Investigating the Impact of SDOH and Chronic Disease Risk Factors in Underserved Communities with System Dynamics and Machine Learning

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INTRODUCTION

Chronic diseases are long-lasting conditions that usually can be controlled but not cured. People living with chronic illnesses often must manage daily symptoms that affect their quality of life and experience acute health problems and complications that can shorten their life expectancy.

Chronic Diseases

- Cancer
- Diabetes
- Heart Diseases
- Stroke
- Chronic Kidney Disease(CKD)

Center for Disease Control (CDC)[1]

- Leading cause of death and disability
- Accounting for 70% of all Deaths in the US.
- Also accounting for 75% of total healthcare costs.

- Majority Population
- Minority Populations (disproportionately)

RACIAL DIVERSITY IN THE US

As of 2021, 42% of all the people inside the US were from diverse ethnic backgrounds. This group included:

Majority and Minority Populations

- 58% White
- 9% Hispanic
- 12% Black
- 6% Asian
- 1% of American Indians or Alaska Natives
- less than 1% were Native Hawaiians or Other Pacific Islanders
- 5% classified themselves as another racial category [2].

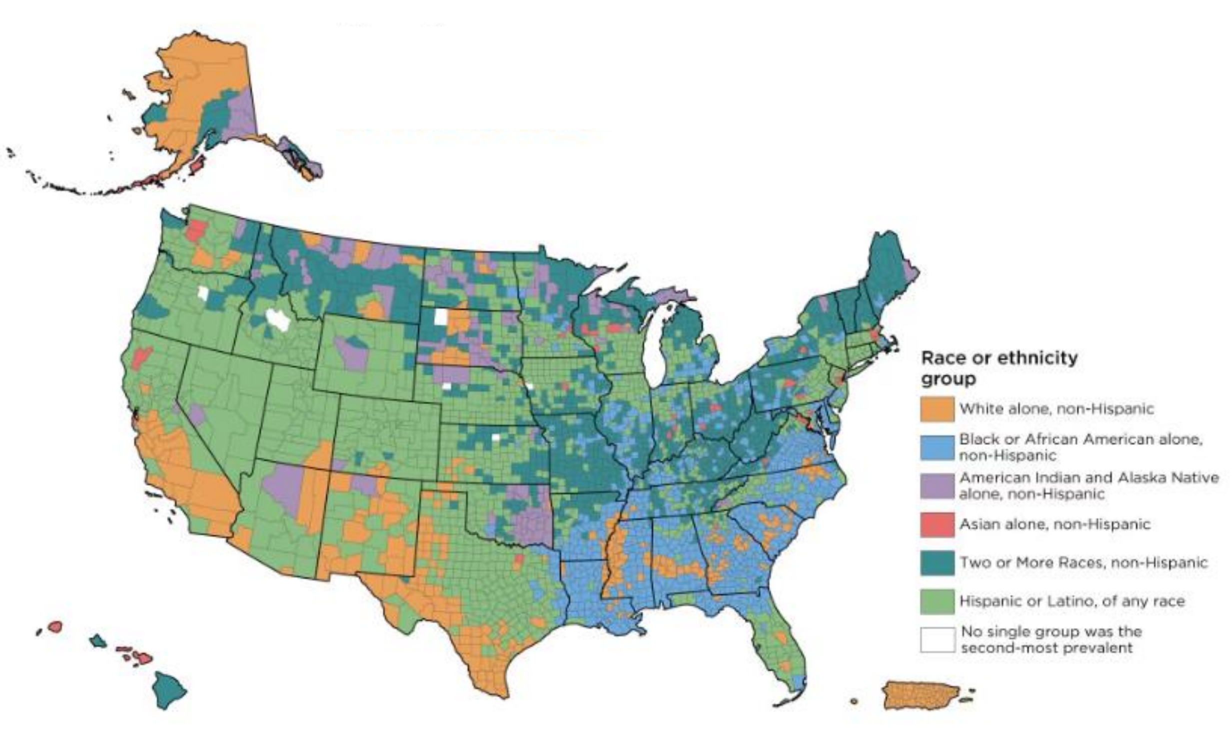

Figure 1: US Racial/Ethnicity Group by County [3].

SOCIAL DETERMINANTS OF HEALTH

Social determinants of health (SDOH) are non-medical conditions in which individuals are born, grow, live, work, learn, worship, and age. These conditions significantly influence their health and communities, shaping lifestyle decisions leading to health-related outcomes.

Five Areas of SDOH Category [4]

- Economic Stability
- Education Access and Quality
- Healthcare and Quality Access
- Neighborhood and Built Environment
- Social and Community Context

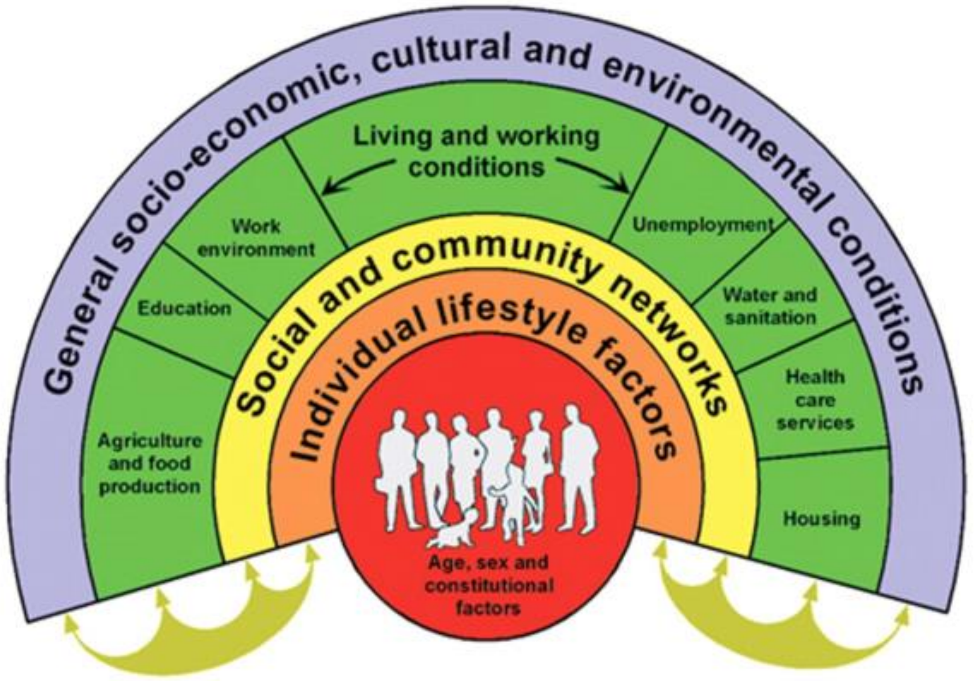

Figure 2: SDOH Impact on Minority Populations [5]

CHRONIC DISEASE RISK FACTORS

Chronic disease risk factors enhance or increase the possibility of developing chronic disease. They initiate and further contribute to the incidence and prevalence of these chronic diseases, thereby negatively influencing individuals' health and quality of life.

Types of Chronic Diseases Risk Factors

Modifiable risk factors

Unhealthy Diet, High Tobacco Intake, Physical Inactivity, Obesity, High Blood Pressure, and High Alcohol Consumption

Non-modifiable risk factors

Age, Gender, Genetic composition, and Race or race

PROBLEM STATEMENT

- Problem: Chronic diseases disproportionately affect minority and underserved communities.
- Complexity: Chronic disease is influenced by interactions between Social Determinants of Health (SDOH) and risk factors.
- Gap: Existing approaches did not apply an integrated framework to understand these interactions.
- Aim: This research aimed to develop and validate a system dynamics model and machine learning approach.
- Goals: Uncover root causes, predict trends, and enhance healthcare access and equity in minority populations.

RESEARCH PURPOSE

- Aim: Employ system dynamics to model and simulate interactions of SDOH and chronic disease risk factors, focusing on their impacts on health outcomes in minority populations in the US.
- Priority Areas: Economic Stability, Neighborhood and Physical Environment, Education, Community, and Social Contexts, and Healthcare System.
- Goals:
  - Assess the effectiveness of various healthcare interventions.
- Machine Learning Aspect: Develop algorithms to analyze numerical output data from the system dynamics model, finding patterns in how SDOH influences health outcomes.
- Causal Understanding: Illuminate causal pathways between significant population health risk factors and health outcomes.
- Policy Focus: Identify policy options impacting health outcomes like mortality, chronic diseases, disability, and unhealthy behavior.

RELATED WORK

Section	Key Themes	Findings and Contributions
Role of SDOH in Health Outcomes	Impact of non-medical factors on health	Bharmal et al.: Three methodologies for studying SDOH; Cockerham et al.: Four key SDOH theories [6].
SDOH in Minority Populations	Socioeconomic factors affecting minorities	Alcendor: Effects of COVID-19 on minorities; Russo et al.: SDOH and CVD in minorities [7].
Interactions of SDOH & Chronic Diseases	Complexity of interactions between SDOH & chronic diseases	Public health studies: Connection to unhealthy behaviors, and SES [8].
Prevalence of Chronic Diseases in Minorities	Sociocultural factors in self-care among ethnic minorities	Gallant et al.: Sociocultural aspects of chronic illness self-care [9].
Machine Learning in Chronic Disease Prediction	Use of machine learning algorithms for prediction	Battineni et al.: Review of ML in CDs; Chen et al.: CNN-based multimodal disease risk prediction [10].
System Dynamics Modeling in Healthcare	Application of system dynamics in healthcare scenarios	Loyo et al.: SD model of Cardiovascular Disease Risks; Ciplak and Barton: Istanbul's hospital waste management [11].
Gaps & Combined Approach	Need for fusion of research areas with ML & system dynamics modeling	Highlighting gaps and the need for a combined approach to deeply understand interplays between SDOH and chronic diseases

Table 1: Research Literature

METHODOLOGY

Integration of Approaches

Creating a unique methodological framework integrating system dynamics modeling with machine learning to study SDOH and chronic diseases in minority communities.

System Dynamics Modeling

- Used as an exploratory tool to understand complex interactions and feedback loops.
- Focuses on the influence of SDOH factors on health outcomes in minority populations.
- Provides graphic representations of non-linear correlations and temporal time delays.
- Enables simulation of long-term effects and visualization of how changes in one factor can affect the entire system.

METHODOLOGY CONT'D

Machine Learning

- Utilizes data patterns for prediction and decision-making.
- Employs algorithms trained on data to discover patterns and correlations.
- Uses simulation output data from system dynamics modeling as input.
- System dynamic modeling parameters are used as features, with one or two as targets for predictive processes.

RESEARCH PROCESS DESIGN

Figure 3 shows the process design, which explains the research concepts, steps, and procedures employed. The interactions of SDOH and chronic disease risk factors are complicated and non-linear.

