SOCIAL DETERMINANTS OF HEALTH IN NUECES COUNTY: EVIDENCE FOR LOGIC MODELS INFORMED BY DIVERSE WAYS OF KNOWING

Addressing social determinants of health data integration barriers in Nueces County, Texas

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CONTRIBUTING AUTHORS

The Water Institute: Dr. Kathryn Keating served as lead author of this report, thematic coding analysis lead and lead for visualizing the project's logic models. Dr. Kateryna Wowk served as project director, Action Committee lead, thematic coding lead, and lead for data visualization in the geospatial tool.

Texas A&M University Corpus Christi (TAMUCC): Mukesh Subedee led the curation and organization of all project datasets to make them available through the project's products.

University of Texas at Austin: Dr. Anamitra Chaudhuri led structural equation modeling.

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Action Committee			
Organization	**Representative**	**Position**	**Interest**
Working Group on SDOH Logic Models			
Coastal Bend Council of Governments	Emily Martinez, MPA	Director of Regional Economic Development	Regional gov't
Corpus Christi Planning Department	Annika G. Yankee	Planning Manager	City gov't
Corpus Christi Metropolitan Planning Organization	Craig Casper, AICP, CTP CEP	Senior Transportation Planner	MSA transportation
Coastal Bend Community Organizations Active in Disaster; United Way	Janna Shoe, LBSW-IPR, CRS	Chairperson; Outreach & Disaster Coordinator, Coastal Bend	Non-profit
Coastal Bend Air Quality Partnership	Sharon Bailey Murphy, MPA, CHMM, REM	Executive Director	Regional non-profit
Coastal Bend Center for Independent Living	Judy Telge, BS	Director of Development	Community-based org.
Keepers of the Garden	Tevin Gray, Master Gardener	Owner	Community-based org.
Texas Children in Nature Network	Sarah Coles, MALS, Med	Executive Director	Community-based org.
Esperanza de Tejas	Brianna Davis, MSW	Founder & CEO	Community-based org.
Gulf Reach Institute	Suraida Nañez-James, MS	Founder and CEO	Youth leadership
Working Group on SDOH Data Integration			
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Driscoll Children's Hospital	Beth Becker, BSN/BBA/ RNC NIC/CPHQ and Lesley Martinez MPH, CPH, CIC	Patient Safety Manager	Healthcare System
Amistad Community Health Center	Eric Baggerman, MD	CEO and Pediatrician	Healthcare System
Nueces Center for Mental Health and Intellectual Disabilities	Mark Hendrix MS, LPC	Deputy Chief Executive Officer	Healthcare System
Driscoll Health Plan	Karl Serrao, MD, FAAP, FCCM	Chief Medical Officer and Pediatric Intensivist	Health Insurance

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PREFACE

This project sought to better understand the health disparities and vulnerabilities in at-risk communities in Nueces County, Texas that stem from social determinants of health (SDOHs). These SDOHs were also linked to climate and environmental factors, with the explicit goal of facilitating the integration of data on key SDOH, climate and environmental factors to improve health outcomes and address health disparities. With that goal in mind, the project endeavored to identify and address challenges related to such data integration, including, for example, the capacity needed to identify, access, and curate data, the lack of standardized tools for collecting data, the need to ensure data privacy, and the need for greater collaboration between healthcare providers and social service organizations.

This report provides the evidence base upon which the SDOH logic models were constructed. The report provides a summary of the methodology used and then includes detailed documentation of sources used to understand linkages between SDOHs, climate and environmental factors and health outcomes, including across multiple ways of knowing. The logic models in this report also can be used by technical experts and decision-makers across health, government, social services, academia and more to better target locally-relevant conditions that impact health. The models serve as a guide to prioritize SDOH, climate and environmental data viewing against specific health outcomes in the corresponding geospatial tool (https://geored.org/).

The project team has previous success engaging communities and decision-makers to build and validate relationships between key factors (Olander et al., 2020, 2021) and used a similar process to explore and validate linkages relevant to Nueces County and its at-risk communities. This included implementing a community-based participatory research (CBPR) process with local experts and in the at-risk neighborhood of Molina. The project team brings expertise in advancing CBPR, including specifically in Nueces County (Wowk et al., 2023). This report is the third of four project deliverables:

1. *Priority Actions to Address Key Social Determinants of Health: Recommendations from the Project to Address Social Determinants of Health Data Integration Barriers in Nueces County, Texas*

   Audience: Local and state government representatives; Corpus Christi-Nueces County Public Health District; local health and social service institutions. Purpose: Provide a succinct and high-level project overview and findings, as well as recommendations for next steps to decision-makers.

2. *Social Determinants of Health Data Integration Framework: Addressing Social Determinants of Health Data Integration Barriers in Nueces County, Texas*

   Audience: Public and private health practitioners; social service and community-based representatives; government representatives; academia. Purpose: Guide health practitioners and other interested representatives in various options they can take to assess and integrate SDOH, climate and environmental data, including detailed steps and an assessment of tradeoffs.

3. ***Social Determinants of Health in Nueces County: Evidence for Logic Models Informed by Diverse Ways of Knowing.***

Audience: Technical experts; grant writers. Purpose: Provide detailed documentation on the evidence used to build the project's logic models, including across different ways of knowing.

4. *Geospatial Nueces County Community Health & Environment Tool*

   Audience: Health practitioners; Corpus Christi-Nueces County Public Health District; local and state government representatives; social service institutions; community-based organizations; academia; the public. Purpose: Enable visual analysis of health, SDOH, climate and environment conditions at the census tract level across Nueces County, and make all data available for download and integration. Available at: https://geored.org/

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INTRODUCTION

Texas public health reports identify a need to link health and social care by differentiating between actions taken at the individual level, which address health-impacting needs by connecting patients with social services, and actions taken at the community level, which holistically support systemic changes through, for instance, policy, infrastructure, or social systems (Texas Health Improvement Network [THIN], 2020). Community level action is needed to create conditions that profoundly shape opportunities for health and well-being (Texas Health Institute, 2021). A foundational step is understanding relevant social determinants of health (SDOHs), which play a critical role in identifying and explaining the root causes of health disparities. SDOHs are the non-medical factors that significantly influence health outcomes. These are the conditions in which people are born, grow, live, work, and age, including factors like income, education, housing, and access to nutritious food and safe environments (CDC, 2024). When SDOHs are at a lower quality, as is often seen in marginalized communities, it can significantly exacerbate unequal sensitivities to climate and environmental risks and amplify health disparities (Gao et al., 2023; Putsoane et al., 2024; Smith et al., 2022).

Despite the impact SDOHs have on disparate health outcomes, however, understanding of how data on the conditions in which people live, grow, work and age can be, or is being, integrated with health data systems to improve health outcomes is nascent. Improving this understanding is critical, especially for communities and neighborhoods where non-medical factors may disproportionately impact well-being and quality of life. Such is the case in Nueces County, Texas, home to the City of Corpus Christi, which is ranked 9th in the nation as the most economically disadvantaged, and 6th in the nation as the highest in food insecurity (Patel et al., 2021). Of the county's 353,178 residents, 62% are Hispanic (U.S. Census Bureau, 2020). Many of these communities, such as those in the Westside of Corpus Christi, have faced historic discrimination that has contributed to significant health disparities (Gurrola, 2015; Texas Health Institute, 2021). For example, in a low socio-economic status community of color, the life expectancy rate is 70 years, whereas just 10 miles away individuals of high socio-economic status can expect to live 85 years (Texas Health Institute, 2021). This stark difference in life expectancy becomes clearer when examining chronic diseases in specific neighborhoods, such as the Corpus Christi Westside neighborhood of Molina (census tracts 1703, 1704, 1801 and 1602, **Error! Reference source not found.**) which has higher rates of hypertension, diabetes, obesity, asthma, and depression (Table 1).

PROJECT GOAL & FACTORS OF FOCUS

This project sought to better understand the health disparities and vulnerabilities in Molina and additional at-risk communities in Nueces County that stem from SDOHs. These SDOHs were also linked to climate and environmental factors, with the explicit goal of facilitating the integration of data on key SDOHs to improve health outcomes and address health disparities. Because of the importance of understanding disparities in Molina and similarly disadvantaged neighborhoods throughout the county, the five diseases with higher rates in Molina became the health outcomes of focus for the project (Table 1). These health outcome factors, as well as SDOHs, and climate and environmental factors were selected in collaboration with the project's Action Committee of local experts (see the **Error! Reference source not found.** section for a full list of Action Committee members).

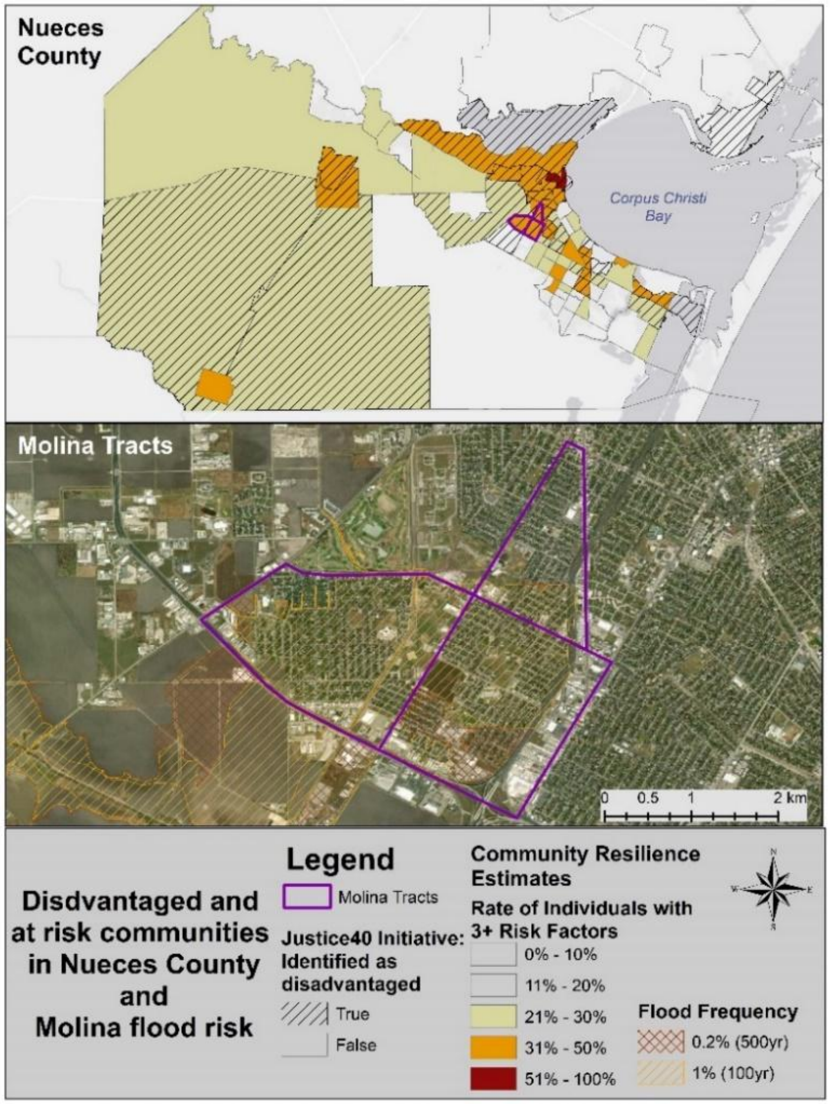


Figure 1. Map of Nueces County and the Molina Neighborhood showing Molina as disadvantaged, with higher risk factors and significant flood risk (Texas Water Development Board, 2022; U.S. Census Bureau, 2020; US Council on Environmental Quality, 2022)

Table 1. Nueces SDOH Project Health Outcome Factors

Chronic Disease	Molina § ¥	Nueces County ¥	Texas ¤	U.S. ¤
Hypertension	41.5	34	32.2	32.4
Diabetes	21.5	14.7	11.5	10.9
Obesity	45.3	39.8	36.1	33.9
Asthma	9.8	9.1	8.4	9.8
Depression	22.8	22.7	18.6	20.5

§ Mean of data for tracts 1703, 1704, 1801 & 1602
¥ Data collected from the CDC PLACES for 2019
¤ Data collected from CDC Behavioral Risk Factor Surveillance System for 2021

Factors related to the above disparities are listed in Table 2 and include, for example, extreme heat for hypertension, food access for diabetes and obesity, and air quality for asthma. These factors also include varying links for mental health concerns, such as rising temperatures and humidity, which are associated with high levels of stress (Ding et al., 2016) and increases in emergency department visits for depression (Vida et al., 2012). Expanding research in this area, especially among Black, Indigenous, and other People of Color (BIPOC), provides the foundation for development and promotion of evidence-based policy recommendations to galvanize systems-level change (Patel et al., 2021) for at risk communities especially vulnerable to climate and environmental factors (Ailshire & Brown, 2020; Chakraborty et al., 2011; Ringquist, 1997).

Table 2. SDOH and Climate and Environment Factors

Access to Greenspace [A]	Heat (C) (E)
Accessible Housing [A]	Flooding (C) (E)
Culture [A]	Storm (C) (E)
Disconnected Youth [N]	Particulate Matter (C) (E)
Employment [M N]	Ozone (C) (E)
Education [M]	Lead Exposure (E)
English Proficiency [M]	Wastewater Discharge (E)
Food Access [N]	Traffic
Hardship* [M]	
Healthcare Access [N]	
Income [M N]	
Literacy [A]	
Race & Ethnicity [M]	
Safety [N]	
Transportation [A]	

[A] SDOH added by Action Committee
[M] SDOH in Molina neighborhood
[N] SDOH in Nueces County
* Hardship combines unemployment, age dependency, education, per capita income, crowded housing, and poverty into a single score (Christus Spohn, 2023)

Whereas the SDOH *Data Integration Framework* report produced for this project focuses on operationalizing data integration for SDOHs and public health systems, this report details the methodological approach for developing the project's logic models. The logic models were used to provide the evidence from multiple ways of knowing on the relationships between major health disparities, SDOHs, environmental and climate factors. The methodology and resulting types and extent of data and information collected is important to consider in the context of the project's GIS product, the *Nueces Community Health & Environment Tool*. Varied decision makers may weigh different types or sources of evidence differently and thus can use the details of logic model building found herein to guide the types of data they choose to view in the tool. For other decision makers or analysts, it may be valuable to understand where different types of knowledge converge, as well as the content of the varied knowledge types. Those details and references are included herein.

