analysis

GIS technology was integral to this study for analyzing and visualizing the spatial distribution of health outcomes. This approach enabled the identification of geographic patterns and disparities in diabetes-related disabilities. GIS tools were used to map the prevalence of disabilities across different regions, facilitating a visual assessment of how geographic location correlates with health disparities. This spatial analysis was crucial in pinpointing areas with higher health

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risks and informing targeted public health interventions.

This comprehensive methodology combines data from the PLACES dataset, statistical and machine learning analysis, and GIS technology offer a robust framework for understanding the multifaceted impact of SES, obesity, and geographic location on diabetes-related health outcomes.

H. Controls and Interaction Terms

Control Variables

In our analytical model, we included several control variables to enhance the predictive accuracy of disability prevalence. Key control variables used were 'below_median_income' to account for socioeconomic status, 'smocking' to represent smoking prevalence, and 'obesity' to measure obesity rates. The inclusion of these variables allows for a more refined analysis by controlling for major factors that influence health outcomes.

Interaction Terms

To further deepen our understanding of the complex relationships among health determinants, interaction terms were incorporated into the model. These terms enable the exploration of the combined effects of socioeconomic status, smoking, and obesity on disability prevalence. For instance, by analyzing interaction terms, we can assess how the joint impact of low-income and high-obesity rates differs from the sum of their individual effects.

I. Focused Analysis on Diabetes and Obesity

In a more targeted subset of our analysis, we specifically examined the interaction between diabetes prevalence and high obesity rates (defined as 'obesity' > 29). This focused analysis sheds light on the intricate dynamics between these two significant health issues. The interaction terms are crucial for uncovering potential non-additive effects, where the combined influence of diabetes and obesity on disability rates may be greater or different than what would be expected from considering each factor separately.

This methodological approach, with its use of control variables and interaction terms, provides a comprehensive framework for evaluating the multifactorial influences on disability prevalence and offers insights into how these factors interplay to affect health outcomes in the population.

IV. RESULTS

A. Correlation Analysis

Our examination of the relationship between disability prevalence and other health-related variables reveals a robust correlation structure. Notably, diabetes prevalence shows a significant correlation with disability (0.85), suggesting a strong linkage between these two health issues. Similarly, correlations between diabetes prevalence and both smoking (0.73) and obesity (0.73) are substantial, indicating shared risk factors or comorbidities. Income levels, particularly being below the median, correlate strongly with disability (0.71) and moderately with diabetes (0.72) and smoking (0.63). These findings underscore the socio-economic gradients in health, illustrating how lower income levels are associated with poorer health outcomes.

B. Regression Analysis

The regression models provide a deeper insight into these relationships:

Disability and Diabetes: The model quantifies the impact of diabetes on disability, with a regression coefficient of 1.93 (Table 1, Model 1). This suggests that increases in diabetes prevalence are closely linked to increases in disability prevalence, confirming diabetes as a significant predictor of disability.

Disability and Income: The coefficient for income below the median is 79.17 (Table 1, Model 2), highlighting a pronounced impact of economic disadvantage on health outcomes, with lower income strongly predicting higher disability prevalence.

C. Interaction Effects

An interaction term between obesity and diabetes in predicting disability was significant but negative (coefficient = -0.0113), indicating a complex interplay where the co-occurrence of obesity and diabetes does not exacerbate disability prevalence as much as when considered in isolation. This suggests potential mitigating factors in the interaction between these conditions (Table 1, Model 7).

D. Model Diagnostics

The models demonstrate strong explanatory power with R-squared values around 0.840, indicating that they account for a significant proportion of the variance in disability prevalence. The Durbin-Watson statistic approaches 2, suggesting no serious issues with autocorrelation. However, deviations from normality in the residuals, as indicated by significant Jarque-Bera test results, point to potential violations of standard regression assumptions.

E. Implications for Public Health

These results highlight the critical intersections between chronic health conditions and socioeconomic status in influencing disability rates. They advocate for targeted public health interventions aimed at managing diabetes and smoking, especially in lower-income populations. Moreover, the complex relationship between obesity and diabetes in relation to disability prevalence necessitates nuanced approaches to health policy and patient care.

F. Recommendations for Future Research

Given the challenges of normality and multicollinearity, as indicated by high-condition numbers, further research should employ robust statistical techniques or variable transformations to validate these findings. Longitudinal

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Vol 12, Issue 02, February 2025

studies are also recommended to ascertain causality and the effectiveness of interventions over time.