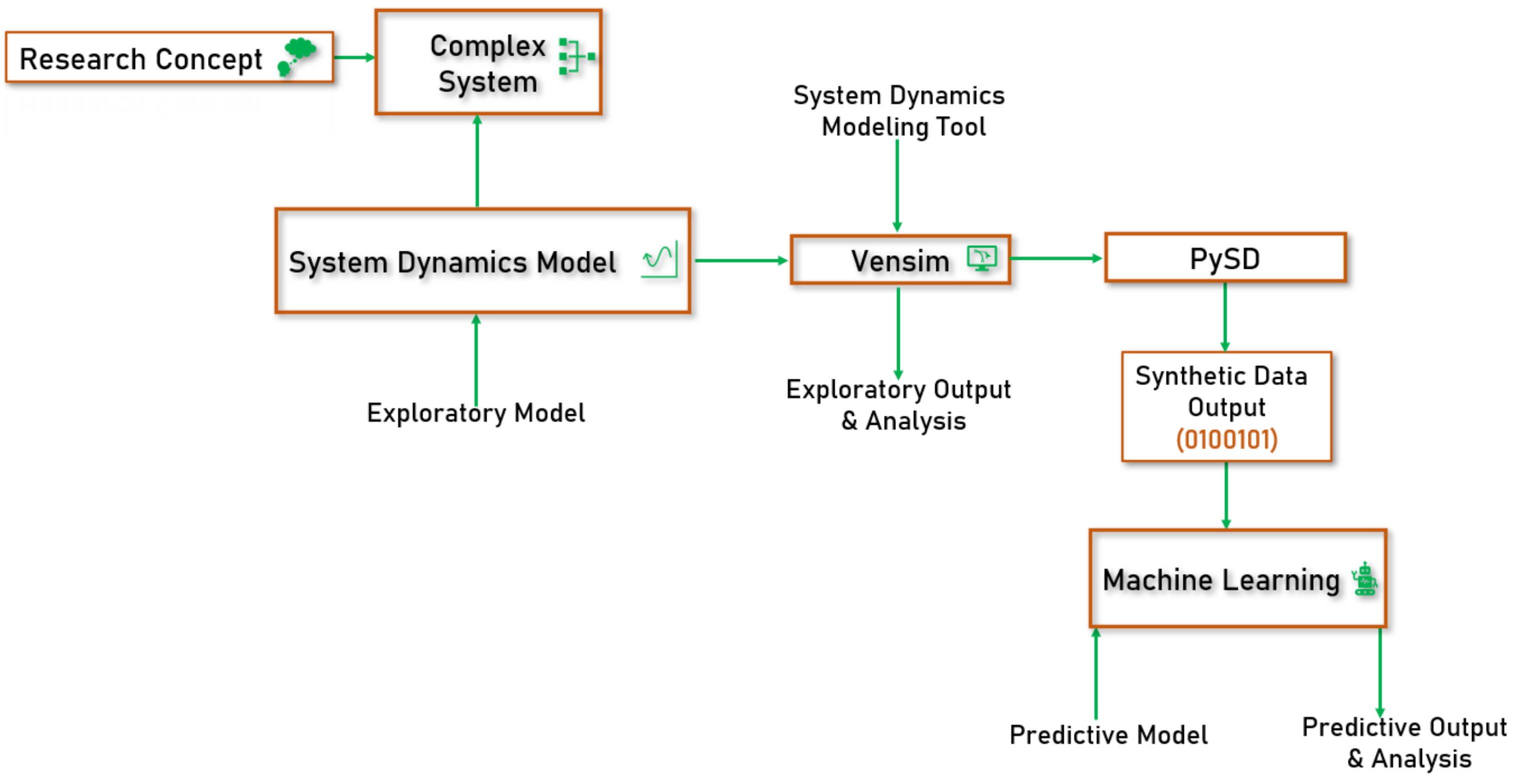

Figure 3: The Research Process Design

PYTHON SYSTEM DYNAMICS (PySD)

PySD is a Python library that converts system dynamics models from commercial tools like Stella® and Vensim® into Python. It was first developed and released by James Houghton in 2014.

Functional Elements

- Parsing: Analyzing the structure of models.
- Implementing: Bringing models into function.
- Building: Creating models.
- Solving: Finding solutions or results for models.

Features

- Importing and modifying model inputs.
- Breaking models into submodules.
- Isolating parts of a model for individual running.
- Storing intermediate simulation results.

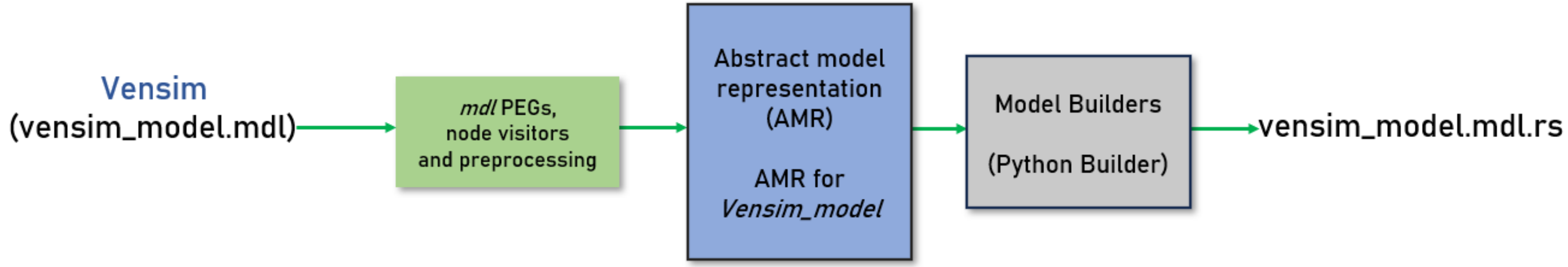

Figure 4: PySD Parsing-Building Logic

CHRONIC DISEASE RISK FACTORS

Chronic disease risk factors enhance or increase the possibility of developing chronic disease. They initiate and further contribute to the incidence and prevalence of these chronic diseases, thereby negatively influencing individuals' health and quality of life.

Types of Chronic Diseases Risk Factors

- Modifiable risk factors
  - Unhealthy Diet, High Tobacco Intake, Physical Inactivity, Obesity, High Blood Pressure, and High Alcohol Consumption
- Non-modifiable risk factors
  - Age, Gender, Genetic composition, and Race or race

SYSTEM DYNAMICS MODELING (SD)

System Dynamics (SD) is a computational technique employed to model and simulate the dynamics and challenges of complex systems over time.

Building Components:

- Stocks: Accumulative quantities or states that take on specific values over time.
- Flows: Rates at which quantities change over time, including:
  - Inflow: Increases the stock over time.
  - Outflow: Decreases the stock over time.
- Variables: Intermediate calculations or values crucial to the model but not classified as stocks or flows.
- Parameters: Define the external circumstances of the simulation.

SYSTEM DYNAMICS MODELING (SD)

Feedback Loops in SD

These represent different types of feedback that can occur in a system.

- Reinforcing Loop (Positive Feedback Loop (R))
- Balancing Loop (Negative Feedback Loop (B))

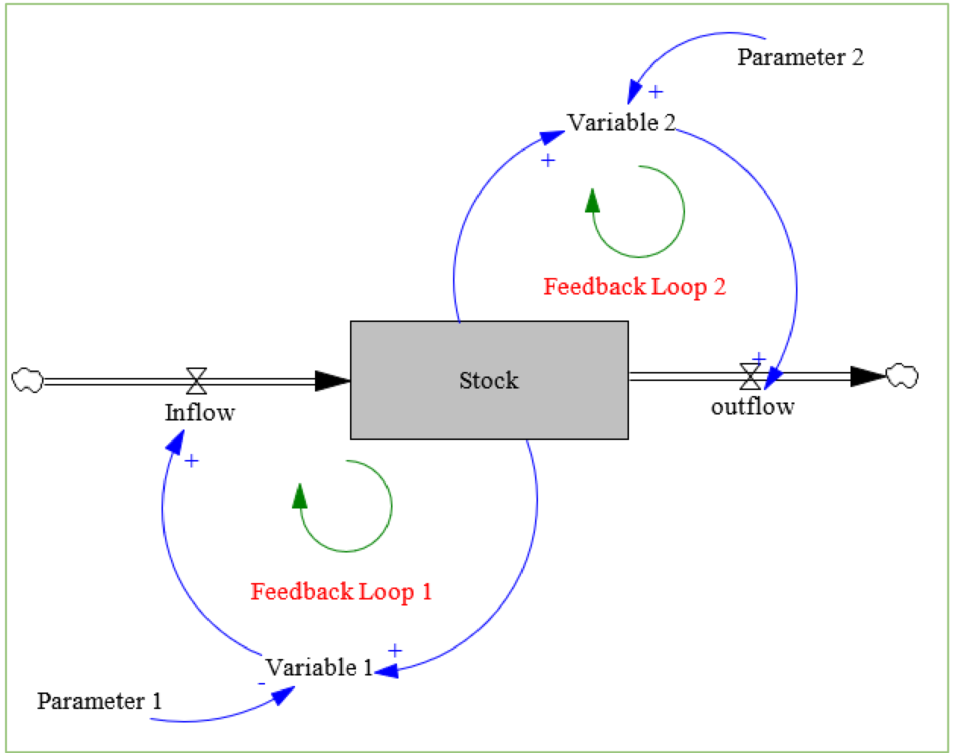

Figure 5: Visualization of SD Modeling Components

FEEDBACK LOOPS

Reinforcing Loop (Positive Feedback Loop (R)):

- Behavior: Amplifies system behavior, leading to changes in the same direction (e.g., exponential growth or decline).
- Example: Poor physical activity leads to obesity, resulting in more health issues. Lack of exercise and poor diet further increase health complications.
- Visualization: Represented by arrows in a clockwise direction, with a positive sign (+) indicating an increment in the forward direction.

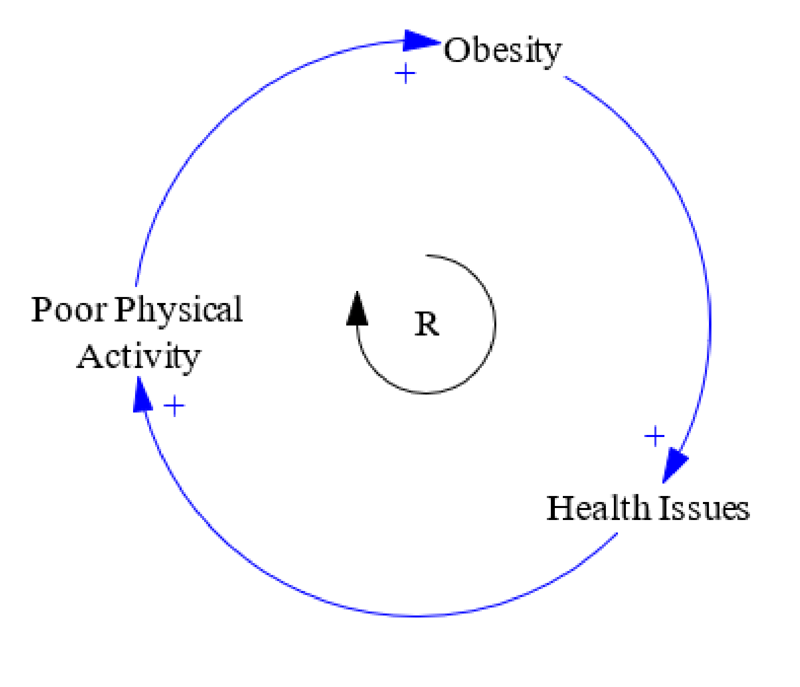

Figure 6: The Reinforcement Loop Sample Visualization in SD

FEEDBACK LOOPS CONT'D

Balancing Loop (Negative Feedback Loop (B)):

- Behavior: Seeks to maintain a desired state or balance, working to counteract any deviation from the goal.
- Example: Increased health awareness leading to efforts to improve air and water quality, thus reducing poor quality and chronic diseases.
- Visualization: Represented by arrows in an anticlockwise direction, with a negative sign (-) indicating a decrement in the forward direction.