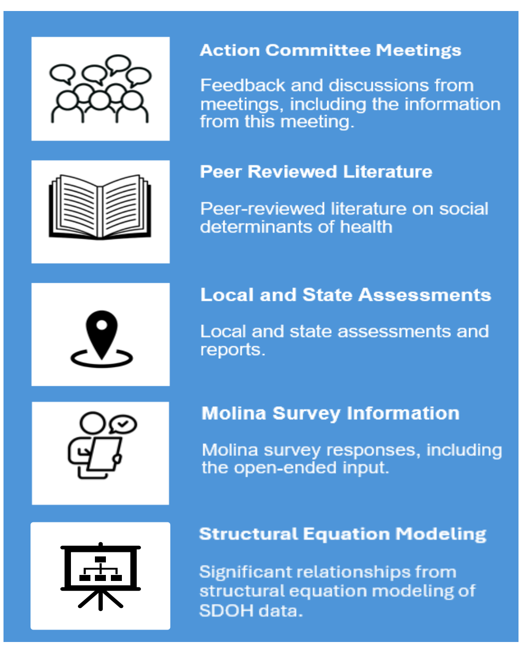
PART I: LOGIC MODELS METHODOLOGY OVERVIEW

This section describes key concepts and methods used to build the project's logic models. In particular, Part I highlights the following elements:

- *Importance of Diverse Ways of Knowing* provides background on why different types of evidence were sought and used to build the logic models.
- *Logic Models: Visualizing Connections to Health in Nueces County* provides further context on what logic models are and how the approach was adapted to meet the needs of the project.
- *Methodology to Build SDOH Logic Models* describes the process used to incorporate multiple ways of knowing, including a description of the qualitative coding and analysis conducted and a summary of how quantitative analysis was incorporated through structural equation modeling.

IMPORTANCE OF DIVERSE WAYS OF KNOWING

No single source of information can provide a comprehensive picture of how SDOHs and environmental factors contribute to health disparities in Nueces County. Thus, it is important to use diverse ways of knowing and evidence when trying to understand key SDOHs at the local level (The Robert Wood Johnson Foundation [RWJF], 2024). Doing so can provide the more nuanced picture needed to consider complex factors at play across social, economic, and environmental conditions that impact the health of residents. For example, while quantitative data can identify neighborhoods that may have challenges with educational attainment, qualitative data is needed to further understand why challenges exist and how they affect peoples' lives (Stickley et al., 2022).



Data collected at national and state levels provide broad context on health and environmental conditions, while community-level data offer more granular insights into neighborhood characteristics and health outcomes. Individuals who live or work in, or are otherwise deeply connected to, the Molina neighborhood and other communities across the county bring essential place-based perspectives and expertise. To build the logic models for this project, the approach focused on using multiple sources or evidence, or ways of knowing, as see in Figure *2*.

By integrating these sources of information into a single set of logic models, the analysis can highlight where multiple ways of knowing converge and where localized data and community expertise offer critical additional insights.

Figure 2. Ways of knowing integrated into Nueces County Health Equity logic models

LOGIC MODELS: VISUALIZING CONNECTIONS TO HEALTH IN NUECES COUNTY

Purpose

The logic model approach used to conceptualize connections across SDOHs, climate, environment, and health relied a mixed-method design, allowing for integration of linkages that arise from structured data as well as unstructured and semi-structured data (e.g., local knowledge) to qualify and contextualize changes needed for marginalized groups (Ota et al., 2022). The purpose of developing the logic models was to:

1. Integrate diverse ways of knowing to demonstrate interrelationships among health outcomes, social determinants of health, and climate and environmental conditions.
2. With diverse ways of knowing, identify which SDOH, climate and environmental factors are related to health outcomes.
3. Increase understanding among health practitioners, government officials, non-profits, and more on specific datasets that can be used to assess SDOH impacts to health and health disparities in Nueces County. The geospatial Nueces Community Health & Environment tool makes data available to facilitate such assessment, which also are described in the SDOH Data Integration Framework (Wowk et al., 2025).

SDOH Definitions

As mentioned above, all SDOH, climate, and environmental factors were selected in collaboration with the project's Action Committee comprised of local experts. Partners across the project's interdisciplinary team worked to define each SDOH early on to ensure a shared understanding was developed that resonated with diverse perspectives for Nueces County (Table 3).

Table 3. Nueces SDOH Project Definitions

SDOH	Definition
Economic Stability	
Income	Money received, especially on a regular basis, for work or through investments.
Employment	Activity in which an individual works or performs a service in exchange for wages or other remuneration. This encompasses aspects such as job security, workplace environment, income level, and access to resources.
Accessible Housing	Accessible affordable housing refers to housing that is both economically within reach for individuals and specifically designed or modified to meet the needs of people with disabilities or those who are disadvantaged due to age or other factors. Affordable housing is housing that a household can pay for while still having enough money for other necessities.
Hardship	Hardship combines unemployment, age dependency, education, per capita income, crowded housing, and poverty into a single score
Education Access and Quality	
Education	Level of educational attainment, including the knowledge and skills needed to make informed health decisions, understand health information, and engage in healthier lifestyles.
English Proficiency	A person's ability to use and comprehend spoken and written English effectively, enabling them to communicate meaningfully in various contexts.

SDOH	Definition
Literacy	Literacy is defined as the ability to read, write, speak, and listen effectively, enabling individuals to communicate and make sense of the world around them.
Healthcare Access and Quality	
Healthcare Access	The extent to which people have equitable, affordable, and available access to needed healthcare services. This definition includes both physical accessibility and availability via financial means, transportation options, and other factors.
Neighborhood and Built Environment	
Food Access	Extent and characteristics of individuals or communities that lack access to healthy and affordable food options. It involves assessing factors such as food sources, income levels, and coping strategies at the household level.
Access to Green Space	Refers to the availability and proximity of natural environments, such as parks, gardens, and woodland areas, for community use. It is essential for promoting physical activity, social interaction, and overall well-being, as these spaces encourage outdoor activity and foster a sense of community.
Transportation	Transportation is closely linked with built environment factors. It can also impact access to employment, education, healthy food, social engagements, faith-based institutions, and health care. Access to reliable transportation includes access to a personal vehicle, safe environments for walking or biking, and/or access to adequate public transportation services.
Social and Community Context	
Race & Ethnicity	Race refers to groups of people classified based on physical traits, such as skin color, hair texture, or eye shape. Ethnicity pertains to cultural characteristics, including shared language, food, music, dress, values, and beliefs, which are often connected to common ancestry.
Disconnected Youth	Refers to teenagers and young adults aged 16 to 24 who are neither employed nor enrolled in school. This term highlights the challenges faced by individuals who are not in education, employment, or training (NEET).
Safety	The condition of not being in danger or of not being dangerous. Safety can also refer to the control of recognized hazards in order to achieve an acceptable level of risk.
Culture	Culture is a broad concept that encompasses the social norms, institutions, and behaviors of a human society, as well as the knowledge, beliefs, arts, laws, customs, capabilities, and habits of the people in those groups. It can also be defined as the characteristic features of everyday existence shared by people in a place or time, such as diversions or a way of life.

METHODOLOGY TO BUILD SDOH LOGIC MODELS

Logic Models Introduction

Logic models are visual tools that support design, planning, communication, evaluation and learning. They are graphic interpretations to organize information about how the world works, or is anticipated to work, conveying schemes, projects or programs in a concise format (Knowlton & Phillips, 2012). While logic models have been used for some time to support program performance evaluation (McLaughlin & Jordan, 1999), increasingly they are being used to understand complex systems and to capture the adaptive nature of systems and interventions in healthcare (Mills et al., 2019).

To analyze the complex relationships between health, the environment and SDOH while ensuring equity was placed at the center of the work, the team relied on the social well-being framework for logic models as presented in Ota et al. (2022), which emphasizes equitable process over eventual outcomes (Ota et al., 2022). However, in building an initial version of the models to bring to the Working Group for comment, the project team ran into a challenge. Logic models most often depict the expected outputs and outcomes of a theory of change or a program, providing an evidence base for a specified end (Knowlton & Phillips, 2012). Yet the task of this project was not to understand the anticipated effects from a specific action or intervention, but rather to understand which SDOH, climate and environmental factors impacted which health outcomes. The project team thus adapted the approach to focus on mapping the complexity of connections, instead of identifying pathways that lead to specific outputs and outcomes

Analysis of Themes Across Multiple Ways of Knowing

The logic models were drafted using peer-reviewed literature as well as state and local assessments that identified relationships between SDOHs and health outcomes (Figure 3). The analysis further considered how SDOHs were related to climate and/or environmental factors. All documents were gathered in the qualitative analysis software program MAXQDA and were analyzed using a code structure, which is further detailed below in the *Description of Qualitative Coding and Analysis* section.

Following an analysis of themes in the peer-reviewed literature and local and state assessments, the initial draft of the logic models was developed. The SDOH Logic Models Working Group and broader Action Committee iteratively reviewed these draft models and provided detailed feedback on the relationships in the models. They also discussed whether the analysis was reflective of their local experiences on-the-ground in Nueces County, especially through their work with at-risk communities in the county.

The thematic and content analysis then facilitated incorporation of the semi-structured data into the logic models (Krippendorff, K., 1989; White & Marsh, 2006). The SDOH Logic Model Working Group and Action Committee input was recorded and included in the qualitative analysis as semi-structured data, along with survey results from engagement efforts in the Molina neighborhood (Figure 3). All input was transcribed, coded, and iteratively analyzed to further inform not only key relationships between SDOHs and health outcomes, but also how these relationships impacted health disparities in at-risk communities.

Description of Qualitative Coding and Analysis

MAXQDA is a qualitative data analysis tool used for coding and analyzing source materials, conducting mixed-methods analysis, and creating data visualizations (VERBI Software, 2021). Data from the SDOH Logic Model Working Group were imported into MAXQDA for structured thematic coding and analysis. A pre-defined codebook was developed from the key SDOH, climate and environment factors, and health outcomes identified in earlier stages of the project. Through iterative feedback from the Logic Model Working Group, transportation was added as an emergent SDOH theme and included in the analysis.

Project team members coded passages based on these themes. The MAXQDA Code Relations Browser (CRB) tool was then used to visualize the relationships between codes within an entire set of documents. The CRB export presents the frequency of co-occurrence between codes (VERBI Software, 2021). For each health outcome, the frequency of co-occurring codes was examined as to whether an SDOH, climate or environmental factor was identified as having a causal relationship with a health outcome (termed "driver"), or whether an SDOH, climate or environmental factor was identified as being correlated to the health outcome (termed "link"). Factors were coded as causal when the evidence identified it as such (primarily peer-reviewed literature and state and local assessments, but also in some cases Action Committee concurrence).

For the full MAXQDA CRB export, including the corresponding number of co-occurring codes, please refer to the associated table in the discussion of each model.

Integration of Structural Equation Modeling (SEM)

The project team used structural equation models (SEMs) to quantitively measure the dependence relationships among the project's structured variables of interest (Table 1 and Table 2). An SEM is a system of linear equations that assigns a coefficient to each dependent relationship. The coefficients quantify the strength of the dependence relationships and can be estimated given a dataset using standard statistical software. *Appendix A: Structural Equation Modeling: Detailed Results* provides a detailed overview of the structural equation modeling approach.

Figure 3 below outlines the types of information analyzed to inform the initial version of the logic models, which in turn informed the Action Committee and the SEM process. With community input from Molina, the project was able to produce a final, integrated model.

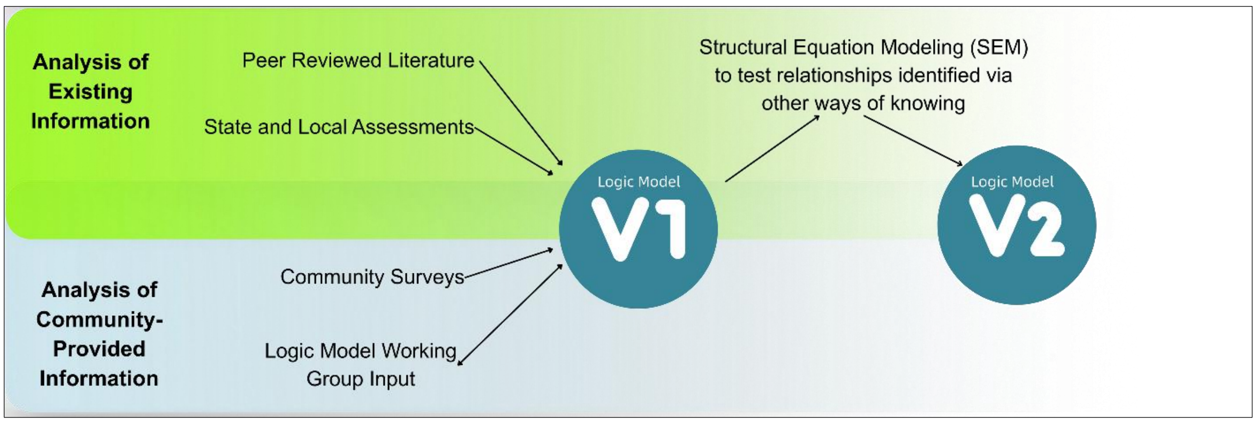


Figure 3. Sequential approach to integrating different ways of knowing into logic model development.

The results of all analyses follow in *Part II: Data Sources for Diverse Ways of Knowing*. Included in these results are all data supporting the creation of the logic models. Summaries of the evidence for each of the links in the model are also provided below.

PART II: DATA SOURCES FOR DIVERSE WAYS OF KNOWING

This section describes each of the data sources used as a way of knowing in building the SDOH logic models including SDOH Logic Model Working Group and Action Committee Input, Peer-Reviewed Literature, State and Local Assessments, Molina Community Survey Input and Structural Equation Modeling (SEM).

SDOH LOGIC MODEL WORKING GROUP AND ACTION COMMITTEE INPUT

The SDOH Logic Model Working Group was established to integrate local expertise in the co-development of an evidence-informed understanding of the relationships between SDOH, climate, and environmental factors, and their potential connections to specific health outcomes in Nueces County.

The Working Group met primarily through virtual sessions, which involved structured discussions on SDOHs and iterative reviews of preliminary linkages identified through analyses of peer-reviewed literature and local and state data sources. This culminated with an in-person workshop that was held in June 2025 with participation from all Action Committee members, including the SDOH Logic Model Working Group and the SDOH Data Integration Working Group. This workshop served to refine and finalize a suite of logic models illustrating different forms and strengths of evidence supporting these connections.

Qualitative data were collected throughout this collaborative process. Data types include documentation from workshop activities, transcripts of group discussions, and records of one-on-one meetings and written correspondence.

Figure 4. Example of a facilitated discussion output from a meeting with the SDOH Logic Model Working Group. Photo Courtesy of Dr. Katya Wowk

PEER-REVIEWED LITERATURE

A foundational list of peer-reviewed research on SDOHs was compiled for analysis. This initial list of research was derived from several sources, including the project funding request for applications, the works cited list from the initial proposal, and additional team expert knowledge. Additional sources were identified over the course of the project, allowing for expansion of the literature review to further assess initial links discovered from these foundational documents. A full list of peer-reviewed literature included in this analysis can be found in the references section of this document.