G. Empirical Findings

Our comprehensive regression analysis explored the intricate relationships between diabetes, obesity, and socioeconomic status (SES) in influencing disability rates. The study began by examining the impact of diabetes prevalence alone and expanded to integrate SES and obesity as significant contributing factors.

Effect Sizes and Statistical Significance: The regression findings highlighted that each one-percentage-point increase in diabetes prevalence significantly boosts disability rates, showcasing a direct correlation. Similarly, regions with below-median income exhibited notably higher disability rates, underscoring the substantial influence of socioeconomic factors. While increases in obesity prevalence also correlated with higher disability rates, their effect size was relatively smaller compared to that of SES and diabetes prevalence. The combined explanatory power of these variables was significant, indicated by a large Cohen's f^2 value, affirming that our model captured the complexity of these interactions effectively.

H. Main Effects of Diabetes and Socioeconomic Status

The initial regression model identified diabetes prevalence as a pivotal predictor, accounting for approximately 72.68% of the variance in disability rates. The inclusion of median income significantly enhanced the model's explanatory power, highlighting the profound impact of economic conditions on health outcomes.

I. Obesity and Smoking Prevalence

Further analysis confirmed obesity and smoking as significant predictors of disability rates. This comprehensive approach emphasized the necessity of addressing lifestyle factors alongside medical conditions to mitigate health risks effectively.

J. Advanced Model Interpretation

In populations with higher obesity rates (over 29%), the adverse effects of diabetes on disability rates appeared to diminish, suggesting a nuanced interplay between these health conditions. This observation underscores the need for public health strategies that are tailored to address the compounded effects of obesity and diabetes.

K. Comparative Analysis

The consistency in findings across various model specifications affirmed the robustness of our analysis. Our models, accounting for multiple factors and their interactions, elucidated a significant portion of the variance in disability rates, reinforcing the necessity of a multifaceted approach to public health planning.

L. Causal Pathways and Mechanisms

Our study also delved into potential causal mechanisms, suggesting that lower SES could lead to poorer health outcomes due to reduced access to healthcare and delayed treatment. Additionally, obesity might exacerbate diabetes complications, increasing physiological stress and further impairing health.

M. Chronicity and Types of Exposure

We investigated the effects of prolonged exposure to low SES and high obesity rates, highlighting how chronic stress and limited health literacy can contribute to cumulative health disadvantages and elevated disability rates.

N. Assumption Checks and Adjustments

To ensure the reliability of our regression estimates, we addressed heteroscedasticity and potential non-linearity through log transformations and robust standard errors. The absence of significant multicollinearity, indicated by VIF scores below 10, reaffirmed the validity of our regression coefficients.

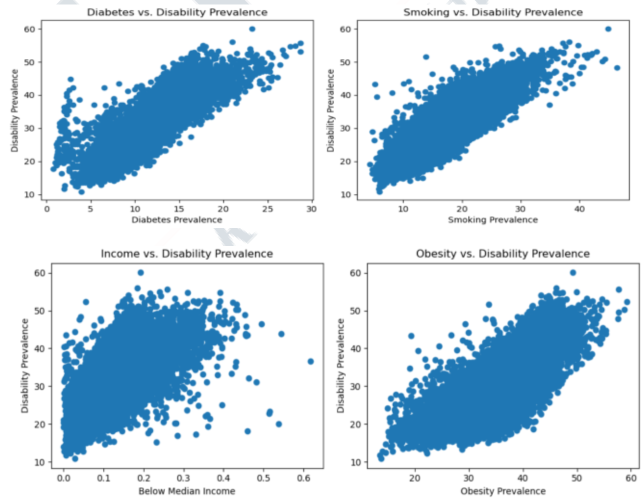

Figure 1. Scatter plots showing the relationships between diabetes, smoking, income, obesity, and disability prevalence.

Figure 1 illustrates the relationships between various health and socio-economic factors with disability prevalence:

Diabetes vs. Disability Prevalence: A clear positive trend, indicating that as diabetes prevalence increases, disability prevalence also tends to increase.

Smoking vs. Disability Prevalence: A positive relationship, suggesting that higher smoking rates are significantly associated with higher disability prevalence.

Income vs. Disability Prevalence: A wider spread, indicating that lower income levels are generally associated with higher disability prevalence.