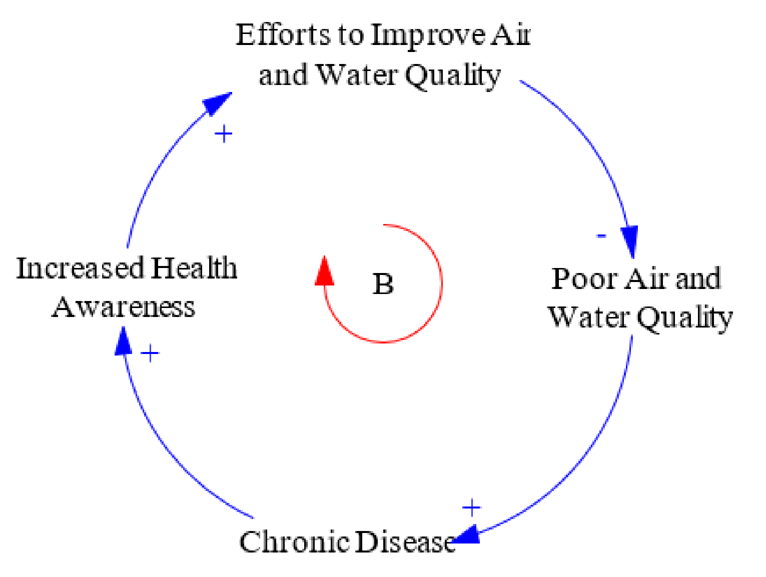

Figure 7: Balancing Loop Sample Visualization in SD

APPLICATION OF SD

This research applies system dynamics to address the complexity and dynamics of the interactions between SDOH and chronic disease risk factors, specifically in minority populations.

Application Modes of SD in the Research:

- Causal Loop Model or Diagram: Helps understand and visualize how different factors are interrelated and influence each other.
- Stock and Flow Model: As explained in previous sections, this model represents accumulative quantities and rates of change, key to understanding the progression and interaction of factors over time.

APPLICATION OF SD CONT'D

Data Sources and Variable Selection:

- Objective: Careful selection of research modeling variables, including SDOH and chronic disease risk factors.
- Methods:
  - Reviewing empirical studies and comprehensive literature.
  - Expert consultations.
  - Observations within the targeted population to understand relevant variables for specific communities.

CAUSAL LOOP DIAGRAM (CLD)

The Causal Loop Diagram of the Interplay between SDOH and Chronic Disease Risk Factors

Economic Stability	Neighborhood and Physical Environment
Poverty	Air and Water Quality
Unemployment	Residential Segregation
Health Expenditure	Access to Exercise Opportunities
Health Insurance	Housing Problems

Education	Community and Social Context
School Completion	Social Associations
Inequalities in Education	Social Isolation
Health Knowledge	School Segregation
School Enrollment	Health Disparities

Healthcare System	Health Behaviors
Chronic Diseases	Alcohol Consumption
Demand for Healthcare	Drug Abuse
Access to Care	Obesity
Provider Linguistic and Cultural Competency	Physical Inactivity
Awareness and Efforts to Improve Cultural Competency	-
Communication with Healthcare Providers	-
Health Disparities	-

Chronic Disease Risk Factors
High Blood Pressure/Cholesterol
Increased Rates of Low Birth Weight
Stress

Table 2: SDOH Variables in the Model

CAUSAL LOOP DIAGRAM (CLD)

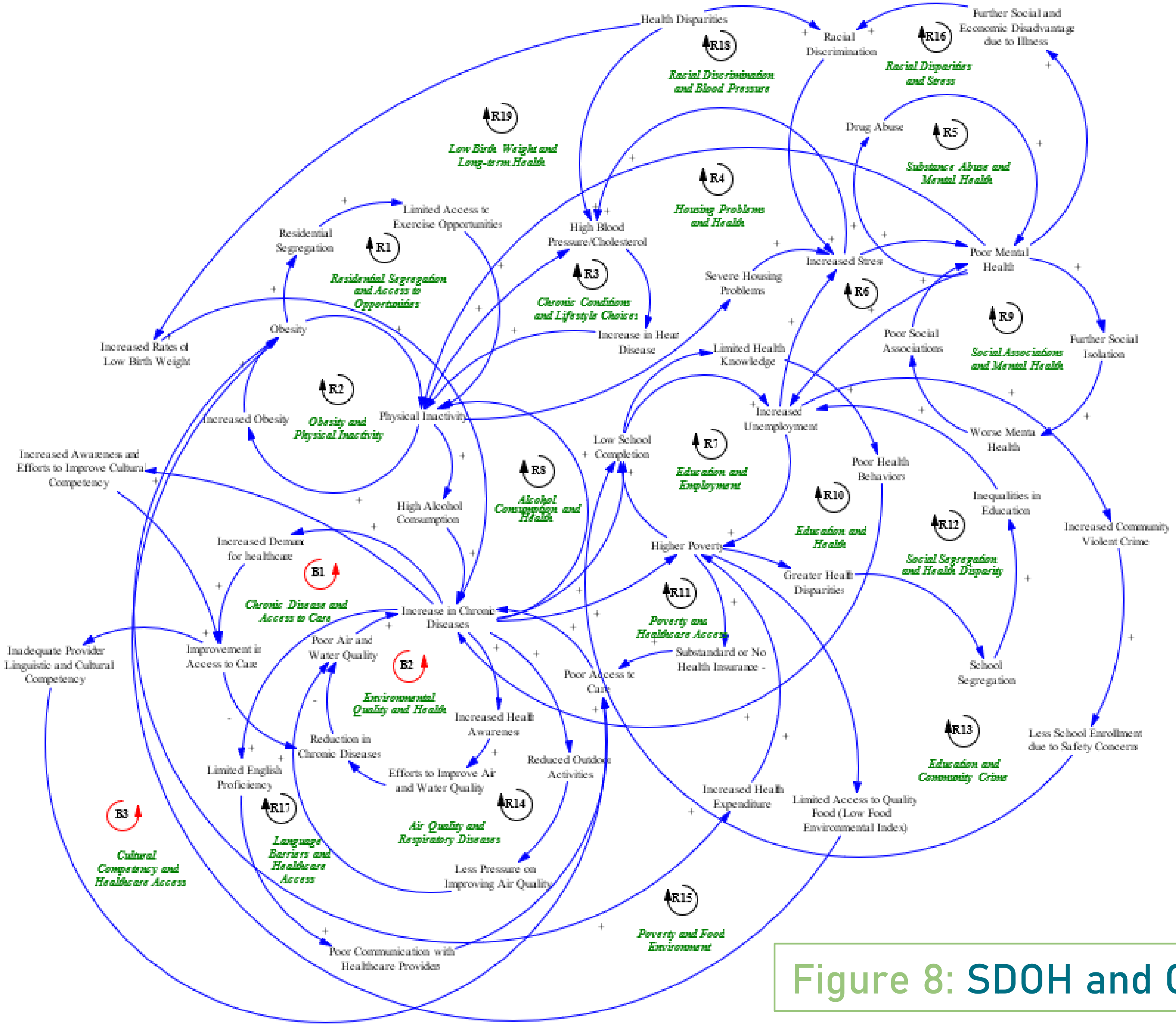

Figure 8: SDOH and Chronic Disease Risk Factors Interactions

CAUSAL LOOP DIAGRAM (CLD) CONT'D

The Causal Diagram of the Interaction of the Chronic Disease Risk Factors

Chronic Disease Risk Factors	
High Alcohol Consumption	Physical Inactivity
Obesity	Higher Risk of Chronic Diseases
Poor Prevalence of Smoking	Physical Distress
Poor Food Environmental Index	Poor Physical Health
Poor Diet and Chronic Diseases	High-Stress Levels
Poor Mental Health	Poor Access to Exercise Opportunities
Further Limitation in Exercise	Limited Exercise and Obesity
High Blood Pressure	Increase in Heart Diseases
High Rates of Substance Abuse	Increased Use of Substances
High Hormone Levels	Genetic Susceptibility to Chronic Diseases
High Blood Cholesterol	Aging

Table 3: Chronic Disease Risk Factors Variables in the Model

CAUSAL LOOP DIAGRAM (CLD) CONT'D

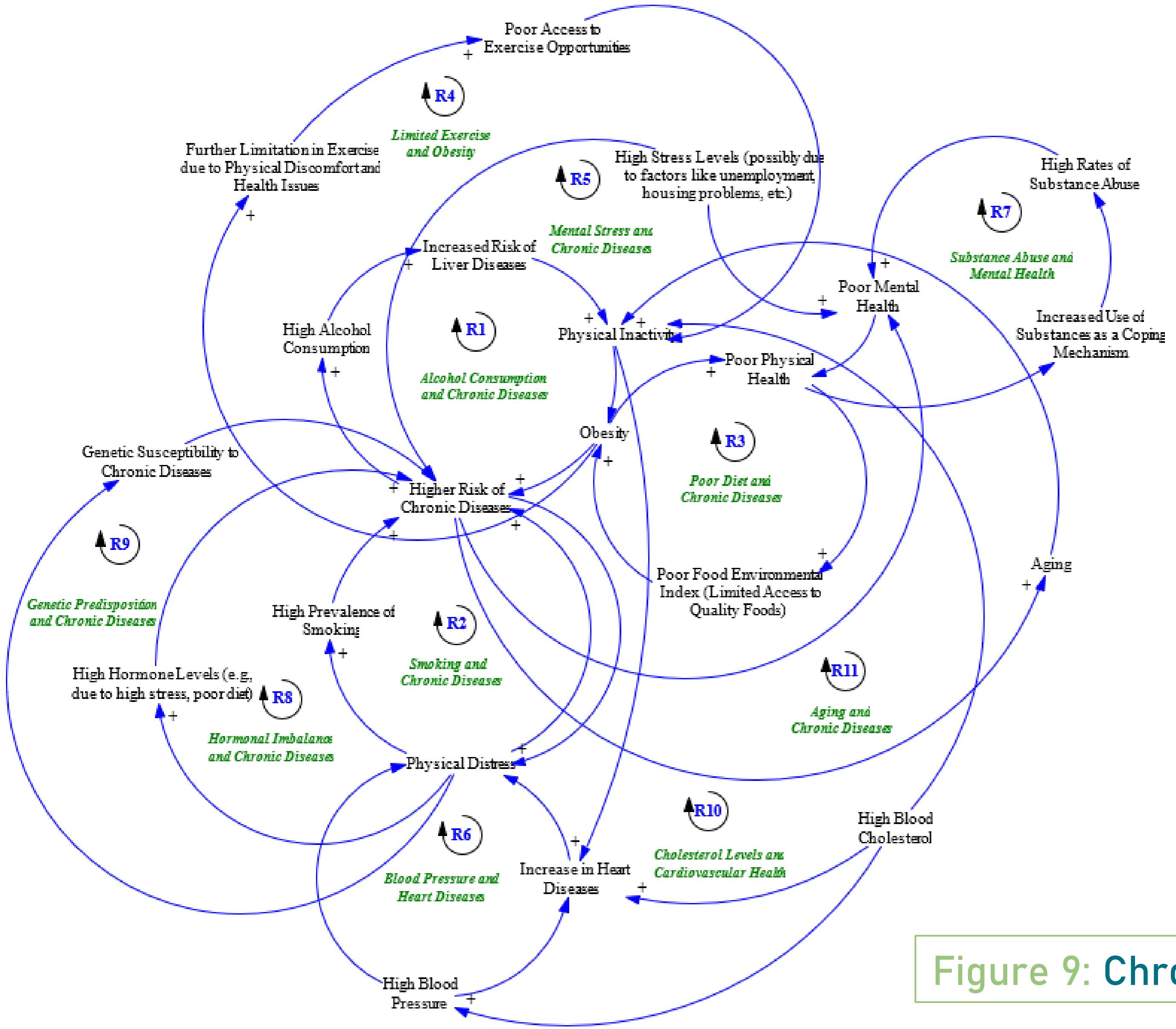

Figure 9: Chronic Disease Risk Factors Interactions

STOCK AND FLOW MODEL DESIGN

Figure 10 shows the process design of the system dynamics model. This diagram presents how the SDOH factors influence the chronic disease risk factors in minority populations in the US.