STATE AND LOCAL ASSESSMENTS

To incorporate more localized information on health in Texas and Nueces County, relevant state and local assessments were compiled and included in the analysis. These sources encompassed community-level needs assessments and related reports. Additional reports were identified for inclusion through consultations with the SDOH Logic Model Working Group and the Action Committee. A complete list of the state and local assessments used in this analysis is provided in the references section of this document.

MOLINA COMMUNITY SURVEY INPUT

A Molina Neighborhood Survey was conducted in all four neighborhood census tracts. Survey questions were specifically crafted for Molina residents to identify perspectives on SDOHs, climate, and environmental factors as related to health in their families and community, as well as assets they currently have that help build and implement solutions. Surveys were collected through in-person, face-to-face interviews. A total of 42 surveys were collected in March 2025. Data collection for this component of the project was conducted under the oversight of the Texas A&M University-Corpus Christi Institutional Review Board (IRB) (IRB Number: TAMU-CC-IRB-2023-0981).

Figure 5. Photo of Molina Survey and Outreach. Project team members discuss health topics and collect survey responses during a community event in Molina, TX. Photo Courtesy of Suraida Nanez-James.

STRUCTURAL EQUATION MODELING (SEM)

Source of Information

The structural equation modeling conducted for this project used data from a variety of sources. Additional information about the source data can be found Appendix A of the *SDOH Data Integration Framework* report associated with this project (Wowk, K. et al., 2025).

SEM Introduction

Structural Equation Modeling (SEM) is a statistical framework that allows researchers to examine complex relationships among multiple variables at the same time. Unlike standard regression, which looks at one outcome and a handful of predictors, SEM can simultaneously account for direct effects (e.g., how environmental factors/indices or social determinants causally affect or predict a health outcome) and correlations among predictors (e.g., how income and environmental factors are related). This makes it especially useful in public health, where multiple social and environmental factors interact to influence outcomes such as depression, diabetes, hypertension, obesity, or asthma.

A key strength of SEM is that it provides a flexible way to test theoretical models grounded in prior research. For example, in the depression model, the project team examined how storm surge, flood, race/ethnicity, and health insurance coverage predict depression, while also allowing for correlations between social and environmental factors such as income, housing costs, air pollution, and heat exposure. SEM also provides a unified statistical test of model fit, letting the analyst assess whether the hypothesized relationships are consistent with the observed data.

At the same time, SEM has some natural limitations. The technique cannot prove causality on its own as it does not explore/search over possible model spaces; it can only evaluate whether the proposed or postulated model is consistent with the data. Results can also be sensitive to model specification (if certain paths are mistakenly included or omitted), measurement quality, and sample size. Finally, SEM requires careful interpretation, as correlations do not always imply direct influence.

Understanding Causation and Significance in SDOH Logic Models

The project team identified causation, termed "drivers," where evidence was found to substantiate such a linkage. Causation was initially identified where types of evidence (primarily peer-reviewed or state and local reports, but in some cases also through concurrence of the Action Committee) stated the relationship as causal. The identified causal relationships were then evaluated through SEM to understand if the causal relationships identified were consistent with project data (detailed in Appendix A of the *SDOH Data Framework* report associated with this project [Wowk, K. et al., 2025]).

Elsewhere, the team identified correlations, or links, where evidence noted a relationship exists (i.e., two factors are linked, though the model cannot tell one how). Similarly, SEM was used to evaluate which of those links were statistically significant with project data.

Significant relationships identified through SEM, i.e., where structural equation modeling resulted in a p-value < 0.05, are represented in each logic model below. Appendix B of this report provides detailed interpretation of SEM findings and full logic models.

PART III: LOGIC MODELS

ASTHMA LOGIC MODEL

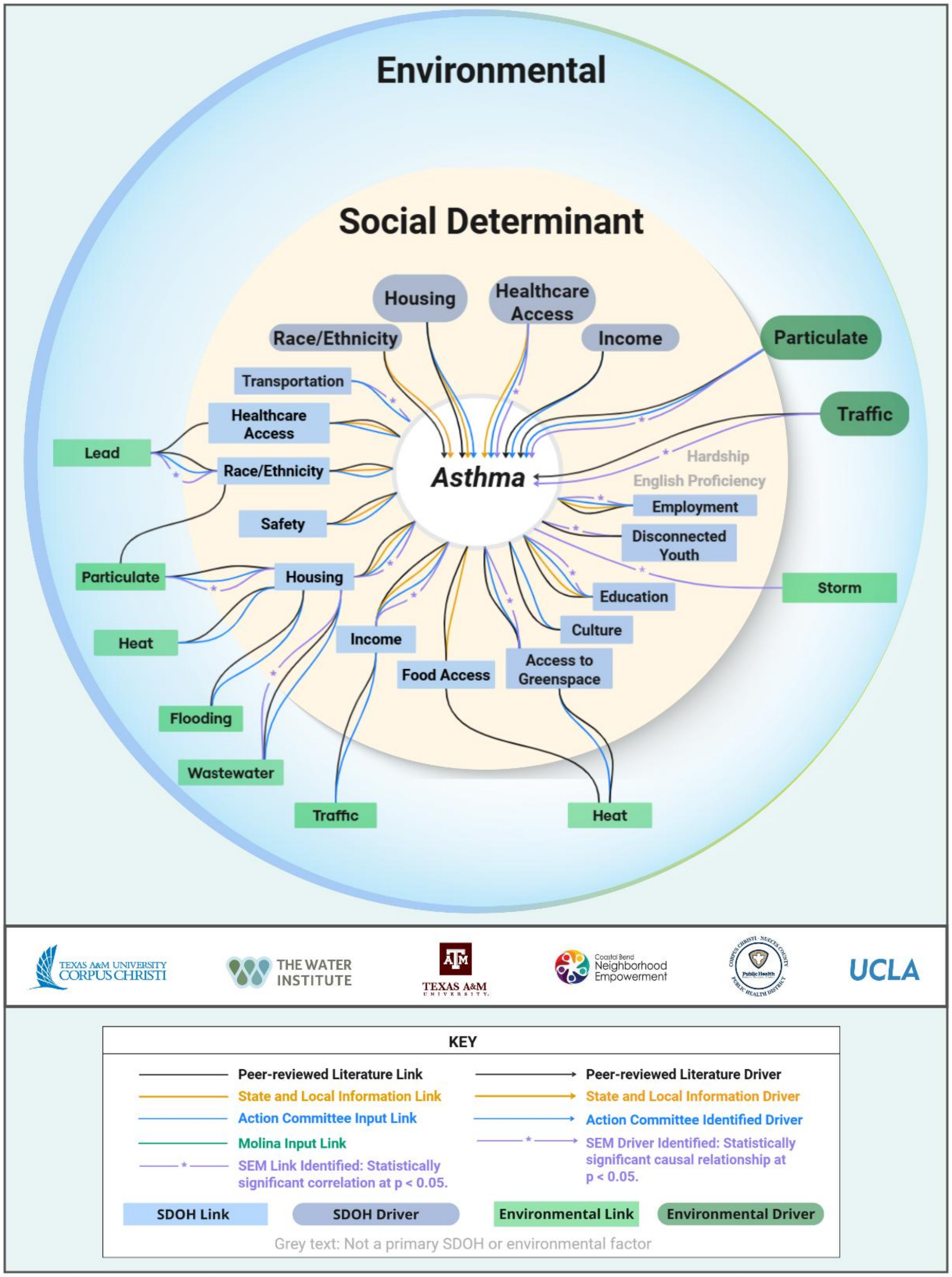


Figure 6. Logic model for asthma, showing different kinds of evidence demonstrating different SDOHs as links or drivers of the health outcome. Structural Equation Modeling links and drivers are marked with an asterisk (*) to indicate relationships that are statistically significant with p-value < 0.05, meaning there can be reasonable confidence that there is some non-zero association.

Interpretation: Asthma Logic Model

The logic model shows which SDOHs are linked in a causal or correlated manner to asthma as an outcome. It depicts data from peer-reviewed literature, state and local reports, expert input from the project's Logic Model Working Group and Action Committee and community level input from an at-risk neighborhood in the county.

The model connects SDOHs to the outcome of asthma, distinguishing between drivers and links. Climate and environmental factors are also illustrated as drivers of health outcomes or links to SDOHs.

Areas of Convergence

Areas of convergence highlight where multiple lines of evidence align in linking social determinants of health and climate/environmental factors to asthma.

SDOH Drivers

The following SDOHs emerged as drivers of asthma across multiple ways of knowing.

- **Housing** (Bullard & Wright, 1993; CDC, 2013; Lave & Seskin, 1970; Leung & Takeuchi, 2011; THIN, 2020)
- **Healthcare access** (Amistad Community Health Center, 2023; THIN, 2020, p. 2023)
- **Income** (Brulle & Pellow, 2006)
- **Race/ethnicity** (Brulle & Pellow, 2006; Leung & Takeuchi, 2011; THI, 2022)

Climate/ Environmental Drivers

The following climate/environmental factors are identified as key drivers of asthma.

- **Particulate** (Bullard & Wright, 1993; Lave & Seskin, 1970)
- **Traffic-**(CDC, 2013)

Links across SDOH Factors

- Links between asthma and healthcare access, race/ethnicity, safety, housing, and income are supported by multiple ways of knowing.

> "Particulate info data is very important"
>
> "Trust in healthcare system affects people accessing healthcare"
>
> "People may not have transportation to drs appt or rely on someone else to take them if they can't miss their appt and treatment"
>
> *-SDOH Action Committee Member Comments*

Areas of Opportunity

The areas of opportunity below identify underexplored relationships that warrant additional exploration to advance understanding and inform data-driven interventions.

Links across SDOH and Climate/Environmental Factors

- The links between climate/environmental factors and SDOH are represented primarily in the peer-reviewed literature and SEM modeling. Local data and perspectives could contribute to a more nuanced understanding of this relationship.

Supporting Information: Asthma Logic Model

Table 4. MAXQDA CRB Output, SDOH and Asthma: Frequency of Co-Occurrence by Data Source

Outcome	Connection Type	Data Source	Culture	Disconnected Youth	Education	Employment	English Proficiency	Food Access	Greenspace	Hardship	Healthcare Access	Housing	Income	Race/ Ethnicity	Safety	Transportation
Asthma	Driver	Action Committee	1	0	1	0	0	1	1	0	2	2	2	0	0	0
		Peer Reviewed Literature	0	0	0	1	0	0	0	1	0	4	1	6	1	0
		Local/State Reports	0	0	0	0	0	0	0	0	4	2	0	1	0	0
		Molina Community Survey	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Link	Action Committee	9	0	5	5	0	2	7	0	11	15	12	3	1	1
		Peer Reviewed Literature	14	12	12	11	12	12	12	13	16	14	6	19	13	0
		Local/State Reports	0	0	1	1	0	5	0	0	9	9	1	1	1	0
		Molina Community Survey	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 5. SDOH and Asthma Links: References

SDOH	State and Local Assessments	Peer Reviewed Literature
Culture	N/A	Leung & Takeuchi 2011; Brulle & Pellow 2006; CDC 2013
Disconnected Youth	N/A	Brulle & Pellow 2006
Education	THIN 2020	Brulle & Pellow 2006
Employment	THIN 2020	Brulle & Pellow 2006
English Proficiency	N/A	Brulle & Pellow 2006
Food Access	THIN 2020	Brulle & Pellow 2006
Greenspace	N/A	Brulle & Pellow 2006
Hardship	N/A	Leung & Takeuchi 2011; Brulle & Pellow 2006
Healthcare Access	THIN 2020; Amistad Community Health Center 2023	Leung & Takeuchi 2011; Brulle & Pellow 2006; CDC 2013
Housing	THIN 2020; Amistad Community Health Center 2023	Brulle & Pellow 2006; CDC 2013
Income	THIN 2020	Lave & Seskin 1970; NASEM 2017; CDC 2013
Race/Ethnicity	Christus Spohn 2023	Leung & Takeuchi 2011; Brulle & Pellow 2006; CDC 2013; NASEM 2017
Safety	THIN 2020	Brulle & Pellow 2006; CDC 2013; NASEM 2017
Transportation	N/A	N/A

DEPRESSION LOGIC MODEL

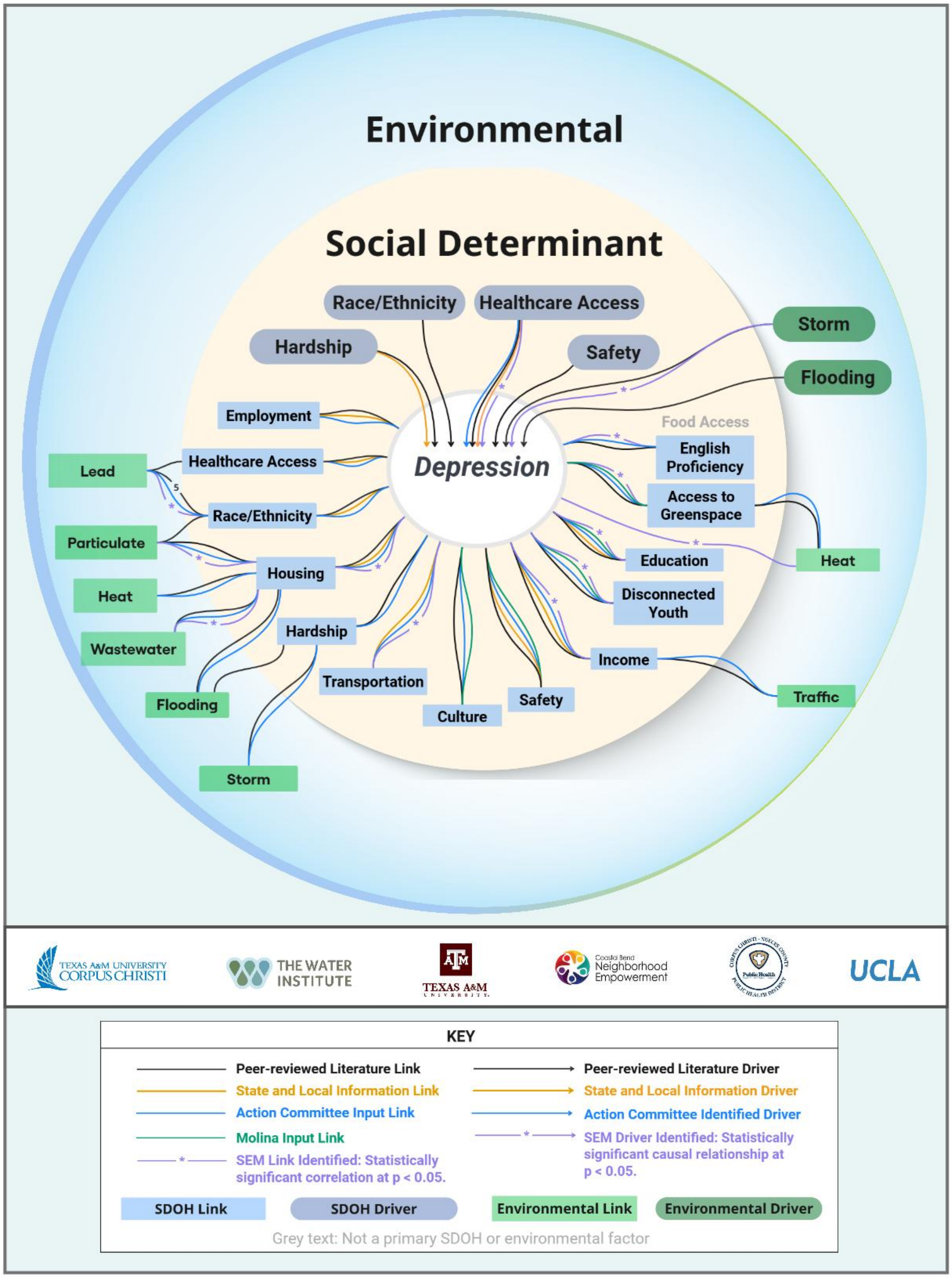


Figure 7 Logic model for depression showing different kinds of evidence demonstrating different SDOHs as links or drivers of the health outcome.Structural Equation Modeling links and drivers are marked with an asterisk (*) to indicate relationships that are statistically significant with p-value < 0.05, meaning there can be reasonable confidence that there is some non-zero association.