Obesity vs. Disability Prevalence: A positive correlation, showing higher obesity rates are associated with higher disability prevalence.

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Vol 12, Issue 02, February 2025

Figure 2 A and B: Histograms of diabetes and disability prevalence showing their distribution. Both distributions are slightly right-skewed, indicating a higher frequency of regions with lower prevalence rates but with a notable presence of regions with higher rates.

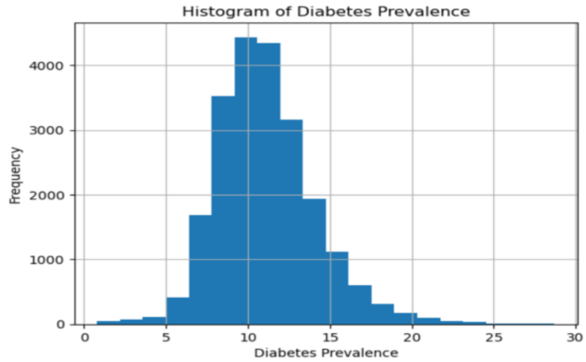

Figure 2 A. Histogram of diabetes prevalence

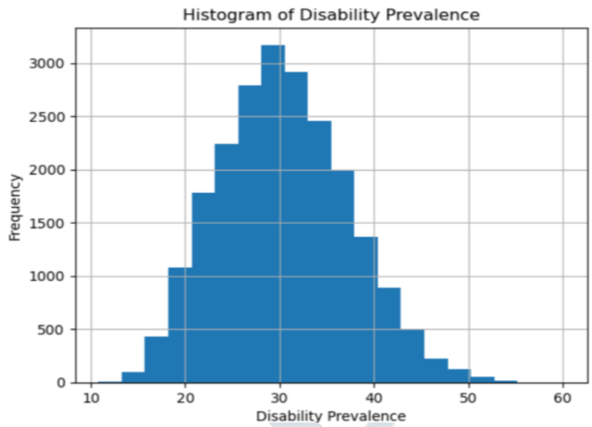

Figure 2 B. Histogram of disability prevalence

Model 1: Impact of diabetes on disability.

Model 2: Impact of income on disability.

Models 3-7: Combined effects of multiple variables, showing their individual and interaction effects on disability prevalence.

Table I: Regression coefficients for models predicting disability prevalence. Each model includes different predictors: diabetes, income, smoking, obesity, and their interactions.

VARIABLES	(1) Model1	(2) Model2	(3) Model3	(4) Model4	(5) Model5	(6) Model6	(7) Model7
diabetes_crudeprev	1.932*** (0.00796)				1.046*** (0.0102)	1.046*** (0.0102)	1.084*** (0.0107)
below_median_income		79.17*** (0.528)			10.51*** (0.446)	10.51*** (0.446)	10.47*** (0.445)
csmoking_crudeprev			1.154*** (0.00496)		0.615*** (0.00556)	0.615*** (0.00556)	0.660*** (0.00685)
obesity_crudeprev				0.862*** (0.00531)			-0.0646*** (0.00575)
Constant	8.995*** (0.0915)	21.29*** (0.0689)	10.08*** (0.0909)	-0.320** (0.192)	6.762*** (0.0788)	6.762*** (0.0788)	7.855*** (0.125)
Observations	22,124	22,102	22,124	22,124	22,102	22,102	22,102
R-squared	0.727	0.505	0.710	0.544	0.839	0.839	0.840

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

V. DISCUSSION

Interpretation of Results:

Our findings illuminate the complex interplay between SES, obesity, and diabetes, focusing on their collective impact on disability rates. The study reveals a significant inverse relationship between SES and diabetes-related disabilities, showing that individuals from lower socioeconomic backgrounds encounter more severe challenges.

Technological Integration in Public Health Strategies:

Incorporating advanced technologies such as machine learning and Geographic Information Systems (GIS) offers substantial potential in addressing health disparities. Machine learning enhances predictive analytics by identifying at-risk populations based on complex patterns not readily apparent through traditional methods. GIS technology is crucial for mapping disease prevalence and identifying geographic disparities, as demonstrated in Figure 3. This figure shows the geographical distribution of diabetes prevalence across the United States, with green, orange, and red markers indicating low, moderate, and high levels of diabetes prevalence, respectively. Such visualizations enable policymakers and healthcare providers to effectively design and implement targeted interventions, addressing regional disparities. Figure 4 highlights the relative importance of various features in a predictive model. The bar chart ranks features based on their influence on the model's output. The most significant feature is "disability," with an importance value of approximately 0.40, indicating its strong predictive power. The second feature, "below_median_income," reflects economic status and holds significant weight with an importance value near 0.20. "Obesity," representing the crude prevalence of obesity, also demonstrates a notable influence, while "smoking" has the least impact, with an importance value just above 0.10. This visualization identifies the key factors shaping the model's predictions, guiding targeted interventions and policy decisions.