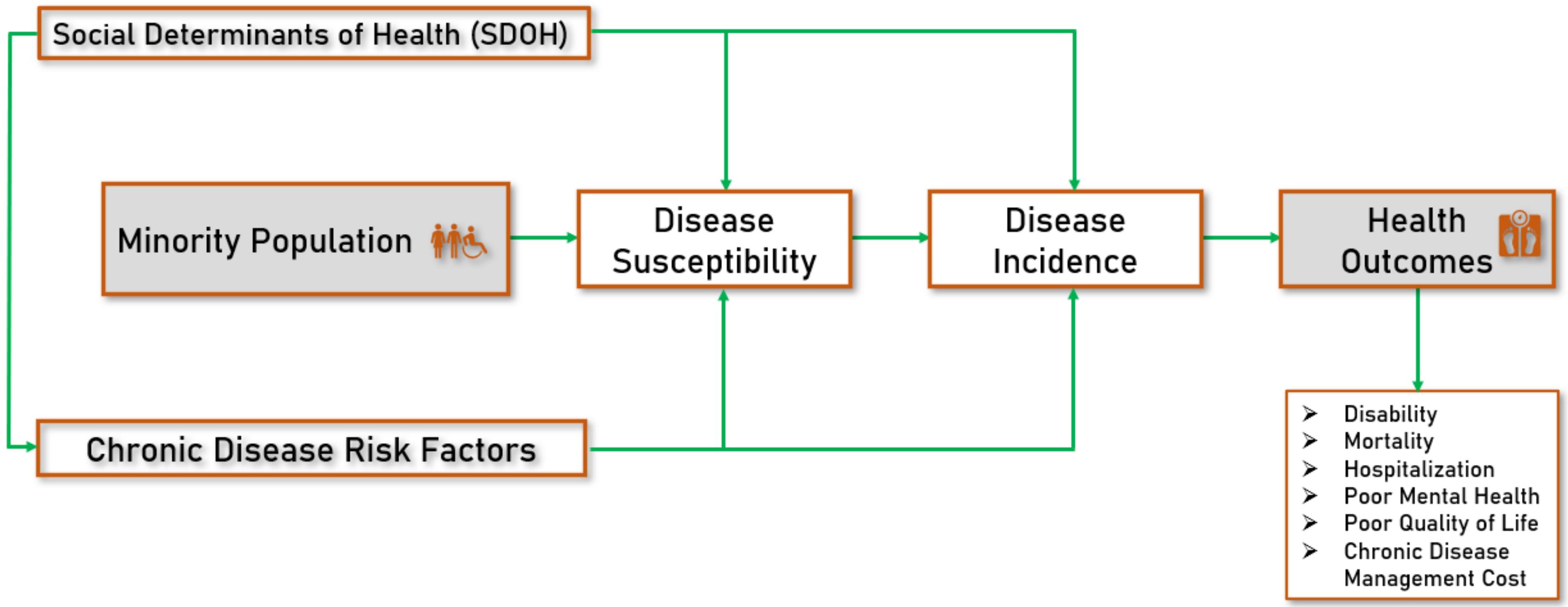

Figure 10: The System Dynamics Model Design Process

RESEARCH STOCK AND FLOW MODEL

Model Stocks
Minority Population
Susceptible Minority Population
Minority Population with Two or More Chronic Diseases
Recovered Minority Population from Two or More Chronic Diseases
Hospitalized Minority Population
Minority Population with Poor Mental Health
Proportion of the Minority Population with Mortality
Minority Population with Poor Quality of Life
Minority Population with Disability

Model Flows
Susceptibility Transition
Chronic Disease Onset
Susceptibility After Recovery
Recovery After from Two or More Chronic Diseases
Poor Quality of Life
Mortality
Poor Mental Health Mortality
Hospitalization from Poor Mental Health
Disability Prevalence
Mental Health Prevalence

SDOH
Low School Completion
Increased Unemployment
Low Income
Higher Poverty
Poor Access to Quality Care
Limited Access to Care
Poor Air and Water Quality
Health Issues
Limited Access to Quality Food
Inadequate Provider Linguistic and Cultural Competency
Limited English Proficiency
Substandard or No Health Insurance
School Segregation
Increased Community Violent Crime
Less School Enrollment due to Safety Concerns
Poor Communication with Healthcare Providers
Poor Social Associations
Residential Segregation
Racial Discrimination

Chronic Disease Risk Factors
Alcohol Consumption Level (High)
Physical Distress
High Blood Sugar
High Blood Pressure Incidence
High Cholesterol Incidence
Smoking (Tobacco Abuse)
Obesity
Physical Inactivity
Age
Poor Mental Health Status
High Hormone Levels (Imbalance)
Poor Diet (Malnutrition)
Drug/Substance Abuse

Interventions
Limited English Proficiency Interventions
Poor Air and Water Quality Interventions
Health Issues Interventions
Limited Access to Quality Food Interventions
Poor Communication with Healthcare Providers Interventions
Substandard or No Health Insurance Interventions
Increased Community Violent Crime Interventions
Less School Enrollment due to Safety Concerns Interventions
Poor Access to Quality Care Interventions
School Segregation Interventions
Inadequate Provider Linguistic and Cultural Competency Interventions
Racial Discrimination Interventions
Smoking (Tobacco Abuse) Interventions
Physical Distress Interventions
Physical Inactivity Interventions
Alcohol Consumption Level (High) Interventions
Drug/Substance Abuse Interventions
Obesity Interventions
High Blood Sugar Interventions
Poor Mental Health Status Interventions
High Hormone Levels (Imbalance) Interventions
High Blood Pressure Incidence Interventions
High Cholesterol Incidence Interventions
Poor Diet (Malnutrition) Interventions
Limited Access to Care Interventions

Table 4: Stock and Flow Model Variables

RESEARCH STOCK AND FLOW MODEL

The research employs the stock and flow system dynamics model to explore the interactions between Social Determinants of Health (SDOH) and chronic disease risk factors in minority populations over 50 years from 2020 to 2070. Utilizing Vensim's settings and the Euler method, the model combines previous causal loop diagrams and stock and flow parameters to understand the complex dynamics of these interactions and potential interventions to mitigate adverse health outcomes.

Parameter	Value
INITIAL TIME	2020
FINAL TIME	2070
TIME STEP	0.0078125
Units of Time	Year
Integration Type	Euler

