COMMUNITY HEALTH WORKERS: AN EXAMINATION OF STATE POLICIES AND ANALYSIS OF A HEALTHCARE-BASED INTERVENTION FOR DIABETES MANAGEMENT

Elinor Alice Hansotte

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Doctoral Committee

Cynthia Stone, DrPH, MSN, RN, Chair

Brian E. Dixon, PhD, MPA, FACMI, FHIMSS

April 24, 2023

Ross Silverman, JD, MPH

Lisa Staten, PhD

DEDICATION

To Gavi and Ori: I love you more than all the moons of Jupiter.

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COMMUNITY HEALTH WORKERS: AN EXAMINATION OF STATE POLICIES AND ANALYSIS OF A HEALTHCARE-BASED INTERVENTION FOR DIABETES MANAGEMENT

Community Health Workers (CHW) are trusted frontline members of the public health workforce with a unique understanding of the communities they serve. CHW interventions have been shown effective and economical in improving certain health outcomes, including diabetes-related complications and self-management. The ability of CHWs to relate to patients in a culturally appropriate manner positions them to better address social determinants of health and inequities than many allied health professionals. State-level CHW legislation varies by jurisdiction and can direct CHW processes including definitions, funding, and scope of practice. The Diabetes Project – Indianapolis Neighborhoods (DIP-IN) intervention employs clinic-based CHWs to work with high-risk patients with diabetes in three Indianapolis communities with disproportionately high diabetes prevalence rates. DIP-IN CHWs are based in select Eskenazi Health Federally Qualified Health Centers and deliver services to patients primarily through home visits or phone calls.

This dissertation examines CHW policies and the impact of the DIP-IN CHW intervention on patient outcomes in relation to a comparison group. This dissertation includes three studies 1) a state-level policy surveillance exploring legislation that includes best practices for CHW policy, 2) a study using a difference-in-difference approach through the application of generalized linear mixed models to estimate the effect of DIP-IN on A1C and hospital outcomes, and 3) a study using multivariate

regression and negative binomial modeling to estimate the impact of DIP-IN on COVID-19 hospitalization and length of stay. As financing influences duration and application of CHW interventions, this dissertation aims to explore the landscape over time of CHW legislation and evaluate a privately funded CHW program model intended to improve health outcome among high-risk patients with diabetes. It also aims to strengthen the knowledge base for CHW involvement in improving clinical-community linkages to support diabetes management.

Cynthia Stone, DrPH, MSN, RN, Chair

Brian E. Dixon, PhD, MPA, FACMI, FHIMSS

Ross Silverman, JD, MPH

Lisa Staten, PhD

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LIST OF ABBREVIATIONS

A1C: Glycosylated hemoglobin (also abbreviated as Hb A1c)
ACA: 2020 Patient Protection and Affordable Care Act
APHA: American Public Health Association
BMI: Body mass index
C3: Community Health Worker Core Consensus Project
CDC: Centers for Disease Control and Prevention
CHW: Community Health Worker
COVID-19: Coronavirus disease 2019
DIP-IN: Diabetes Impact Project – Indianapolis Neighborhoods
ED: Emergency department
EMR: Electronic medical record
FSPH: Indiana University Fairbanks School of Public Health
FQHC: Federally Qualified Health Centers
ICU: Intensive care unit
INCHWA: Indiana Community Health Workers Association
LISC: Local Initiatives Support Corporation
LOS: Length of stay
MCPHD: Marion County Public Health Department
SDOH: Social determinants of health
SOC: Standard Occupational Classification
U.S.: United States

CHAPTER ONE: INTRODUCTION

Community Health Workers

The purpose of this dissertation is to examine the landscape of CHW policy at the state level and evaluate the impact of the first three years of the Diabetes Impact Project – Indianapolis Neighborhood (DIP-IN) program's health system-based CHW intervention. This dissertation is composed of three papers 1) a state-level policy surveillance exploring prevalence of CHW best practice legislation, 2) a study applying generalized linear mixed methods approach to estimate the effect of DIP-IN on A1C and hospital outcomes, and 3) a study using multivariate regression and negative binomial modeling to estimate the association of DIP-IN on COVID-19 hospitalization and length of stay.