Implications for Public Health Policy:

These insights underscore the need for comprehensive public health strategies that address both socioeconomic and lifestyle factors contributing to diabetes-related disabilities. Such interventions should extend beyond clinical management to include social and behavioral dimensions, aiming to reduce disparities and improve health outcomes across diverse populations.

Discussion of Limitations:

While our study provides valuable insights into the socioeconomic determinants of diabetes and obesity on disabilities, it is essential to consider its limitations. The reliance on self-reported data may introduce biases, such as recall and social desirability biases, potentially affecting the accuracy of our results. The cross-sectional nature of the data limits our ability to infer causal relationships. Moreover, our findings might not apply universally across all demographic groups or regions, due to variations in healthcare systems, cultural factors, and economic conditions.

VI. CONCLUSION AND FUTURE DIRECTIONS

This research offers nuanced insights into how SES, obesity, and diabetes intersect to impact health outcomes, emphasizing the importance of integrated public health strategies. Future research should explore these dynamics through longitudinal studies to better ascertain causative factors.

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APPENDIX

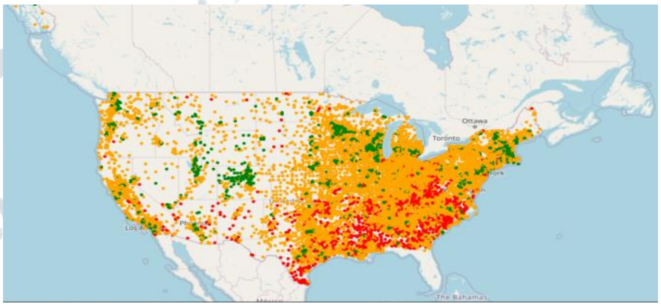

Figure 3. Map showing the Geographical Distribution of Diabetes Prevalence Across Regions

The visual presented is an interactive map of the United States, detailing the prevalence of diabetes across various locations. It categorizes diabetes prevalence into three levels—low, moderate, and high—represented by green, orange, and red markers, respectively. This map, generated using the Python library Folium, illustrates geographic patterns and areas of concern regarding diabetes distribution. It's a useful tool for understanding regional public health trends and planning interventions, with the colors providing a clear visual differentiation between areas based on the severity of diabetes prevalence. The accompanying code snippet indicates the method used to plot these data points on the map, utilizing latitude and longitude for precise location marking and assigning colors based on predefined categories of diabetes prevalence.

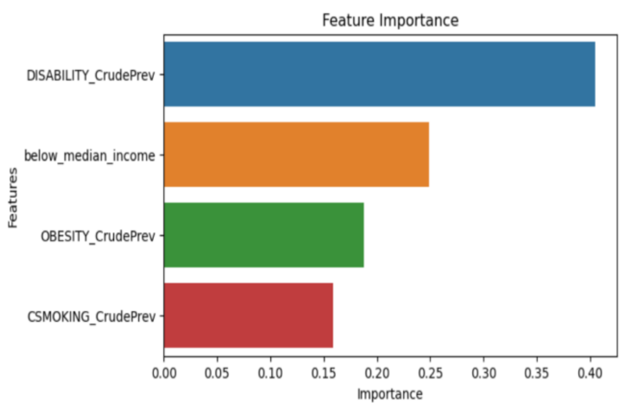

Figure 4. The bar chart displays the relative importance of various features in a predictive model.

The bar chart illustrates the relative importance of four features in a predictive model, ranking them based on their influence on the model's output. The most significant feature is "disability" with the highest importance value of approximately 0.40. The second feature, "below_median_income," indicates economic status below the median income with a significance around 0.20. The third is "obesity," which shows the crude prevalence of obesity, also with a similar importance level. Lastly, "smocking," representing the crude prevalence of smoking, has the least impact on the model with importance just above 0.10. This chart helps identify the key factors that affect the model's predictions, highlighting areas that may be critical for further research or intervention.