Table 4: Time boundaries for the model

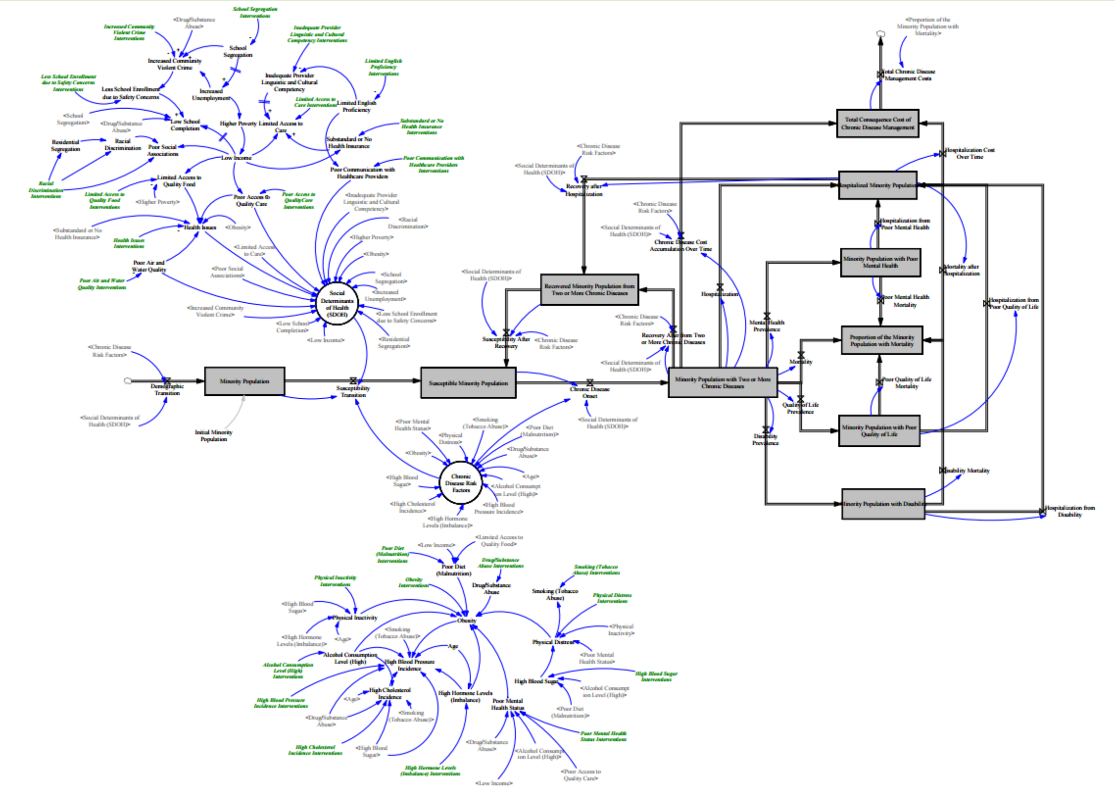

Figure 8: The SD using Stocks and Flows

RESEARCH STOCK AND FLOW MODEL

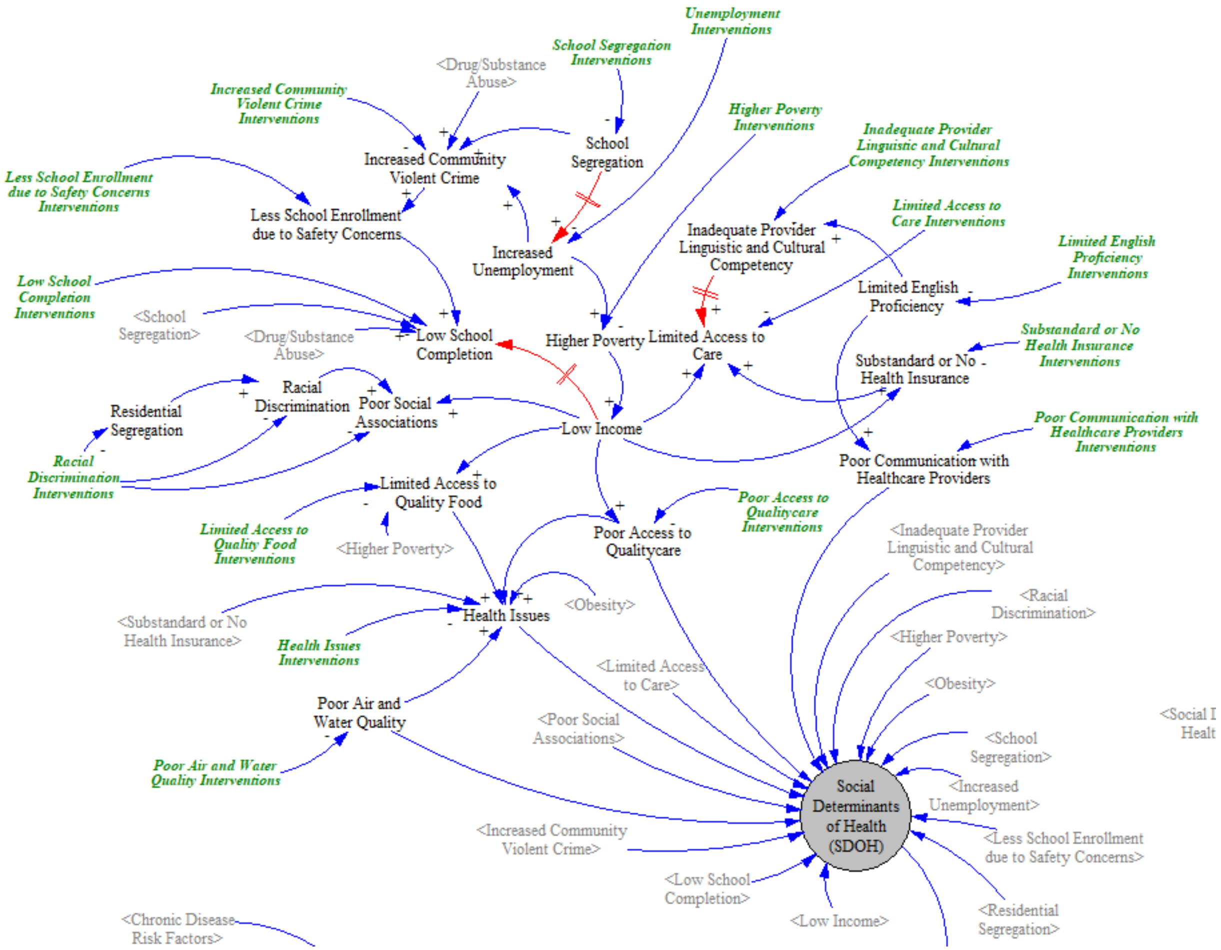

Figure 9: The SD using Stocks and Flows Section 1

RESEARCH STOCK AND FLOW MODEL

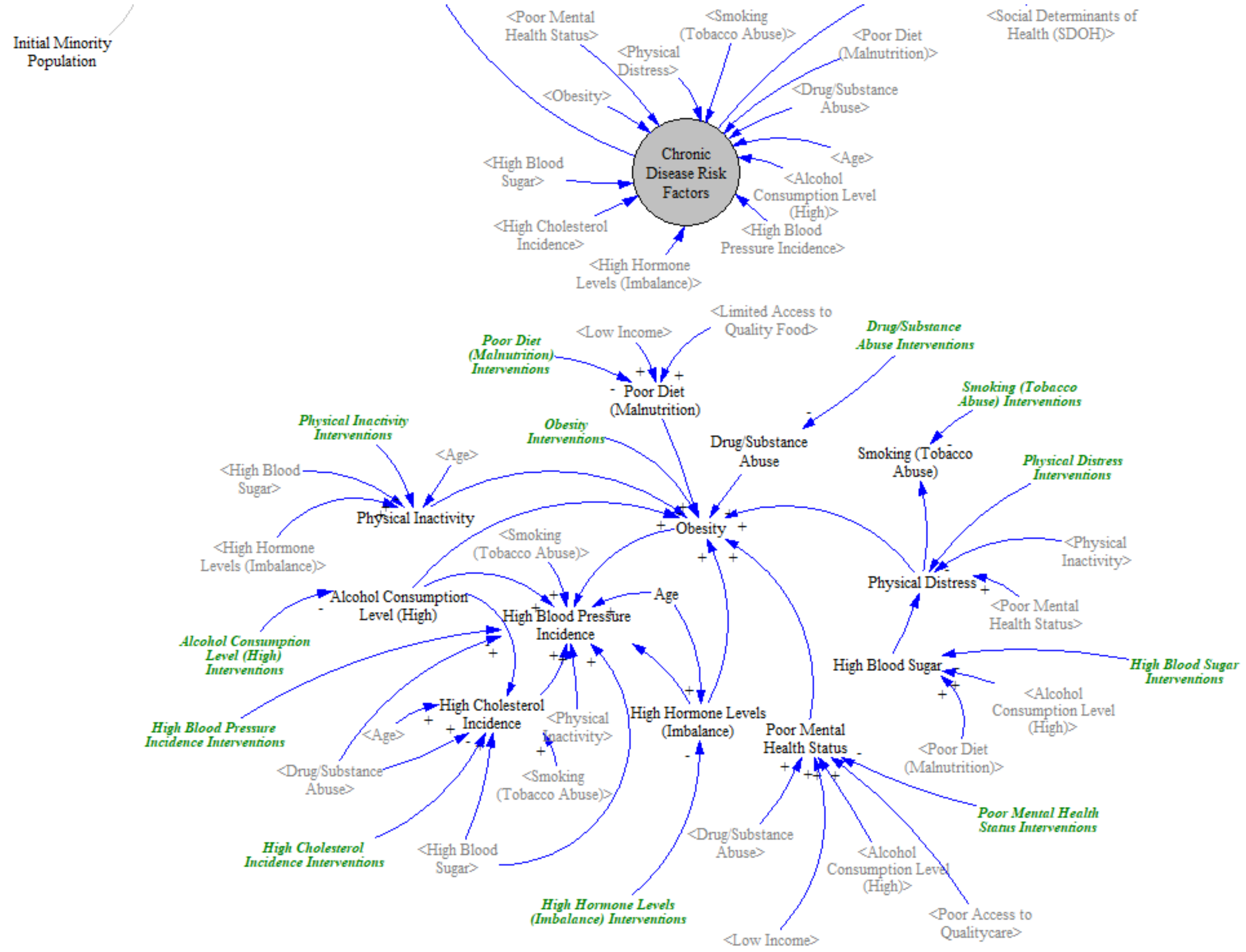

Figure 10: The SD using Stocks and Flows Section 2

RESEARCH STOCK AND FLOW MODEL

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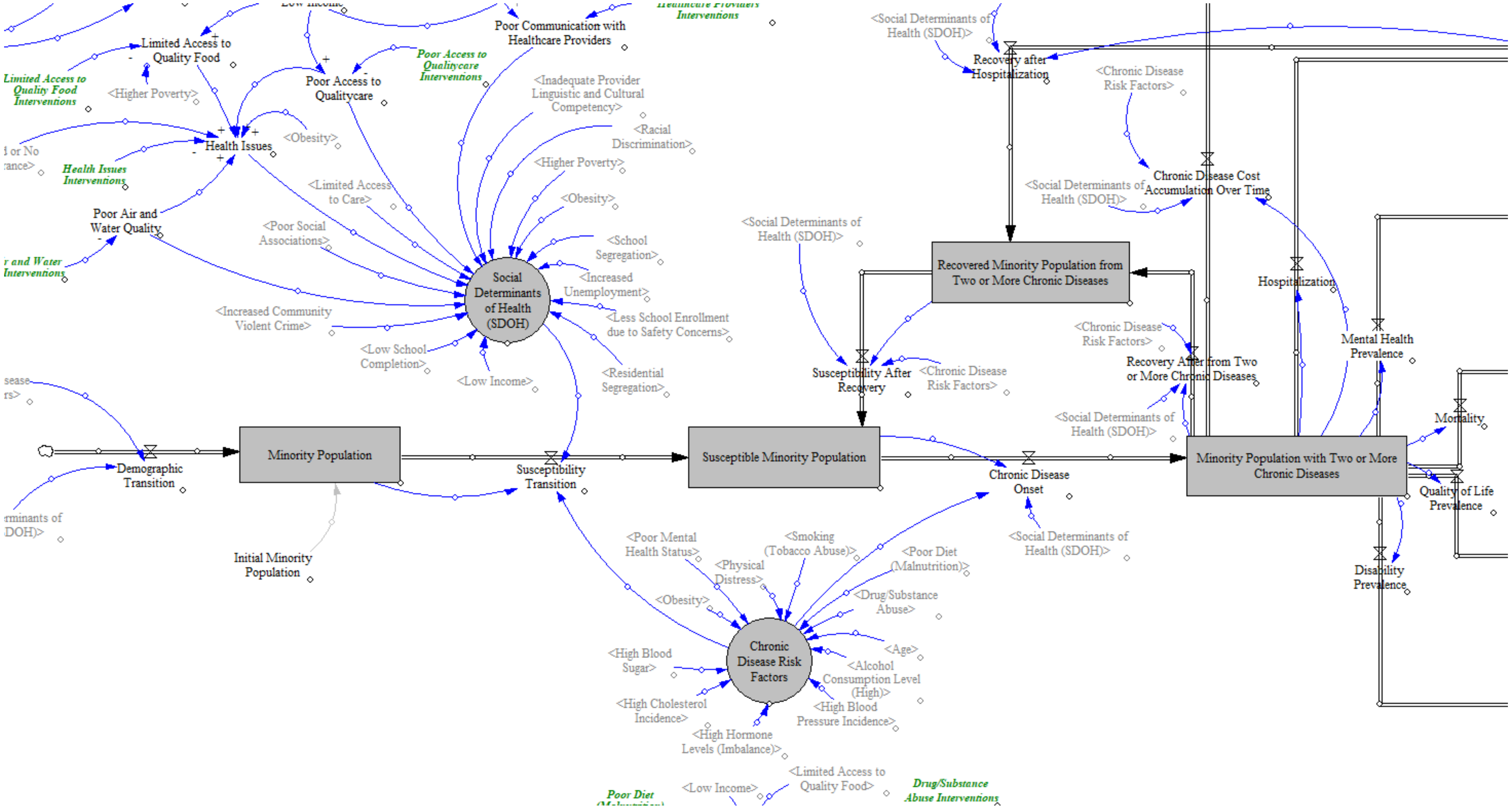