Interpretation: Depression Logic Model

The logic model shows which SDOHs are linked in a causal or correlated manner to depression as an outcome. It depicts data from peer-reviewed literature, state and local reports, expert input from the project's Logic Model Working Group and Action Committee and community level input from an at-risk neighborhood in the county. The number between the links represents the number of times the link or driver was mentioned.

The model connects social determinants of health to the outcome of depression, distinguishing between drivers and links. Climate and environmental factors are also illustrated as drivers of health outcomes or links to social determinants of health.

Areas of Convergence

Areas of convergence highlight where multiple lines of evidence align in linking social determinants of health and climate/environmental factors to depression.

SDOH Drivers

The following SDOHs emerged as drivers of depression across multiple ways of knowing.

- **Hardship** (NASEM, 2017; THI, 2022)
- **Healthcare access** (Amistad Community Health Center, 2023; NASEM, 2023; THI, 2022)
- **Safety** (NASEM, 2017)
- **Race/ethnicity** (Brulle & Pellow, 2006; Leung & Takeuchi, 2011; NASEM, 2017)

Links across SDOH and Climate/Environmental Factors

- Links between **depression** and the social determinant of **safety** were identified by all four data sources (action committee, local and community reports, peer-reviewed literature, and the local community survey in Molina).

> "Maslow's hierarchy of needs comes up. **Safety** is a big [part of] where you live, and where you live also impacts how flooding impacts…**mental health**"
>
> -SDOH Action Committee Member Comments

> What are your hopes or dreams for the neighborhood?
>
> **"Safety for Children"**
>
> If your hopes become reality, how would that impact your well-being?
>
> **"We could come out more, interact with the neighborhood.**
>
> -Molina Community Survey Respondents

- Culture was linked to depression by the action committee, Molina survey, and peer-reviewed literature.

"**Social isolation** and factors that affect it. [For Example] **social media, safety, heat**"

"**Food** is one of the key areas Action Committee members can impact, and that

their organization has witnessed a sharp decrease in cooking between immigrants who have just arrived in the area and those who have been here years. While some of the **mental health** challenges seem to be generational and **cultural, food and activity levels** seem to consistently degrade."

-SDOH Action Committee Member Comments

"Would love to do community events. Love to connect with others…to help."

"Community events, building community…more happiness, more friendship"

-Molina Community Survey Respondents

- Flooding was linked with the social determinants of hardship and housing by both the peer-reviewed literature and the action committee.

Areas of Opportunity

The areas of opportunity below identify underexplored relationships that warrant additional exploration to advance understanding and inform data-driven interventions.

Climate/Environmental Drivers

- Exposure to storms and flooding are identified as climate/environmental drivers of depression in both the peer-reviewed literature (Mason et al., 2010a) and SEM modeling. Local data and perspectives could contribute to a more nuanced understanding of this relationship.
- A link between exposure to storms and flooding and hardship was identified in both the peer-reviewed literature and the action committee. Local data and reports could contribute more granular community-level information about this relationship.

Supporting Information: Depression Logic Model

Table 6. MAXQDA CRB Output, SDOH and Depression: Frequency of Co-Occurrence by Data Source

Outcome	Connection Type	Data Source	Culture	Disconnected Youth	Education	Employment	English Proficiency	Food Access	Greenspace	Hardship	Healthcare Access	Housing	Income	Race/ Ethnicity	Safety	Transportation
Depression	Driver	Action Committee	0	0	0	0	0	0	0	0	1	0	0	0	0	0
		Peer Reviewed Literature	0	0	0	1	0	1	1	3	1	1	1	14	7	0
		Local/State Reports	0	0	0	0	0	0	0	1	3	0	0	0	0	0
		Molina Community Survey	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Link	Action Committee	34	8	7	6	1	4	9	4	9	9	10	3	10	2
		Peer Reviewed Literature	22	22	18	18	14	15	17	72	20	25	11	31	32	0
		Local/State Reports	0	0	1	2	0	1	0	0	13	6	2	4	1	4
		Molina Community Survey	8	1	1	0	0	0	2	0	0	0	0	0	6	0

Table 7. SDOH and Depression Links: References

SDOH	State and Local Assessments	Peer Reviewed Literature
Culture	N/A	Leung & Takeuchi, 2011; Brulle & Pellow, 2006; NASEM, 2017; NASEM, 2023
Disconnected Youth	N/A	Brulle & Pellow, 2006; Mason et al., 2010a; NASEM, 2017; NASEM, 2023
Education	Christus Spohn, 2023	Brulle & Pellow, 2006; NASEM, 2017; NASEM, 2023; Hood et al., 2016; CDC, 2013
Employment	Texas Health Institute, 2021; Christus Spohn, 2023	Han et al., 2022; Brulle & Pellow, 2006; Harrington, 2020; NASEM, 2017; CDC, 2013
English Proficiency	N/A	Brulle & Pellow, 2006; CDC, 2013
Food Access	Christus Spohn, 2023	Leung & Takeuchi, 2011; Brulle & Pellow, 2006; NASEM, 2017
Greenspace	N/A	Leung & Takeuchi, 2011; Brulle & Pellow, 2006; NASEM, 2017; Mears et al., 2020; Clarke et al., 2023
Hardship	N/A	Leung & Takeuchi, 2011; Brulle & Pellow, 2006; Mason et al., 2010a; Harrington, 2020; NASEM, 2017; NASEM, 2023
Healthcare Access	Texas Health Institute, 2021; THIN, 2020; Amistad Community Health Center, 2023; Christus Spohn, 2023	Leung & Takeuchi, 2011; Brulle & Pellow, 2006; Mason et al., 2010a; Harrington, 2020; NASEM, 2017
Housing	Texas Health Institute, 2021; THIN, 2020; Amistad Community Health Center, 2023; Christus Spohn, 2023	Brulle & Pellow, 2006; Leung & Takeuchi, 2011; Mason et al., 2010a; NASEM, 2017; NASEM, 2023
Income	N/A	Leung & Takeuchi, 2011; Brulle & Pellow, 2006; NASEM, 2017; NASEM, 2023
Race/Ethnicity	N/A	Brulle & Pellow, 2006; Mason et al., 2010a; NASEM, 2017; NASEM, 2023
Safety	Christus Spohn, 2023	Brulle & Pellow, 2006; NASEM, 2017; NASEM, 2023; Hood et al., 2016; CDC, 2013
Transportation	Texas Health Institute, 2021; Christus Spohn, 2023	Han et al., 2022; Brulle & Pellow, 2006; Harrington, 2020; NASEM, 2017; CDC, 2013

DIABETES LOGIC MODEL

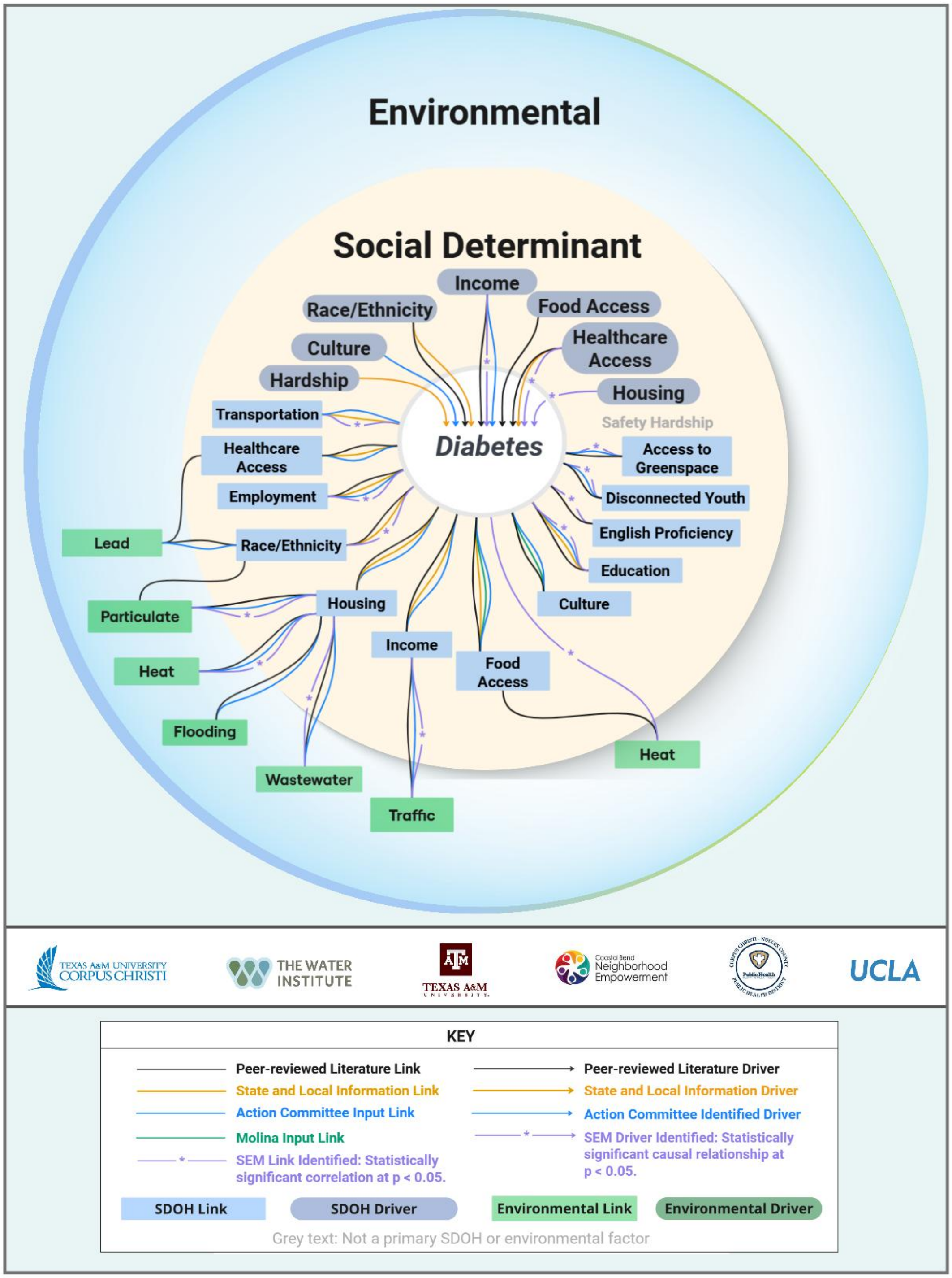


Figure 8. Logic model for diabetes showing different kinds of evidence demonstrating different SDOHs as links or drivers of the health outcome. Structural Equation Modeling links and drivers are marked with an asterisk (*) to indicate relationships that are statistically significant with p-value < 0.05, meaning there can be reasonable confidence that there is some non-zero association.

Interpretation: Diabetes Logic Model

The logic model shows which SDOHs are linked in a causal or correlated manner to diabetes as an outcome. It depicts data from peer-reviewed literature, state and local reports, expert input from the project's Logic Model Working Group and Action Committee and community level input from an at-risk neighborhood in the county. The number between the links represents the number of times the link or driver was mentioned.

The model connects social determinants of health to the outcome of diabetes, distinguishing between drivers and links. Climate and environmental factors are also illustrated as drivers of health outcomes or links to social determinants of health.

Areas of Convergence

Areas of convergence highlight where multiple lines of evidence align in linking social determinants of health and climate/environmental factors to diabetes.

SDOH Drivers

The following SDOHs emerged as drivers of diabetes across multiple ways of knowing.

- **Food access** (CDC, 2013; NASEM, 2017)
- **Healthcare access** (Amistad Community Health Center, 2023; THI, 2022)
- **Income**(Brulle & Pellow, 2006; CDC, 2013; NASEM, 2017)
- **Race/ethnicity** (Brulle & Pellow, 2006; Leung & Takeuchi, 2011; THI, 2022)
- **Culture**
- **Hardship** (THI, 2022)

Links across SDOH and Climate/Environmental Factors

- Links between diabetes and the social determinants of **food access**, **housing**, **culture**, **education**, and **income** were identified by the action committee, local and community reports, and peer-reviewed literature.

> "[Connections to] culture and food. Food choices, and food shows care"
>
> -SDOH Action Committee Member Comments

- A link between **heat** and **food** access was identified in the peer-reviewed literature (NASEM, 2017).
- A link between **traffic** and **income** was identified in both the peer-reviewed literature (CDC, 2013) and the action committee.

> "So let's not just focus on **how close people live to industry**. Look at the places that are really heavily populated, where there's a lot of **automobile traffic**.
>
> **"Tree-lined streets** naturally lower **traffic** speeds
>
> -SDOH Action Committee Member Comment*s*

Areas of Opportunity

The areas of opportunity below identify underexplored relationships that warrant additional exploration to advance understanding and inform data-driven interventions.

Climate/Environmental Drivers

- There are no identified climate/environmental drivers of diabetes in the model. Additional inquiry could illuminate potential climate/environmental drivers of diabetes, or validate the absence observed through the ways of knowing integrated into this logic model.