Figure 11: The SD using Stocks and Flows Section 3

RESEARCH STOCK AND FLOW MODEL

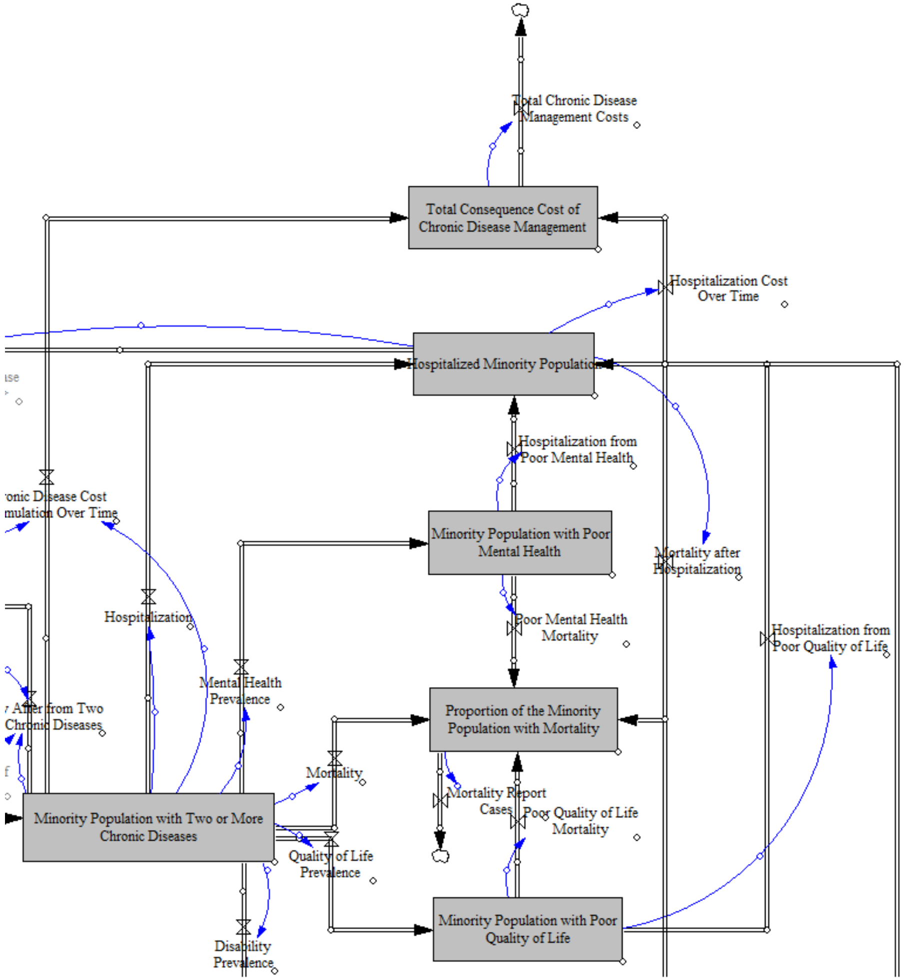

Figure 12: The SD using Stocks and Flows Section 4

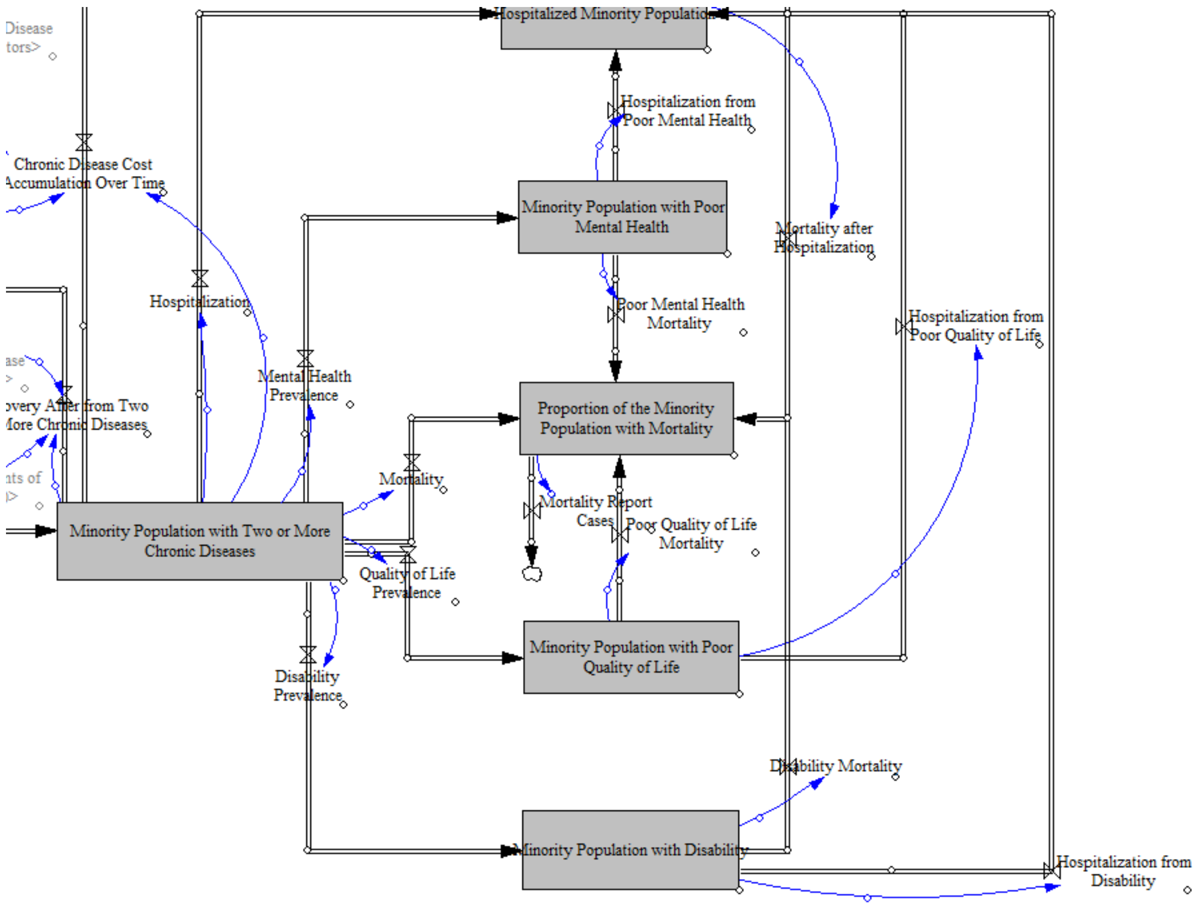

Figure 13: The SD using Stocks and Flows Section 5

SD EQUATION ANALYSIS

A system dynamics model's general differential and integral form equations are described below. These equations connect the concepts of stocks (S), flows (inflows I and outflows O), and time (t).

SD Differential Form

Equation:

$$\frac{dS}{dt} = I - O$$

Explanation:

- S: Stock or the state of the system at a given time.
- I: Inflow, or how much is added to the stock per unit of time.
- O: Outflow, or how much is subtracted from the stock per unit of time.
- $\frac{dS}{dt}$: The rate of change of the stock over time, equal to the inflow minus the outflow.

SD Integral Form

Equation:

$$S(t) = S(t_0) + \int_{t_0}^{t} (I(\tau) - O(\tau))d\tau$$

Explanation:

- $S(t)$: Stock at a given time t.
- $S(t_0)$: Initial value of the stock at the starting time t_0.
- $I(\tau)$ and $O(\tau)$: Inflow and outflow at time τ respectively.
- Integral $\int_{t_0}^{t}(I(\tau) - O(\tau))d\tau$: Accumulated net inflow (inflows minus outflows) over the time period from t_0 to t.
- Behavior: If inflows exceed outflows, the stock will increase; if outflows exceed inflows, the stock will decrease.

SD RESEARCH EQUATIONS

- Equation Structure: The model consists of equations for various parameters, including stocks, flows, auxiliary variables, and interventions.
- Simulation Rendering: Each component has its equation to enable error-free simulation.
- Software: Vensim system dynamics software is used, where stocks are generally in integral form, and other parameters have numerical equations.
- Weight Representation: The variable w_n represents the weight of the influence or impact of each variable in the model, where n is an integer (1, 2, 3, ... n). For example, w_1 represents a 10% impact of SDOH or chronic disease risk factors in the minority population.
- Equation Categories: The equations include demographic, susceptible, and chronic disease onset equations to indicate the incidence of chronic conditions in minority populations over time.

SD Research Equation Samples

$$\begin{aligned}\textbf{Susceptibility Transition} =& w_1 \times \text{Minority Population} \\ & \times w_2 \times \text{Social Determinants of Health (SDOH)} \\ & \times w_3 \times \text{Chronic Disease Risk Factors}\end{aligned}$$

$$\begin{aligned}\textbf{Demographic Transition} =& w_1 \times \text{Social Determinants of Health (SDOH)} \\ & \times w_2 \times \text{Chronic Disease Risk Factors}\end{aligned}$$

$$\begin{aligned}\textbf{Minority Population}(t) = \text{Minority Population}(t_0) + \int_{t_0}^{t} \text{Demographic Transition}(\tau) \\ - \int_{t_0}^{t} \text{Susceptibility Transition}(\tau) d\tau\end{aligned}$$

Majority and Minority Populations Distribution in the United States

Table 12 displays the population demography in 2022. The demography shows the population category based on the percentages and millions.

Race/Ethnicity	Percentage	Estimated Population
White alone	75.5%	251,591,802
Black or African American alone	13.6%	45,287,112
American Indian and Alaska Native alone	1.3%	4,332,738
Asian alone	6.3%	20,997,116
Native Hawaiian and Other Pacific Islander alone	0.3%	999,862
Two or More Races	3.0%	9,998,627
Hispanic or Latino	19.1%	63,677,974
White alone, not Hispanic or Latino	58.9%	196,202,392

Table 5: Population Distribution in the United States (2022)

APPLICATION OF PySD

The PySD library facilitates the efficient translation and initiation of the Vensim-based system dynamics model into a Python environment. It ensures interoperability with various powerful Python libraries such as Matplotlib, Pandas, Seaborn, and Numpy.

Algorithm 1 Run System Dynamics Model and Save Output to CSV

```
procedure RunSDModel
    model ← read_vensim('SDOH-Chronic Disease Risk Factors.mdl')
    output ← model.run()
    Print(output)
    output.to_csv('SDOH-Chronic Disease Risk Factors.csv')
end procedure
```

Figure 13: The SD using Stocks and Flows Section 5

APPLICATION OF MACHINE LEARNING

Figure 14 describes how the machine learning process is arranged in the research. After the PySD library has been utilized to translate the Vensim model into the Pythonic environment, the numeric outputs of the simulation were saved and then employed in the machine learning procedure.

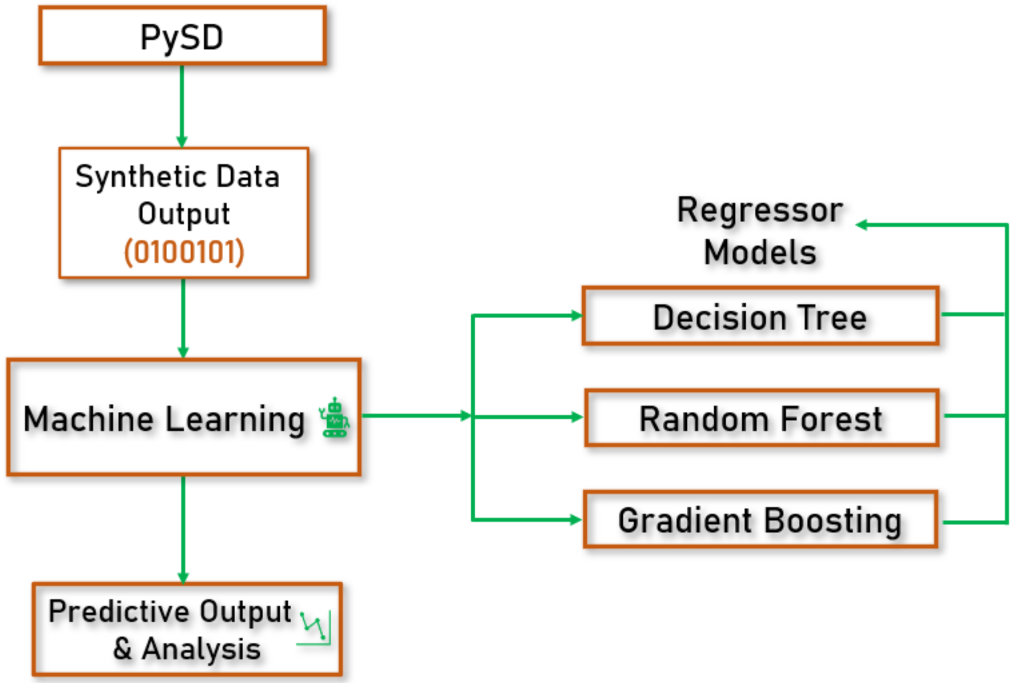

Figure 14: The Research Machine Learning Procedure

RESULTS AND DISCUSSIONS

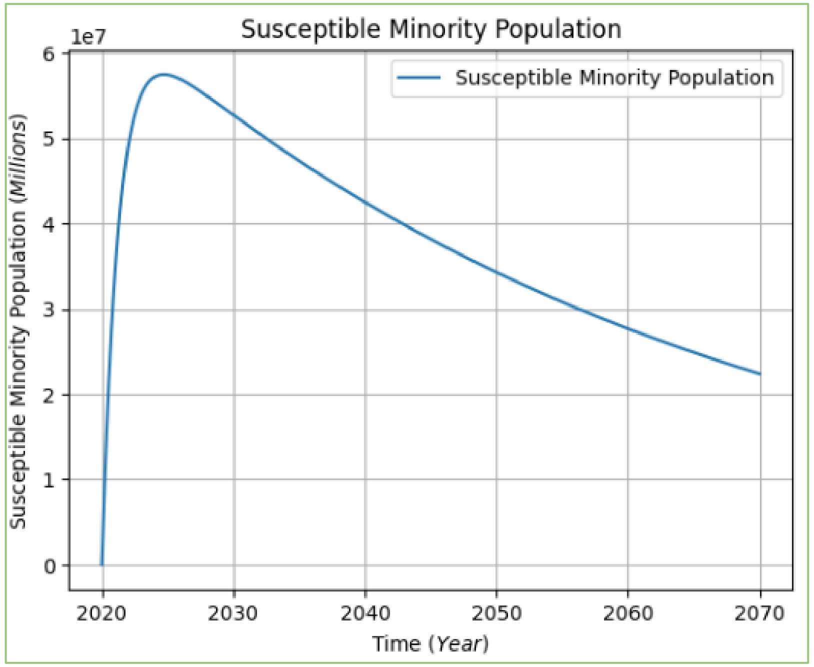

Figure 15: Susceptible Minority Population

Figure 15 shows the trend of the susceptible minority population in the U.S. from 2020 to 2070. The graph indicates an increase to 5.5 million by 2030, then a decline to 2.2 million by 2070. This trend may reflect improvements in interventions like social justice or how vulnerability is defined and assessed.

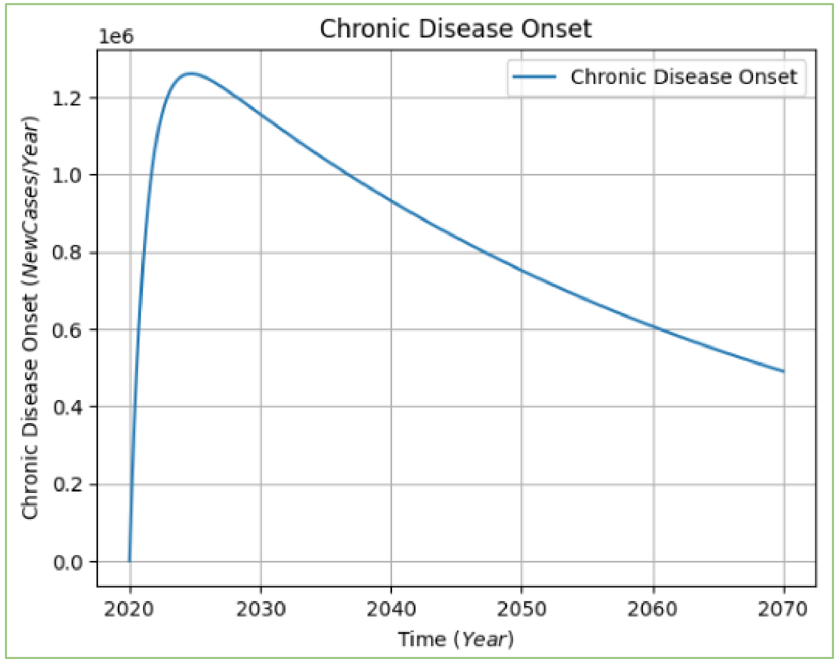

Figure 16: Chronic Disease Onset

Figure 16 depicts the onset of chronic diseases in U.S. minority populations from 2020 to 2070. The graph shows a peak of 1.22 million new cases per year by 2030, then a decline to 1.19 million by 2070, reflecting changes in risk management and intervention measures.

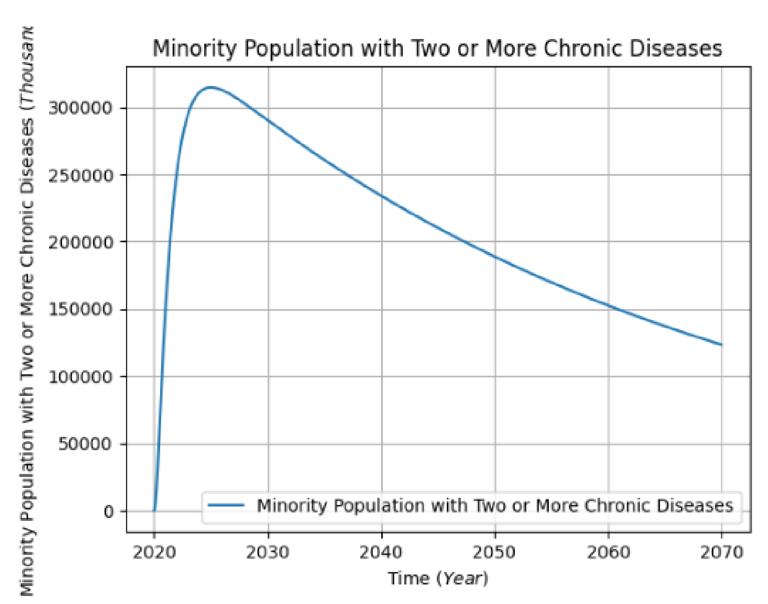

Figure 17: Minority Population with Two or More Diseases

Figure 17 illustrates the trend of minorities with two or more chronic diseases in the U.S. from 2020 to 2070. The graph peaks at 350,000 by 2025, then gradually declines, possibly reflecting future efforts to reduce chronic diseases among these communities.

RESULTS AND DISCUSSIONS [SD]

Implementing Interventions' Effect on SDOH and Chronic Disease Risks Factors in Minority Populations Over Time (Sensitivity Analysis)

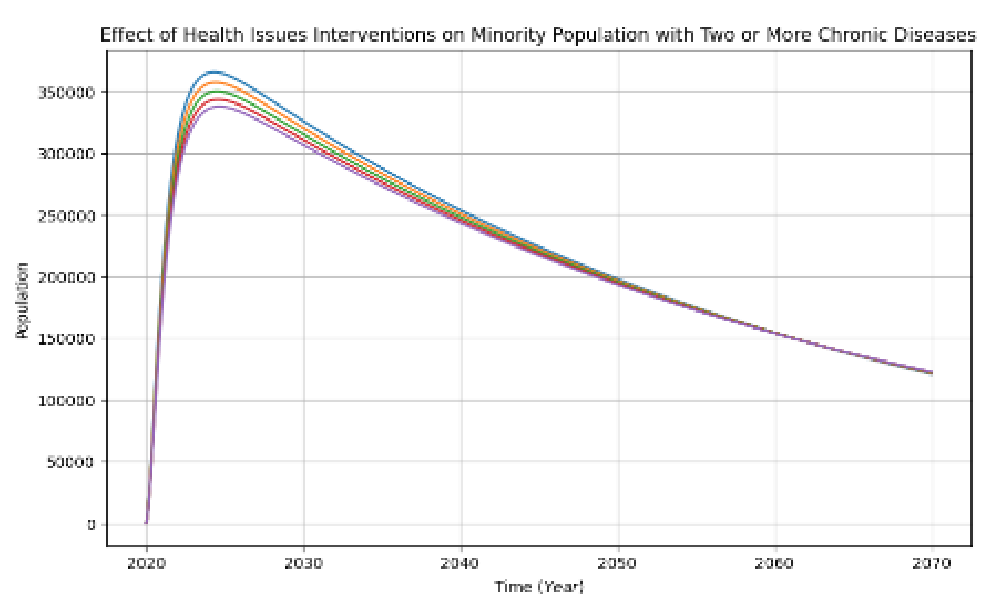

Figure 18: Health Issues Intervention Effect on Minority Population with Two or More Chronic Diseases

Figure 18 depicts the effects of health interventions on minority populations with two or more chronic diseases from 2020 to 2027. The graph reveals latent effects until 2025, peaking at 350,000, followed by a decline through 2070.

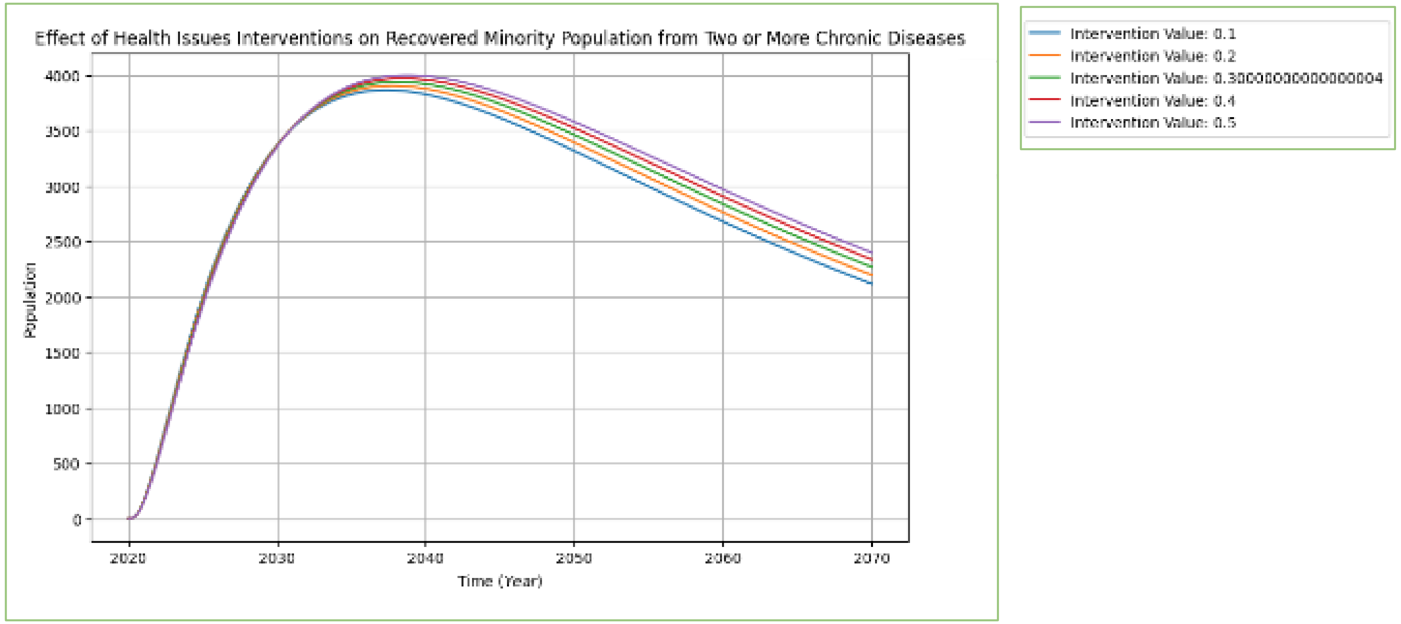

Figure 19: Health Issues Intervention Effect on Recovered Minority Population from Two or More Chronic Diseases

Figure 19 shows the effect of health interventions on recovery rates in minority populations with chronic diseases from 2020 to 2070. The graph illustrates an initial rise, followed by an increase and gradual decline, implying that increased interventions could enhance recovery rates.

RESULTS AND DISCUSSIONS [ML]

The PySD library translates system dynamics modeling into Python scripts for the research. A regression machine learning model targeting the minority population with chronic diseases is created using three algorithms: Random Forest, Gradient Boosting, and Decision Tree.