Supporting Information: Diabetes Logic Model

Table 8 MAXQDA CRB Output, SDOH and Diabetes: Frequency of Co-Occurrence by Data Source

Outcome	Connection Type	Data Source	Culture	Disconnected Youth	Education	Employment	English Proficiency	Food Access	Greenspace	Hardship	Healthcare Access	Housing	Income	Race/ Ethnicity	Safety	Transportation
Diabetes	Driver	Action Committee	1	0	0	0	0	0	0	0	0	0	1	0	0	0
		Peer Reviewed Literature	0	0	1	1	0	3	1	0	0	2	3	6	1	0
		Local/State Reports	0	0	0	0	0	0	0	1	3	0	0	1	0	0
		Molina Community Survey	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Link	Action Committee	18	1	7	1	0	5	1	0	12	1	6	0	0	1
		Peer Reviewed Literature	12	12	16	13	11	15	12	13	15	15	6	22	14	0
		Local/State Reports	0	0	2	3	0	3	0	0	9	4	3	6	1	4
		Molina Community Survey	1	0	0	0	0	1	0	0	0	0	0	0	0	0

Table 9. SDOH and Diabetes Links: References

	State and Local Assessments	Peer Reviewed Literature
Culture	N/A	Leung & Takeuchi, 2011; Brulle & Pellow, 2006
Disconnected Youth	N/A	Brulle & Pellow, 2006; NASEM, 2017
Education	CHRISTUS Spohn Health Needs Assessment 2019; Christus Spohn, 2023	Brulle & Pellow, 2006; NASEM, 2017; Hood et al., 2016; CDC, 2013
Employment	Texas Health Institute, 2021; Christus Spohn, 2023	Han et al., 2022; Brulle & Pellow, 2006; NASEM, 2017
English Proficiency	N/A	Brulle & Pellow, 2006
Food Access	THIN, 2020; Christus Spohn, 2023	Brulle & Pellow, 2006; NASEM, 2017; CDC, 2013
Greenspace	N/A	Brulle & Pellow, 2006; NASEM, 2017
Hardship	N/A	Leung & Takeuchi, 2011; Brulle & Pellow, 2006; CDC, 2013
Health care Access	Texas Health Institute, 2021; THIN, 2020; Amistad Community Health Center, 2023; Christus Spohn, 2023	Leung & Takeuchi, 2011; Brulle & Pellow, 2006; CDC, 2013
Housing	Texas Health Institute, 2021; Amistad Community Health Center, 2023; Christus Spohn, 2023	Brulle & Pellow, 2006; NASEM, 2017; CDC, 2013
Income	Texas Health Institute, 2021; THIN, 2020; Amistad Community Health Center, 2023; Christus Spohn, 2023	Han et al., 2022; Brulle & Pellow, 2006; NASEM, 2017; CDC, 2013
Race/Ethnicity	Texas Health Institute, 2021; Christus Spohn, 2023	Leung & Takeuchi, 2011; Brulle & Pellow, 2006; Hood et al., 2016; CDC, 2013
Safety	Christus Spohn, 2023	Brulle & Pellow, 2006; NASEM, 2017; Hood et al., 2016
Transportation	Texas Health Institute, 2021; Christus Spohn, 2023	N/A

HYPERTENSION LOGIC MODEL

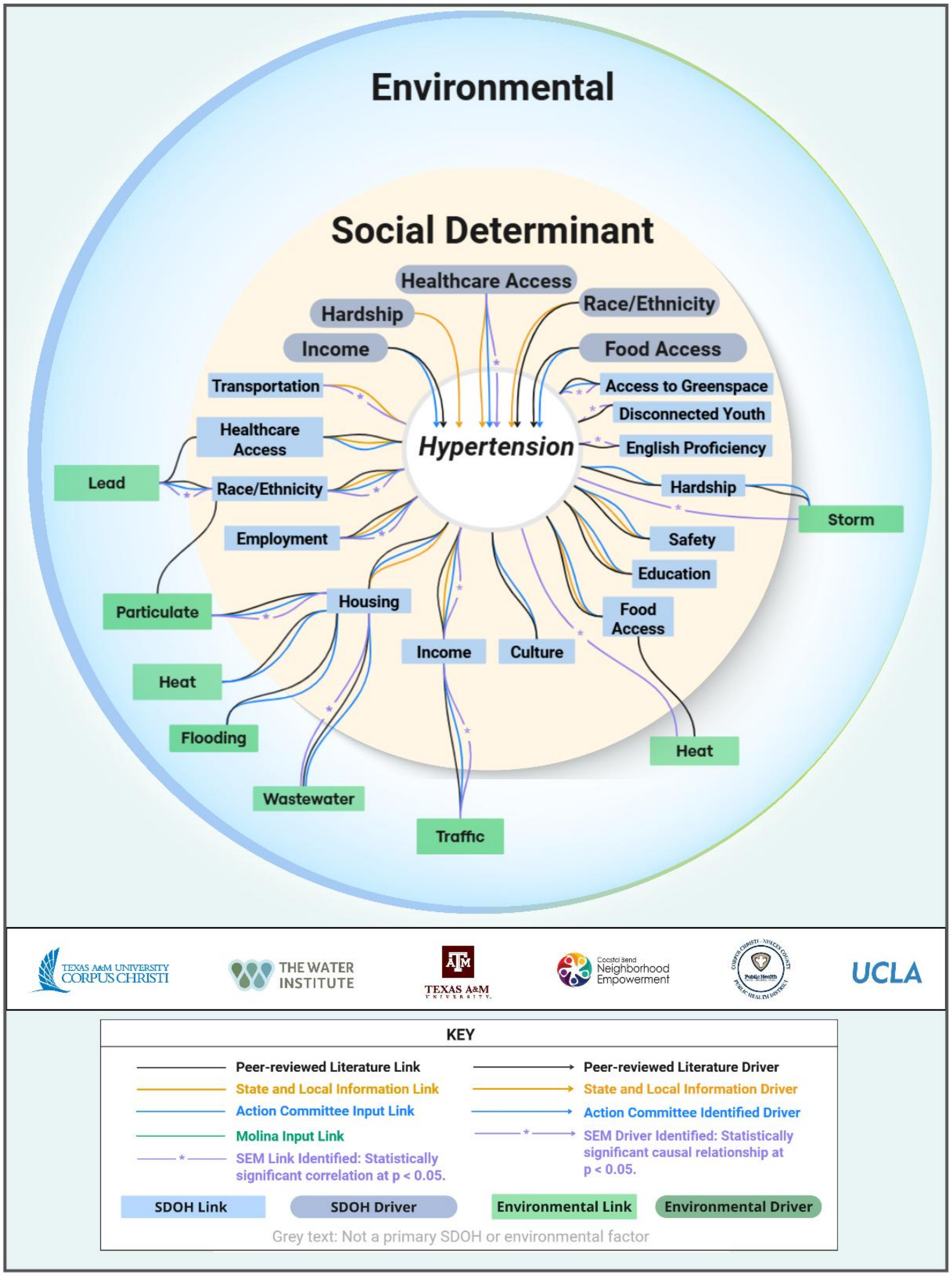


Figure 9. Logic model for hypertension showing different kinds of evidence demonstrating different SDOHs as links or drivers of the health outcome. Structural Equation Modeling links and drivers are marked with an asterisk (*) to indicate relationships that are statistically significant with p-value < 0.05, meaning there can be reasonable confidence that there is some non-zero association.

Interpretation: Hypertension Logic Model

The logic model shows which SDOHs are linked in a causal or correlated manner to hypertension as an outcome. It depicts data from peer-reviewed literature, state and local reports, expert input from the project's Logic Model Working Group and Action Committee and community level input from an at-risk neighborhood in the county. The number between the links represents the number of times the link or driver was mentioned.

The model connects social determinants of health to the outcome of asthma, distinguishing between drivers and links. Climate and environmental factors are also illustrated as drivers of health outcomes or links to social determinants of health.

Areas of Convergence

Areas of convergence highlight where multiple lines of evidence align in linking social determinants of health and climate/environmental factors to hypertension.

SDOH Drivers

The following SDOHs emerged as drivers of hypertension across multiple ways of knowing.

- **Income** (Brulle & Pellow, 2006; CDC, 2013)
- **Hardship** (THI, 2022)
- **Healthcare access** (Amistad Community Health Center, 2023)
- **Race/ethnicity** (Brulle & Pellow, 2006; Leung & Takeuchi, 2011, 2011; THI, 2022)
- **Food access** (NASEM, 2023)

Links across SDOH and Climate/Environmental Factors

- Links between **hypertension** and the social determinants of **healthcare access, race/ethnicity, employment, housing, education, food access, safety,** and i**ncome** were identified by the action committee, local and community reports, and peer-reviewed literature.

> "There are so many components relating to **stressors** that can lead to **hypertension**. [For example], professional career, work-life balance, cultural expectations, mental health, etc."
>
> "If person does not work or have insurance paying for **hypertension** meds may be cost prohibitive or even going to dr for treatment"
>
> -SDOH Action Committee Member Comments

- A link between storm exposure and hardship was identified in both the peer-reviewed literature (Mason et al., 2010a) and the action committee.

> "[Consider] **compound disasters** and **trauma**."
>
> "So if you rent and you can't afford rental **insurance**, which some insurance companies may not write policies depending upon where you live in Corpus Christi. Various places you may not be able to get renter insurance to cover your contents, and if you can, it can be very expensive."
>
> -SDOH Action Committee Member Comments

Areas of Opportunity

The areas of opportunity below identify underexplored relationships that warrant additional exploration to advance understanding and inform data-driven interventions.

Climate/Environmental Drivers

- There are no identified climate/environmental drivers of hypertension in the model. Additional inquiry could illuminate potential climate/environmental drivers of hypertension, or validate the absence observed through the ways of knowing integrated into this logic model.

Supporting Information: Hypertension Logic Model

Table 10. MAXQDA CRB Output, SDOH and Hypertension, Frequency of Co-Occurrence by Data Source

Outcome	Connection Type	Data Source	Culture	Disconnected Youth	Education	Employment	English Proficiency	Food Access	Greenspace	Hardship	Healthcare Access	Housing	Income	Race/ Ethnicity	Safety	Transportation
Hypertension	Driver	Action Committee	0	0	0	0	0	1	0	0	2	0	1	0	0	0
		Peer Reviewed Literature	0	0	0	1	0	1	0	0	0	1	2	6	1	0
		Local/State Reports	0	0	0	0	0	0	0	1	2	0	0	1	0	0
		Molina Community Survey	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Link	Action Committee	8	0	5	2	0	6	3	4	11	2	6	3	2	0
		Peer Reviewed Literature	12	11	12	12	11	12	11	12	20	12	3	25	13	0
		Local/State Reports	0	0	2	2	0	1	0	0	6	3	2	6	1	4
		Molina Community Survey	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 11. SDOH and Hypertension Links: References

SDOH	State and Local Assessments	Peer Reviewed Literature
Culture	N/A	Leung & Takeuchi, 2011; Brulle & Pellow, 2006
Disconnected Youth	N/A	Brulle & Pellow, 2006
Education	Christus Spohn, 2023	Brulle & Pellow, 2006; Hood et al., 2016
Employment	Texas Health Institute, 2021; Christus Spohn, 2023	Han et al., 2022; Brulle & Pellow, 2006
English Proficiency	N/A	Brulle & Pellow, 2006
Food Access	Christus Spohn, 2023	Brulle & Pellow, 2006; NASEM, 2017
Greenspace	N/A	Brulle & Pellow, 2006
Hardship	N/A	Leung & Takeuchi, 2011; Brulle & Pellow, 2006
Healthcare Access	Amistad Community Health Center, 2023; CHRISTUS Spohn Health Needs Assessment 2019; Christus Spohn, 2023	Leung & Takeuchi, 2011; Brulle & Pellow, 2006; CDC, 2013
Housing	Texas Health Institute, 2021; Christus Spohn, 2023	Brulle & Pellow, 2006; NASEM, 2017
Income	Amistad Community Health Center, 2023; Christus Spohn, 2023	Han et al., 2022; Brulle & Pellow, 2006
Race/Ethnicity	Texas Health Institute, 2021; Christus Spohn, 2023	Leung & Takeuchi, 2011; Brulle & Pellow, 2006; NASEM, 2017; NASEM, 2023; Hood et al., 2016; CDC, 2013
Safety	Christus Spohn, 2023	Brulle & Pellow, 2006; NASEM, 2017; Hood et al., 2016
Transportation	Texas Health Institute, 2021; Christus Spohn, 2023	N/A

OBESITY LOGIC MODEL

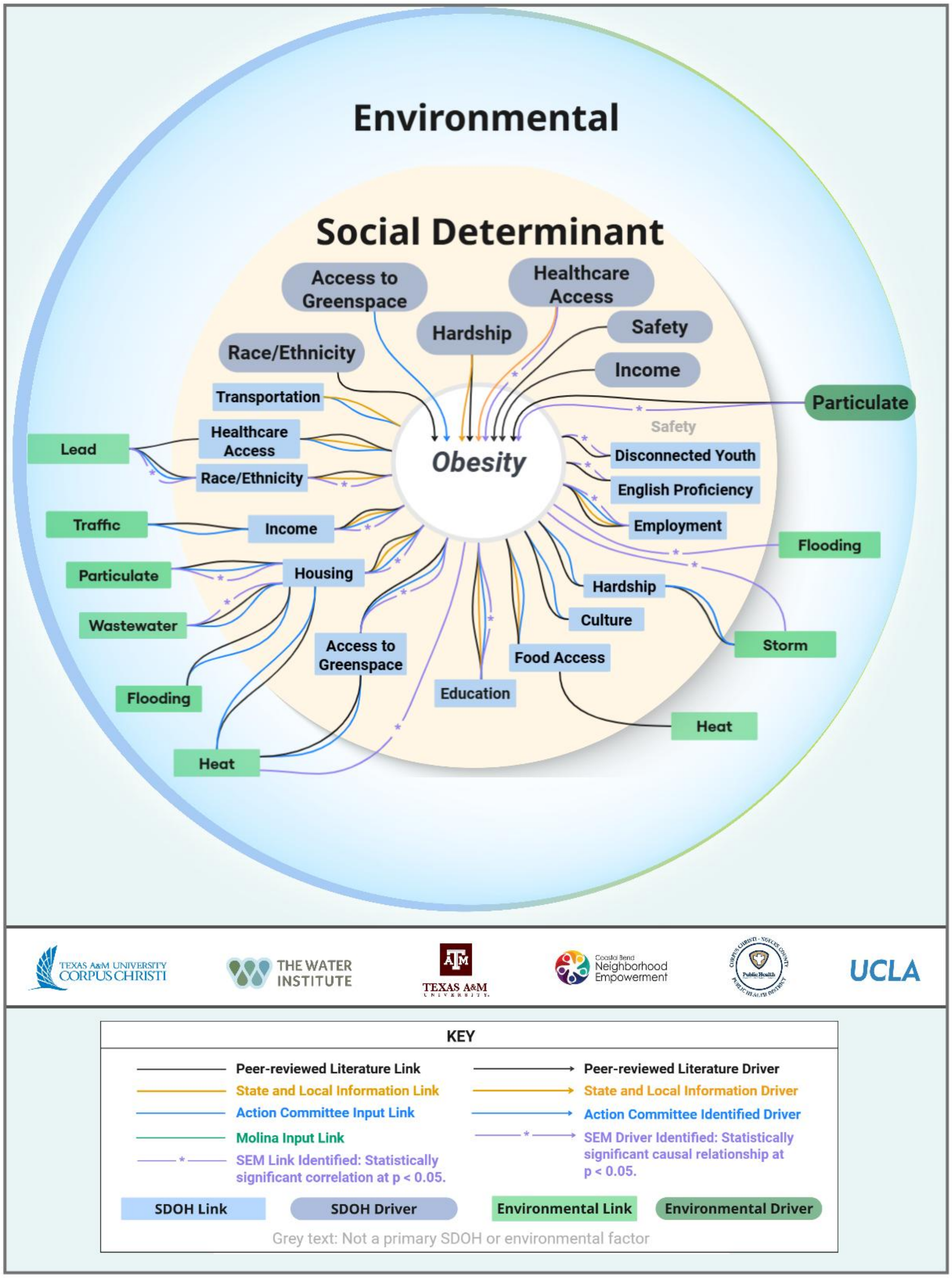


Figure 10. Logic model for obesity showing different kinds of evidence demonstrating different SDOHs as links or drivers of the health outcome. Structural Equation Modeling links and drivers are marked with an asterisk (*) to indicate relationships that are statistically significant with p-value < 0.05, meaning there can be reasonable confidence that there is some non-zero association.

Interpretation: Obesity Logic Model

The logic model shows which SDOHs are linked in a causal or correlated manner to obesity as an outcome. It depicts data from peer-reviewed literature, state and local reports, expert input from the project's Logic Model Working Group and Action Committee and community level input from an at-risk neighborhood in the county. The number between the links represents the number of times the link or driver was mentioned.

The model connects social determinants of health to the outcome of obesity, distinguishing between drivers and links. Climate and environmental factors are also illustrated as drivers of health outcomes or links to social determinants of health.

Areas of Convergence

Areas of convergence highlight where multiple lines of evidence align in linking social determinants of health and climate/environmental factors to obesity.

SDOH Drivers

The following SDOHs emerged as drivers of obesity across multiple ways of knowing.

- **Access to Greenspace**
- **Race/ethnicity** (Brulle & Pellow, 2006; Leung & Takeuchi, 2011)
- **Hardship** (NASEM, 2017; THI, 2022)
- **Healthcare access**(NASEM, 2017)
- **Safety** (NASEM, 2017)
- **Income** (Brulle & Pellow, 2006; NASEM, 2017)

Links across SDOH and Climate/Environmental Factors

- Links between **obesity** and the social determinants of h**ealthcare access, housing, education, food access,** and **employment** were identified by the action committee, local and community reports, and peer-reviewed literature.
- A link between **storm exposure** and **hardship** (Mason et al., 2010a) was identified in both the peer-reviewed literature and the action committee.
- A link between **heat** and **food access** was identified in the peer-reviewed literature (NASEM, 2017).

Areas of Opportunity

The areas of opportunity below identify underexplored relationships that warrant additional exploration to advance understanding and inform data-driven interventions.

SDOH Drivers

- The Action Committee identified **access to green space** as a key drivers of **depression**. This relationship could be further examined using broader community-level data and by analyzing relevant case examples from other communities.

> *"Access to greenspace [would] influence obesity assuming that getting outdoors is linked to exercise."*
>
> *-SDOH Action Committee Member Comment*

Climate/Environmental Drivers

Particulate exposure is identified as a driver of **obesity** (Mears et al., 2020), but this link was identified as an opportunity for further research by the Action Committee during the June 2025 meeting, with feedback such as:

> *"Unsure about particulate link with obesity"*
> *"[Is there a] potential connection to exposure to endocrine disruptors?"*
>
> *-SDOH Action Committee Member Comments*

Supporting Information: Obesity Logic Model

Table 12. MAXQDA CRB Output, SDOH and Obesity: Frequency of Co-Occurrence by Data Source

Outcome	Connection Type	Data Source	Culture	Disconnected	Education	Employment	English	Food Access	Greenspace	Hardship	Healthcare Access	Housing	Income	Race/ Ethnicity	Safety	Transportation
Obesity	Driver	Action Committee	0	0	0	0	0	0	1	0	0	0	0	0	0	0
		Peer Reviewed Literature	0	0	1	1	0	1	0	2	0	1	2	5	2	0
		Local/State Reports	0	0	0	0	0	0	0	1	3	0	0	0	0	0
		Molina Community Survey	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	Link	Action Committee	14	0	3	1	0	15	6	5	3	3	9	0	4	2
		Peer Reviewed Literature	16	14	25	12	14	19	29	12	13	18	6	27	14	0
		Local/State Reports	0	0	1	3	0	2	0	0	8	4	3	6	1	4
		Molina Community Survey	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 13. SDOH and Obesity Links: References

SDOH	State and Local Assessments	Peer Reviewed Literature
Culture	N/A	N/A
Disconnected Youth	N/A	Brulle & Pellow, 2006; NASEM, 2017; NASEM, 2023
Education	Christus Spohn, 2023	Brulle & Pellow, 2006; NASEM, 2017; NASEM, 2023; CDC, 2013
Employment	Texas Health Institute, 2021; Christus Spohn, 2023	Brulle & Pellow, 2006; NASEM, 2017
English Proficiency	N/A	Brulle & Pellow, 2006; CDC, 2013
Food Access	Christus Spohn, 2023	Brulle & Pellow, 2006; NASEM, 2017; CDC, 2013; Mears et al., 2020
Greenspace	N/A	Brulle & Pellow, 2006; CDC, 2013; Mears et al., 2020
Hardship	N/A	Leung & Takeuchi, 2011; Brulle & Pellow, 2006
Healthcare Access	Texas Health Institute, 2021; Amistad Community Health Center, 2023; Christus Spohn, 2023	Leung & Takeuchi, 2011; Brulle & Pellow, 2006; CDC, 2013
Housing	Texas Health Institute, 2021; Amistad Community Health Center, 2023; Christus Spohn, 2023	Brulle & Pellow, 2006; NASEM, 2017; CDC, 2013; Mears et al., 2020
Income	Texas Health Institute, 2021; Amistad Community Health Center, 2023; Christus Spohn, 2023	Brulle & Pellow, 2006; NASEM, 2023; Mears et al., 2020
Race/Ethnicity	Texas Health Institute, 2021	Leung & Takeuchi, 2011; Brulle & Pellow, 2006; NASEM, 2017; NASEM, 2023; CDC, 2013; Mears et al., 2020
Safety	Christus Spohn, 2023	Brulle & Pellow, 2006; NASEM, 2017
Transportation	Texas Health Institute, 2021; Christus Spohn, 2023	N/A

LIMITATIONS

It is important to consider that logic models have limitations in understanding the impact of SDOHs on health outcomes. While such tools are useful in identifying key relationships across SDOH and health outcomes, they do not capture the dynamic and non-linear pathways through which SDOHs, environmental, and climate factors affect health. For example, a single intervention addressing housing instability cannot be easily separated from other factors like economic conditions, education levels, and neighborhood safety, all of which interact in complex ways to influence individual and community health. Furthermore, logic models often focus on intended outcomes, potentially overlooking the unintended or negative consequences of an intervention. This linear approach does not account for feedback loops and the long delays between a social change and its impact on health outcomes, making it difficult to attribute a specific health improvement solely to a single program or policy.

To help address this concern, the project team worked to, at a minimum, identify where significant evidence was found to substantiate relationships. As described above, the team identified causation (drivers) where significant evidence was found to substantiate such a linkage. Causation was initially identified where types of evidence (primarily peer-reviewed or state and local reports, but in some cases also through concurrence of the Action Committee) stated the relationship as causal. The identified causal relationships were then evaluated through SEM to understand if the causal relationships identified were consistent with project data. Significant relationships identified through SEM, i.e., where structural equation modeling resulted in a p-value < 0.05, were included in each logic model. Elsewhere, the team identified correlations, or links, where evidence noted a relationship exists (i.e., two factors are linked, though the model cannot tell one how). Similarly, SEM was used to evaluate which of those links were statistically significant with project data.

A second important consideration for this study is that, as with all analyses, the results are limited by the data that were available to assess key relationships. In particular, data to better understand the significance or impact of culture on health outcomes is wholly lacking, other than anecdotes gathered from the Molina community. In addition, the project team was not successful in gathering data for safety or food security at the census tract level, which was the agreed upon scale of assessment. Disconnected youth and hardship were also difficult to assess as these are composite indicators, and thus choices had to be made during coding on whether the data presented could be used as proxies.

Finally, the SEM used to analyze linkages also comes with limitations. The study was structured such that the relationships in the final version of the logic models were tested through SEM. However, if a key variable were omitted from the model—for example, food access, for which data were not obtained—the results may be misleading and biased. Furthermore, SEM also assumes linear relationships among variables, which may not accurately represent the complex and non-linear ways in which social factors interact to influence health. Finally, SEM's reliance on "goodness-of-fit" indices can be deceptive; a model may statistically "fit" the data well, but that does not guarantee that the model is the correct or most meaningful representation of the underlying social reality.

CONCLUSION

This project integrated diverse types of data and local perspectives to explore how SDOH, climate, and environmental factors shape health outcomes and health disparities in Nueces County. By combining national and state datasets with local assessments and community knowledge, the logic models illustrate where different sources of information align and where local insight adds important context.

The models offer a tool for health practitioners, planners, and community partners to better understand which social and environmental factors are connected to specific health outcomes. This can help guide next steps for data collection to address gaps in understanding about connections between SDOH and health outcomes. It can also support planning and action for local strategies to address health disparities and reduce sensitivity to climate and environmental factors.

Although focused on Nueces County, the sequential, phased approach outlined in this document may be adapted to other communities to help blend multiple ways of knowing to inform decision-making and action toward improved health outcomes for all.

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APPENDICES

APPENDIX A. APPENDIX A: STRUCTURAL EQUATION MODELING: DETAILED RESULTS

A.1 SPECIFICATION OF MODEL

First, the project team standardized the data so that every column in the data matrix has mean 0 and standard deviation 1. Then the team fit the SEM encoded by both 1 and 2 prescribed below.

- For any health outcome (square box at the center) and its causal predictors (rectangles with round corners), we modeled the health outcome (Y) as a linear combination of the observed causal predictors (X_1, X_2, …, X_p) plus an unobserved error term (ε):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p + \varepsilon$$

- where β_0 is the intercept, β_i are the estimated regression coefficients for each predictor X_i, and ε represents random noise capturing unobserved factors. The coefficients in the above linear combinations are called the regression coefficients, which are unknown parameters to be estimated.
- Furthermore, accompanying to the above, the team also considered possible associations (links) among some of the variables, represented by the correlation coefficients between them, which are again unknown parameters to be estimated.

A.1.1 Example

Depression was modeled (Y) as a linear function of several predictors. In the logic model diagrams, these are identified as drivers. In this example, the project team considered drivers race/ethnicity, healthcare access, storm exposure, and flood exposure—plus an unobserved error term (ε):

$$Y = a\cdot\text{Race/Ethnicity} + b\cdot\text{Healthcare Access} + c\cdot\text{Storm} + d\cdot\text{Flood} + \varepsilon$$

Depression = a·Race/Ethnicity + b·Healthcare Access + c·Storm + d·Flood + some unobserved noise.

To understand relationships between linked factors in the logic models, correlation between variables was considered. For every pair of variables V_i and V_j that are assumed to be linked, their correlation coefficient is represented as the unknown parameter r_{ij}:

$$r_{ij} = \text{corr}(V_i, V_j) = \text{cov}(V_i, V_j) / (\sigma(V_i) \times \sigma(V_j))$$

where $\text{cov}(V_i, V_j)$ is the covariance between V_i and V_j, and $\sigma(V_i)$ and $\sigma(V_j)$ are their standard deviations.

A.2 INTERPRETATION OF THE RESULTS

Because the project team standardized the data before running the SEM, the parameter estimates can be interpreted as **standardized regression coefficients**. In simple terms, show how many standard deviations the health outcome (e.g., depression) is expected to change for a one standard deviation change in the predictor, holding other predictors constant. For example, as the estimate for “Health care access → Depression” is **0.303*** (noted on the directed edge), it means that a one standard deviation increase in health care access is associated with a 0.303 standard deviation increase in depression, and the asterisk indicates that this effect is statistically significant (with p-value < 0.05). In contrast, estimates without an asterisk represent associations that were not statistically significant and should be interpreted cautiously.

The bi-directed edges “↔” represent correlations among variables, showing how strongly two social or environmental factors are associated while accounting for the rest of the model. These are also standardized, so values closer to **+1** indicate strong positive associations, values closer to **–1** indicate strong negative associations, and values near **0** indicate weak or no association. Each correlation is again accompanied by a **statistical test of significance**, which assesses whether the observed association truly exists in practice, or it is likely to have arisen by chance (that is, in reality there is no association between them). In the results, an asterisk (*****) marks correlations that are statistically significant with p-value < 0.05, meaning there can be reasonable confidence that there is some non-zero association.

In this way, the model results help identify which environmental and social determinants appear to have the strongest and most consistent links or prediction to health outcomes, while also highlighting which are weaker or not statistically significant.