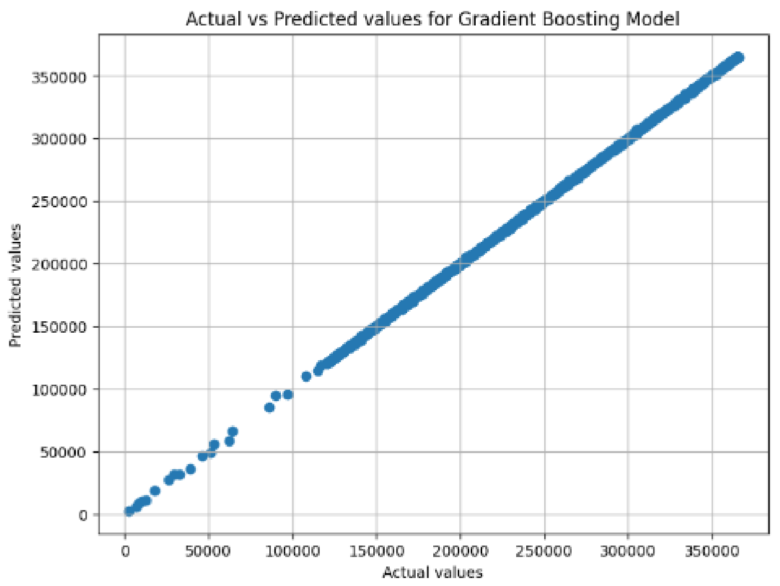

Figure 20: Actual and Predicted Values for Gradient Boost Machine Learning Model

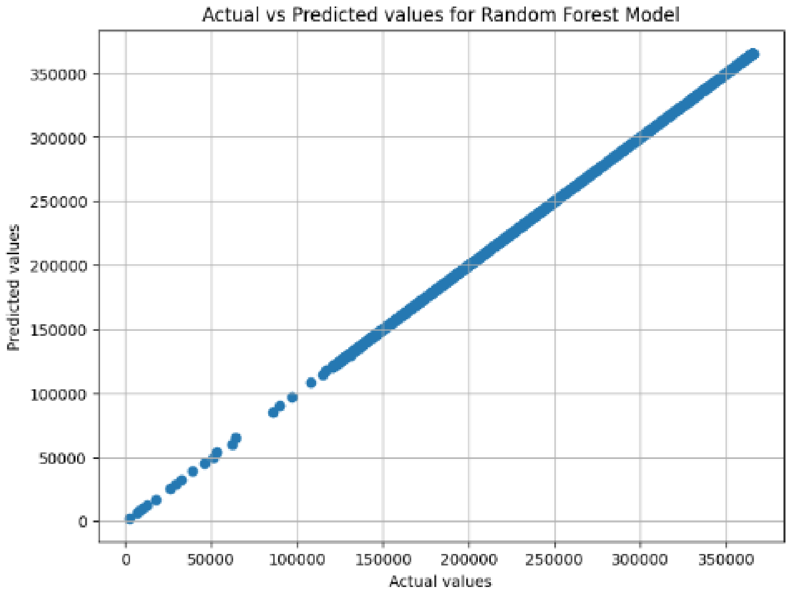

Figure 21: Actual and Predicted Values for Random Forest Machine Learning Model

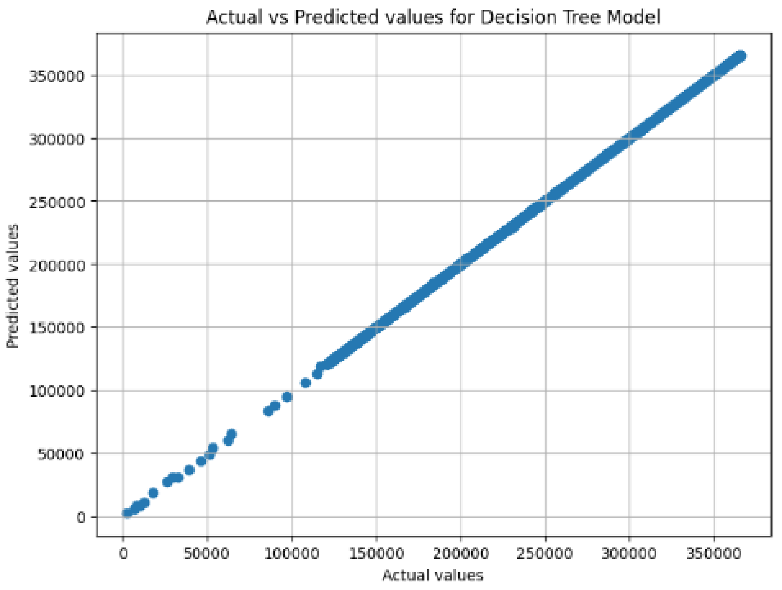

Figure 22: Actual and Predicted Values for Decision Tree Machine Learning Model

Figure 20 depicts a scatter plot for the gradient boosting model, showing a positive correlation between actual and predicted values. Some data points away from the line indicate expected errors, possibly due to model fitting issues or data anomalies.

Figure 21 reveals a scatter plot of the random forest model, illustrating a positive correlation between actual and predicted values. The plot indicates better performance with fewer prediction errors than the gradient boosting model.

Figure 22 illustrates the decision tree model's scatter plot, showing a positive correlation between actual and predicted values. The model is effective but has some errors. It performs better than the gradient boosting model, but the random forest model outperforms it.

RESULTS AND DISCUSSIONS [ML] CONT'D

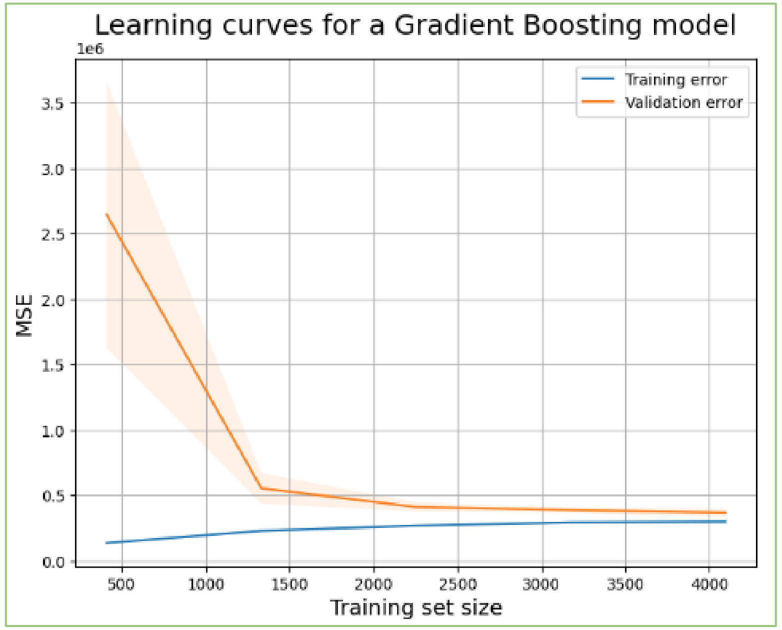

Figure 23: Gradient Boosting Learning Curve

Figure 23 illustrates a learning curve for the gradient boosting algorithm. As the training set size increases, training error decreases, but validation error gradually rises, indicating overfitting. This pattern suggests that the model might struggle with predictions on new, unseen data.

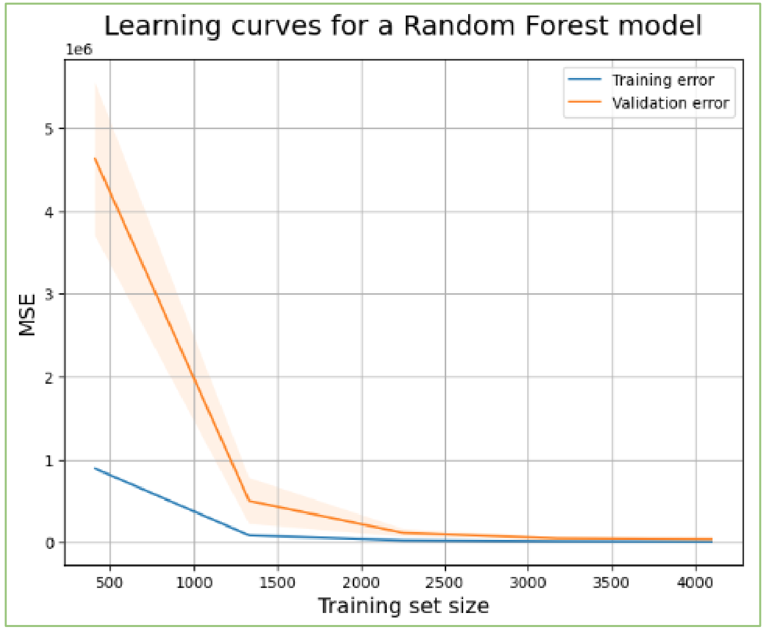

Figure 24: Random Forest Learning Curve

Figure 24 shows the random forest learning curve with training and validation errors decreasing as training data increases. The convergence of the errors suggests a well-balanced model, likely performing well on new data.

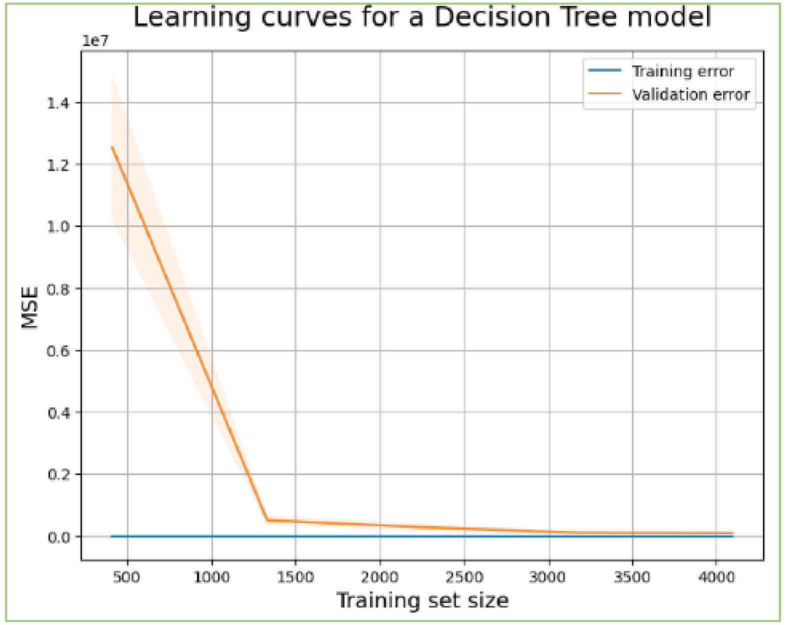

Figure 25: Decision Tree Learning Curve

Figure 25 depicts the decision tree learning curve, highlighting overfitting due to constant training errors. The model's performance is inferior to the random forest model but better than the gradient boosting model.

EVALUATION METRICS

In this research, the performance of three regression models (Random Forest, Decision Tree, and Gradient Boosting) was evaluated using various metrics:

- Mean Absolute Error (MAE): Random Forest had the smallest error of 39.59, making it the best performer.
- Mean Squared Error (MSE) & Root Mean Squared Error (RMSE): Random Forest again had the smallest values with an MSE of 18091.15 and an RMSE of 134.50.
- R-squared & Explained Variance: Random Forest outperformed the others with a value of 0.999997 for both metrics, indicating that it explains most of the variance in the target variable.
- Median Absolute Error (MedAE): Random Forest also had the lowest median error at 14.83.
- Mean Squared Logarithmic Error (MSLE): Random Forest depicted the smallest value of 0.00001, making it the best model if the target variable experiences exponential growth.

Model	MAE	MSE	RMSE	R-Squared	Explained Variance	Median AE	MSLE
Decision Tree	93.76	72017.51	268.36	0.99999	0.99999	41.61	0.00011
Random Forest	39.59	18091.15	134.50	0.999997	0.999997	14.83	0.00001
Gradient Boosting	452.18	401176.45	633.38	0.99994	0.99994	325.79	0.00008

Table 6: Comparison of Regression Models

CONCLUSION

- Chronic Disease Impact: Chronic diseases lead to significant medical expenses, disability, and death in the US, disproportionately affecting people of color due to their environment and socioeconomic status.
- Persistent Disparities: Despite efforts, health disparities persist, particularly affecting low-income Americans and racial minorities, who often have restricted access to treatment and healthcare interventions.
- Complex Interactions: The incidence of chronic diseases is influenced by complex interactions between social determinants of health (SDOH) and risk factors.
- Methodology Employed:
  - System Dynamics Modeling: The study used this approach to explore the interacting factors affecting minority populations' health.
  - Machine Learning Techniques: Predictive analysis was performed, specifically using the Random Forest model, to predict possible health outcomes and develop proactive measures.
- Results:
  - Random Forest Model Performance: It outperformed other models with precise evaluation metrics like MAE of 39.59, MSE of 18091.15, and R-squared of 0.999997.
  - Holistic View Provided: The combined techniques provide a comprehensive view of risk factors and interventions, aiding in potential policy considerations for minority populations.

FUTURE WORK

The research's future work includes avenues for expanding to diverse populations, integrating additional variables, ensuring quality data availability, collaboration with stakeholders, ethical considerations, interdisciplinary collaborations, and policy impact assessment.

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THANK YOU