A.2.1 Detailed Structural Equation Model: Asthma

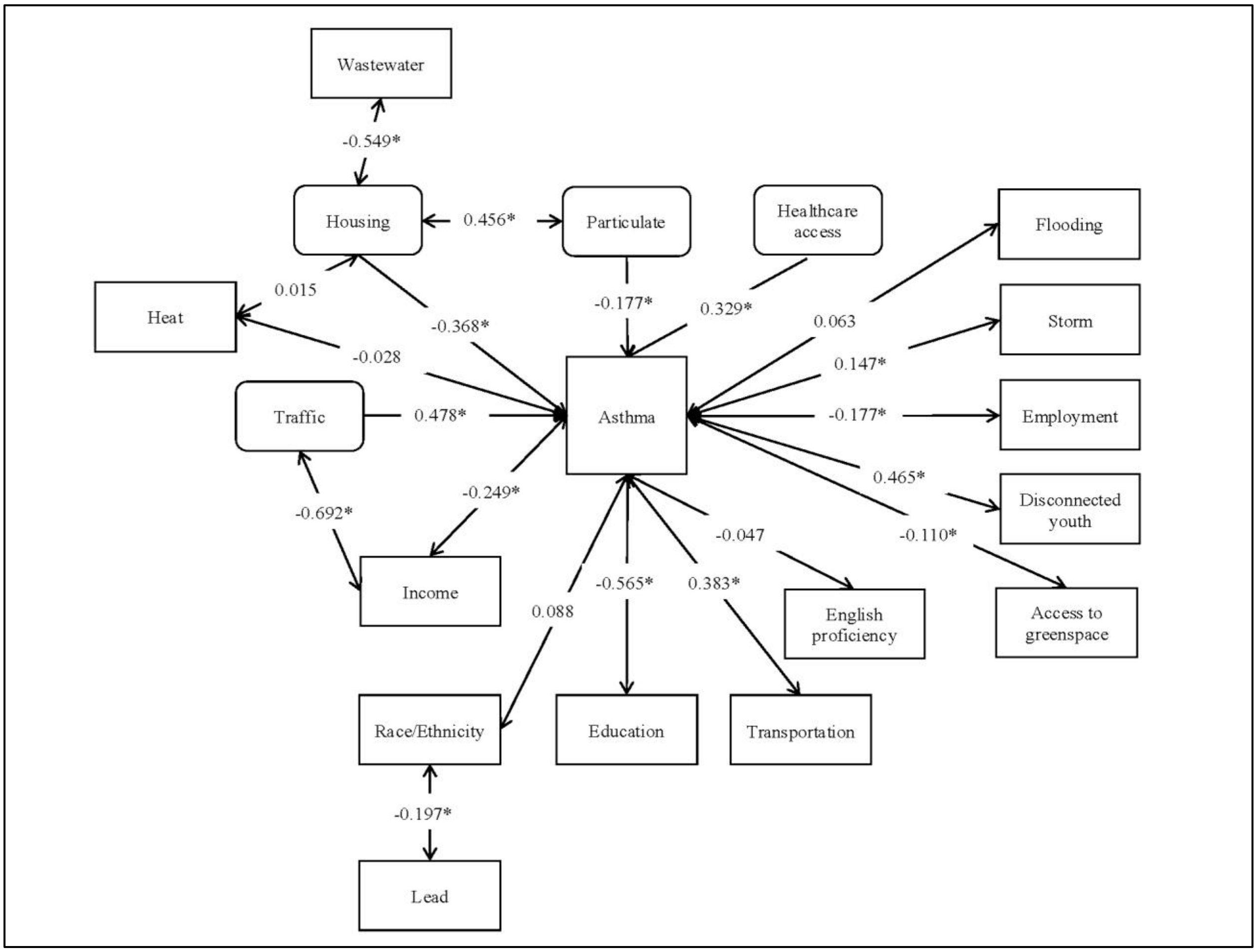

Figure A-1. Detailed Structural Equation Model Diagram for Asthma Outcome

A.2.2 Model Interpretation

The bi-directed edges "↔" represent correlations among variables, showing how strongly two social or environmental factors are associated after accounting for the rest of the model. These are also standardized, so values closer to **+1** indicate strong positive associations, values closer to **–1** indicate strong negative associations, and values near **0** indicate weak or no association.

Each correlation is accompanied by a **statistical test of significance**, which assesses whether the observed association truly exists in practice, or it is likely to have arisen by chance. In the results, an asterisk (*****) marks correlations that are statistically significant with p-value < 0.05, meaning that there can be reasonable confidence that there is some non-zero association.

A.2.3 SEM Equation

Asthma = a·Particulate + b·Traffic + c·Housing + d·Healthcare Access + some unobserved noise.

A.2.4 Detailed Structural Equation Model: Depression

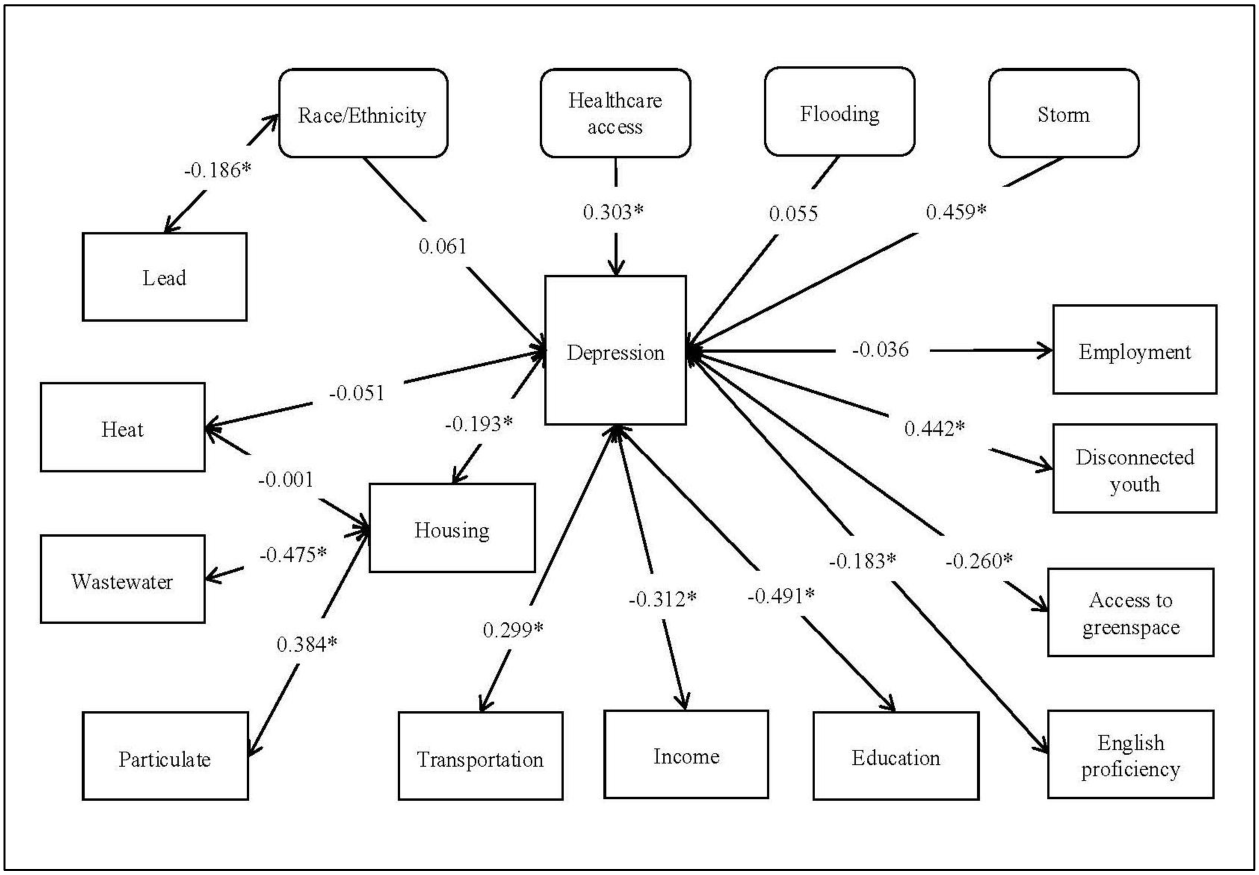

Figure A-2. Detailed Structural Equation Model Diagram for Depression Outcome

A.2.5 Model Interpretation

The bi-directed edges "↔" represent correlations among variables, showing how strongly two social or environmental factors are associated after accounting for the rest of the model. These are also standardized, so values closer to **+1** indicate strong positive associations, values closer to **–1** indicate strong negative associations, and values near **0** indicate weak or no association.

Each correlation is accompanied by a **statistical test of significance**, which assesses whether the observed association truly exists in practice, or it is likely to have arisen by chance. In the results, an asterisk (*****) marks correlations that are statistically significant with p-value < 0.05, meaning we can be reasonably confident that there is some non-zero association.

A.2.6 SEM Equation

$$\text{Depression} = a\cdot\text{Race/Ethnicity} + b\cdot\text{Healthcare Access} + c\cdot\text{Storm} + d\cdot\text{Flood} + \text{some unobserved noise.}$$

A.2.7 Detailed Model Variable Correlations: Hypertension

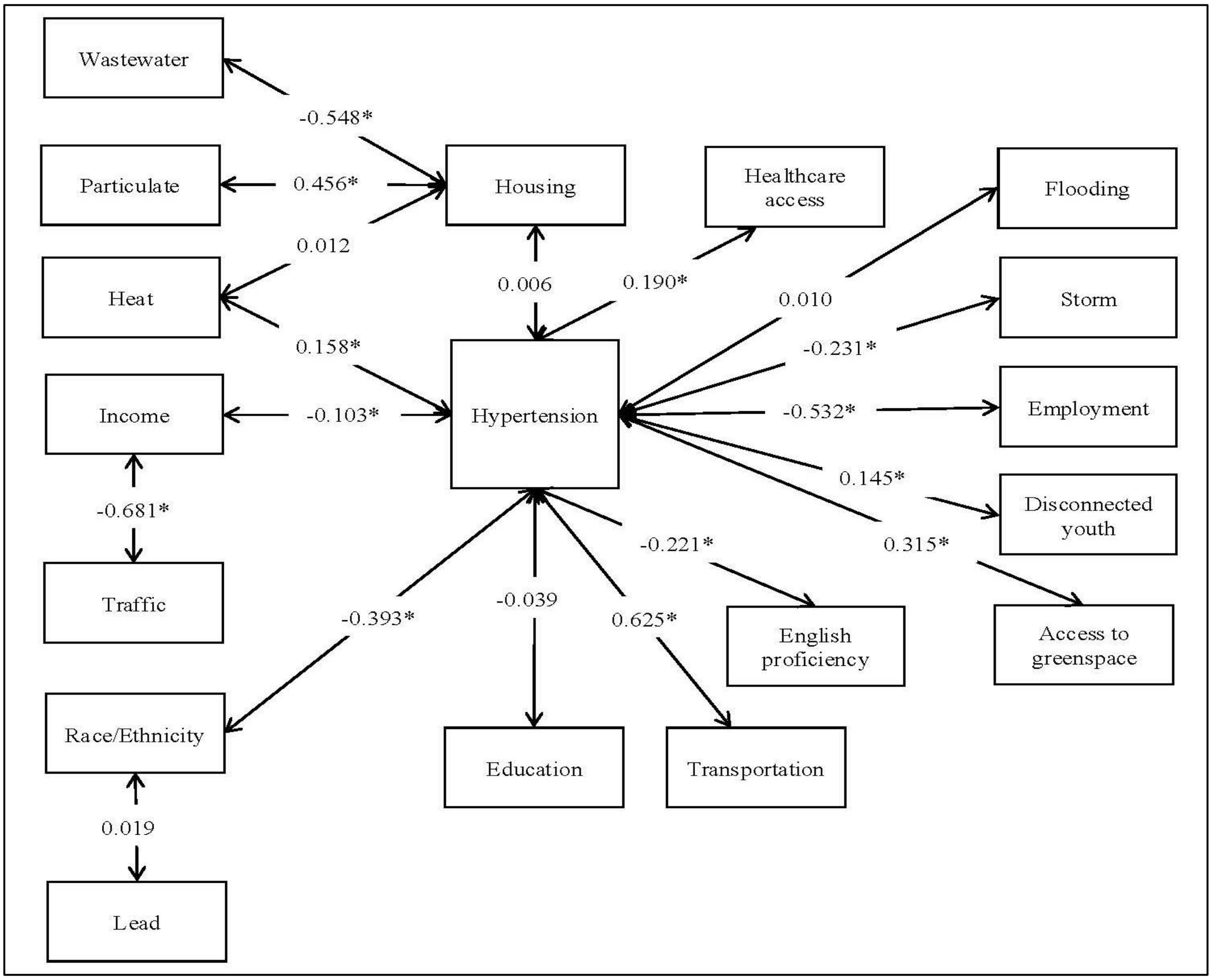

Figure A-3. Detailed Model Diagram of variable correlations for Hypertension Outcome

A.2.8 Model Interpretation

The bi-directed edges "↔" represent correlations among variables, showing how strongly two social or environmental factors are associated after accounting for the rest of the model. These are also standardized, so values closer to **+1** indicate strong positive associations, values closer to **–1** indicate strong negative associations, and values near **0** indicate weak or no association.

Each correlation is accompanied by a **statistical test of significance**, which assesses whether the observed association truly exists in practice, or it is likely to have arisen by chance. In the results, an asterisk (*****) marks correlations that are statistically significant with p-value < 0.05, meaning we can be reasonably confident that there is some non-zero association.

A.2.9 Equation

Only variable correlations are illustrated in the model above.

A.2.10 Detailed Structural Equation Model: Obesity

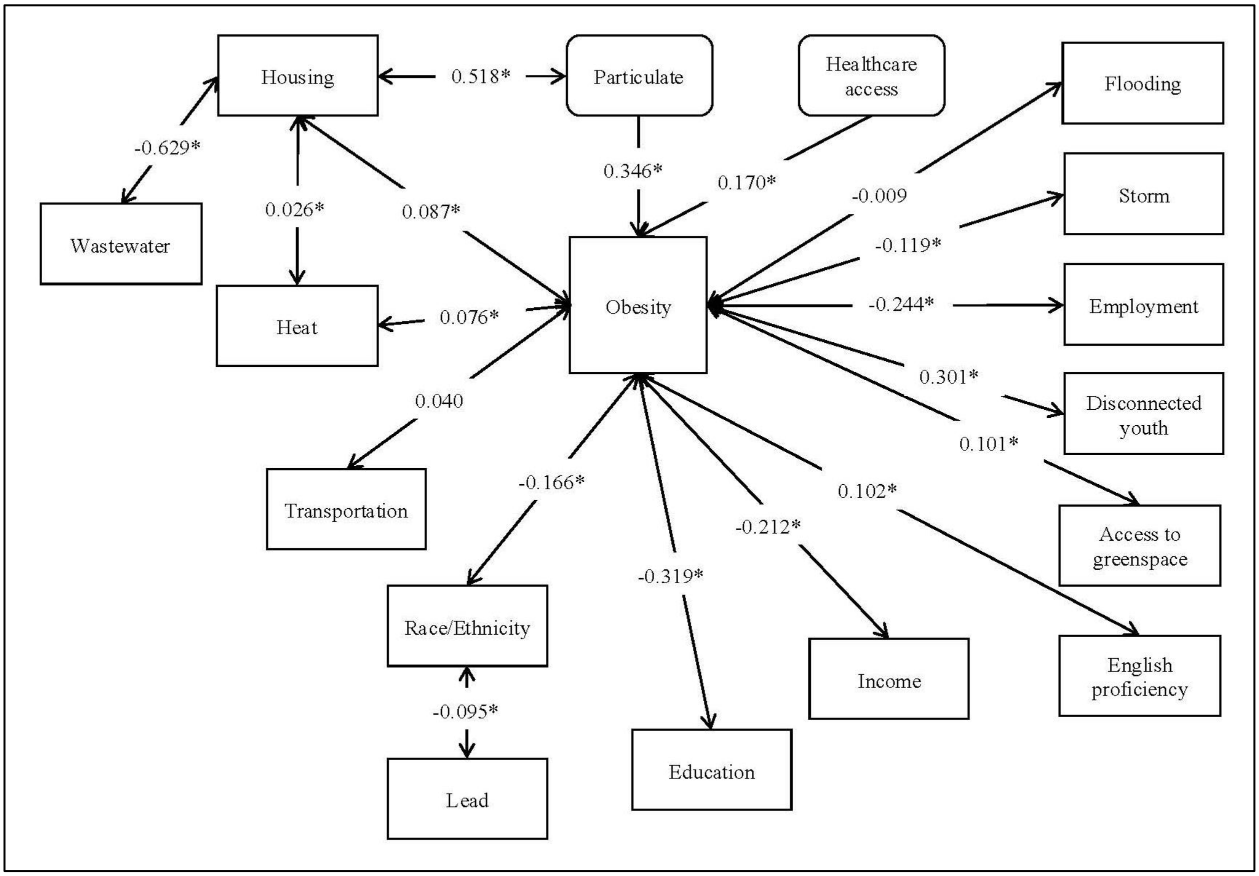

Figure A-4. Detailed Structural Equation Model Diagram for Obesity Outcome

A.2.11 Model Interpretation

The bi-directed edges "↔" represent correlations among variables, showing how strongly two social or environmental factors are associated after accounting for the rest of the model. These are also standardized, so values closer to **+1** indicate strong positive associations, values closer to **–1** indicate strong negative associations, and values near **0** indicate weak or no association.

Each correlation is accompanied by a **statistical test of significance**, which assesses whether the observed association truly exists in practice, or it is likely to have arisen by chance. In the results, an asterisk (*****) marks correlations that are statistically significant with p-value < 0.05, meaning we can be reasonably confident that there is some non-zero association.

A.2.12 SEM Equation

$$\text{Obesity} = a \cdot \text{Particulate} + b \cdot \text{Healthcare Access} + \text{some unobserved noise.}$$

A.2.13 Detailed Structural Equation Model: Diabetes

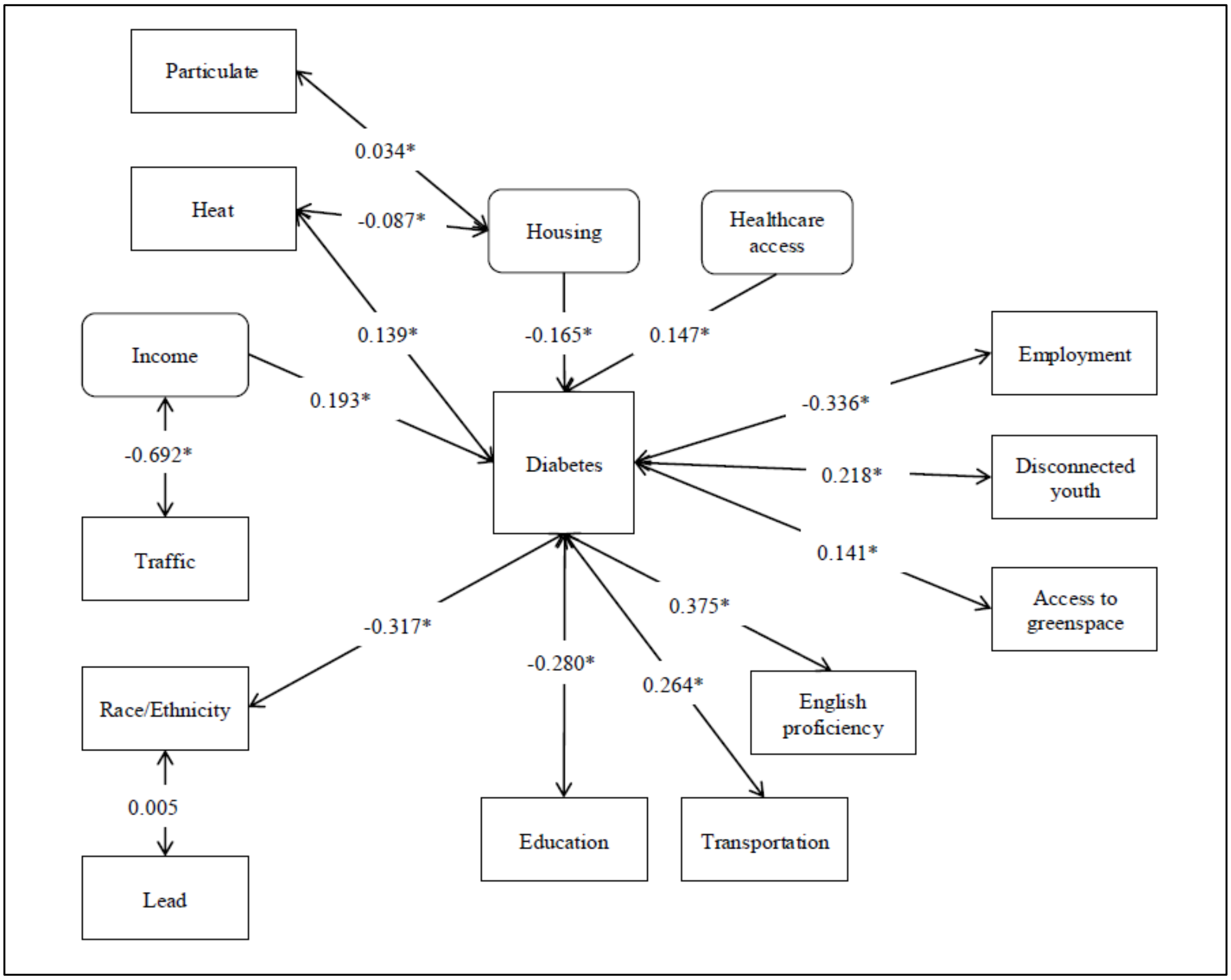

Figure A-1. Detailed Structural Equation Model Diagram for Diabetes Outcome

A.2.14 Model Interpretation

The bi-directed edges "↔" represent correlations among variables, showing how strongly two social or environmental factors are associated after accounting for the rest of the model. These are also standardized, so values closer to **+1** indicate strong positive associations, values closer to **–1** indicate strong negative associations, and values near **0** indicate weak or no association.

Each correlation is accompanied by a **statistical test of significance**, which assesses whether the observed association truly exists in practice, or it is likely to have arisen by chance. In the results, an asterisk (*****) marks correlations that are statistically significant with p-value < 0.05, meaning we can be reasonably confident that there is some non-zero association.

A.2.15 SEM Equation

Diabetes = a·Housing + b·Income + c·Healthcare Access + some unobserved noise.

APPENDIX B. CLIMATE AND ENVIRONMENTAL DRIVERS

Outcome	Type	Data Source	Flooding	Heat	Lead	Ozone	Particulate	Storm	Traffic	UST	Wastewater
Asthma	Driver	Action Committee	0	0	0	0	1	0	0	0	0
		Peer Reviewed Literature	0	0	0	0	2	0	1	0	0
		Local/State Reports	0	0	0	0	0	0	0	0	0
		Molina Community Survey	0	0	0	0	0	0	0	0	0

Outcome	Type	Data Source	Flooding	Heat	Lead	Ozone	Particulate	Storm	Traffic	UST	Wastewater
Depression	Driver	Action Committee	0	0	0	0	0	0	0	0	0
		Peer Reviewed Literature	33	0	0	0	0	5	0	0	0
		Local/State Reports	0	0	0	0	0	0	0	0	0
		Molina Community Survey	0	0	0	0	0	0	0	0	0

Outcome	Type	Data Source	Flooding	Heat	Lead	Ozone	Particulate	Storm	Traffic	UST	Wastewater
Diabetes	Driver	Action Committee	0	0	0	0	0	0	0	0	0
		Peer Reviewed Literature	0	0	0	0	0	0	0	0	0
		Local/State Reports	0	0	0	0	0	0	0	0	0
		Molina Community Survey	0	0	0	0	0	0	0	0	0

Outcome	Type	Data Source	Flooding	Heat	Lead	Ozone	Particulate	Storm	Traffic	UST	Wastewater
Hypertension	Driver	Action Committee	0	0	0	0	0	0	0	0	0
		Peer Reviewed Literature	0	0	0	0	0	0	0	0	0
		Local/State Reports	0	0	0	0	0	0	0	0	0
		Molina Community Survey	0	0	0	0	0	0	0	0	0

Outcome	Type	Data Source	Flooding	Heat	Lead	Ozone	Particulate	Storm	Traffic	UST	Wastewater
Obesity	Driver	Action Committee	0	0	0	0	0	0	0	0	0
		Peer Reviewed Literature	0	0	0	0	1	0	0	0	0
		Local/State Reports	0	0	0	0	0	0	0	0	0
		Molina Community Survey	0	0	0	0	0	0	0	0	0

Table B-1. MAXQDA CRB Output, Climate and Environmental Drivers: Frequency of Co-Occurrences between Climate and Environmental Drivers and Priority Health Outcomes by Data Source

APPENDIX C. CLIMATE AND ENVIRONMENTAL LINKS TO SDOH

Factor	Connection Type	Data Source	Culture	Disconnected Youth	Education	Employment	English Proficiency	Food Access	Greenspace	Hardship	Healthcare Access	Housing	Income	Race/ Ethnicity	Safety	Transportation	Flooding	Heat	Lead	Ozone	Particulate	Storm	Traffic	UST	Wastewater
Flooding	Link	Action Committee	2	2	0	0	0	0	3	4	0	8	6	0	2	0	0	1	0	0	0	13	0	0	0
		Peer Reviewed Literature	0	1	0	0	0	0	0	34	1	7	3	2	1	0	0	2	0	0	0	20	0	0	1
		Local/State Reports	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Molina Community Survey	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Outcome	**Connection Type**	**Data Source**	**Culture**	**Disconnected Youth**	**Education**	**Employment**	**English Proficiency**	**Food Access**	**Greenspace**	**Hardship**	**Healthcare Access**	**Housing**	**Income**	**Race/ Ethnicity**	**Safety**	**Transportation**	**Flooding**	**Heat**	**Lead**	**Ozone**	**Particulate**	**Storm**	**Traffic**	**UST**	**Wastewater**
Heat	Link	Action Committee	1	1	0	0	0	0	7	0	0	7	4	1	4	2	1	0	1	0	0	1	0	0	1
		Peer Reviewed Literature	0	0	0	1	0	3	1	1	0	2	1	1	0	0	2	0	0	0	3	1	0	0	2
		Local/State Reports	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Molina Community Survey	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Outcome	**Connection Type**	**Data Source**	**Culture**	**Disconnected Youth**	**Education**	**Employment**	**English Proficiency**	**Food Access**	**Greenspace**	**Hardship**	**Healthcare Access**	**Housing**	**Income**	**Race/ Ethnicity**	**Safety**	**Transportation**	**Flooding**	**Heat**	**Lead**	**Ozone**	**Particulate**	**Storm**	**Traffic**	**UST**	**Wastewater**
Lead	Link	Action Committee	0	0	0	0	0	0	0	0	0	1	1	2	0	0	0	1	0	0	0	0	0	0	0
		Peer Reviewed Literature	3	2	3	2	2	4	3	2	5	3	2	5	3	1	0	0	0	0	4	0	0	0	3
		Local/State Reports	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Molina Community Survey	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Outcome	**Connection Type**	**Data Source**	**Culture**	**Disconnected Youth**	**Education**	**Employment**	**English Proficiency**	**Food Access**	**Greenspace**	**Hardship**	**Healthcare Access**	**Housing**	**Income**	**Race/ Ethnicity**	**Safety**	**Transportation**	**Flooding**	**Heat**	**Lead**	**Ozone**	**Particulate**	**Storm**	**Traffic**	**UST**	**Wastewater**
Particulate	Link	Action Committee	4	0	2	3	0	1	4	0	4	17	7	0	3	2	0	0	0	0	0	0	5	0	2
		Peer Reviewed Literature	1	1	5	1	3	3	2	3	4	9	11	15	3	2	0	3	4	0	0	0	14	0	3
		Local/State Reports	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Molina Community Survey	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Outcome	**Connection Type**	**Data Source**	**Culture**	**Disconnected Youth**	**Education**	**Employment**	**English Proficiency**	**Food Access**	**Greenspace**	**Hardship**	**Healthcare Access**	**Housing**	**Income**	**Race/ Ethnicity**	**Safety**	**Transportation**	**Flooding**	**Heat**	**Lead**	**Ozone**	**Particulate**	**Storm**	**Traffic**	**UST**	**Wastewater**
Storm	Link	Action Committee	2	2	0	0	0	0	3	3	0	8	6	0	3	1	13	1	0	0	0	0	0	0	0
		Peer Reviewed Literature	0	1	1	0	0	0	0	26	2	4	6	5	2	0	20	1	0	0	0	0	0	0	1
		Local/State Reports	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Molina Community Survey	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Outcome	**Connection Type**	**Data Source**	**Culture**	**Disconnected Youth**	**Education**	**Employment**	**English Proficiency**	**Food Access**	**Greenspace**	**Hardship**	**Healthcare Access**	**Housing**	**Income**	**Race/ Ethnicity**	**Safety**	**Transportation**	**Flooding**	**Heat**	**Lead**	**Ozone**	**Particulate**	**Storm**	**Traffic**	**UST**	**Wastewater**
Traffic	Link	Action Committee	0	0	0	0	0	0	2	0	0	4	5	0	0	0	0	0	0	0	5	0	0	0	0
		Peer Reviewed Literature	0	0	3	0	2	1	0	1	1	6	7	6	0	1	0	0	0	0	14	0	0	0	0
		Local/State Reports	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Molina Community Survey	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Outcome	**Connection Type**	**Data Source**	**Culture**	**Disconnected Youth**	**Education**	**Employment**	**English Proficiency**	**Food Access**	**Greenspace**	**Hardship**	**Healthcare Access**	**Housing**	**Income**	**Race/ Ethnicity**	**Safety**	**Transportation**	**Flooding**	**Heat**	**Lead**	**Ozone**	**Particulate**	**Storm**	**Traffic**	**UST**	**Wastewater**
Wastewater	Link	Action Committee	1	0	1	0	1	0	4	0	0	2	2	0	1	0	0	1	0	0	2	0	0	0	0
		Peer Reviewed Literature	1	1	1	0	1	2	3	1	3	5	2	3	2	0	1	2	3	0		1	0	0	0
		Local/State Reports	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Molina Community Survey	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table C-1. MAXQDA CRB Output, Climate and Environmental Links: Frequency of Co-Occurrences between Climate and Environmental Links and Social Determinant of Health Links by data source

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