Community Health Workers (CHW) are trained frontline public health workers who are trusted members of and/or have an extensive understanding of and share socioeconomic backgrounds with the community served.[1,2] CHWs serve as patient advocates by helping to liaise between the client and healthcare provider, or promote and improve upon community-clinical linkages.[2–4] The background and ability of CHWs to create trusting relationships helps them succeed as peer educators in areas in which traditional healthcare or public health providers often have difficulties reaching patients, such as influencing attitudes, shifting social norms, addressing external barriers and social determinants of health (SDOH), and bolstering self-efficacy.[1,2,5,6] Because of the shared background and trusting relationships that CHWs develop with clients, CHW interventions are a promising approach to increasing access to healthcare for historically marginalized populations.[7] Through culturally appropriate services, CHWs are also able to improve the quality of care, health outcomes for patients, care coordination, and patient satisfaction; this type of intervention also aims to reduce racial and ethnic health inequities.[2,5,8] CHWs are considered a cost-saving intervention for healthcare systems, and they can offer a wide range of strategies and services that aim to assist patients in adopting health behaviors, including: outreach, community education, informal counseling, social support, motivational interviewing, and advocacy.[1,2,4]

The role of CHWs is not uniformly defined, and CHWs have variable licensure and education requirements, as well as roles, responsibilities, and pay, by state.[5] Some states use legislation to define, provide funding mechanisms, or otherwise outline CHW services or training, while other states maintain CHW policies at the state agency level. CHWs are classified as a detailed occupation by the federal government (Standard Occupational Classification (SOC) 21-1094), and the U.S. Bureau of Labor Statistics maintains estimates of the CHW workforce.[4,8] SOC 21-1094 classifies CHWs as workers who:

> "Promote health within a community by assisting individuals to adopt healthy behaviors. Serve as an advocate for the health needs of individuals by assisting community residents in effectively communicating with healthcare providers or social service agencies. Act as liaison or advocate and implement programs that promote, maintain, and improve individual and overall community health. May deliver health-related preventive services such as blood pressure, glaucoma, and hearing screenings. May collect data to help identify community health needs. Excludes "Health Education Specialists" (21-1091)."[4]

In 2000, the CHW Section of the American Public Health Association (APHA) also developed a definition that is widely used:

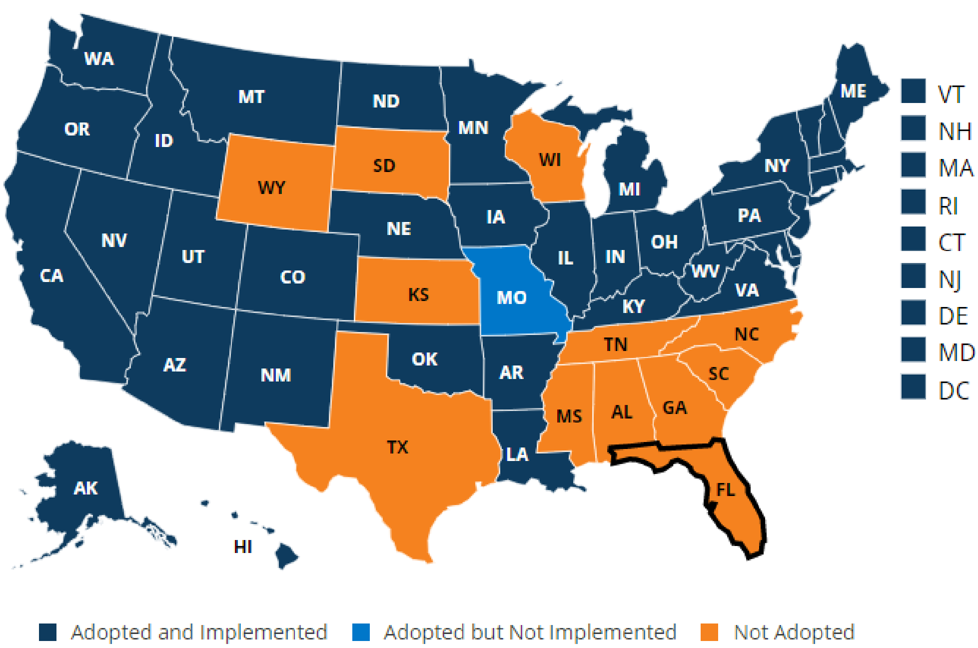
> "A community health worker is a frontline public health worker who is a trusted member of and/or has an unusually close understanding of the community served. This trusting relationship enables the worker to serve as a liaison/link/intermediary between health/social services and the community to facilitate access to services and improve the quality and cultural competence of service delivery."[9, Paragraph 2]

Workforce surveys estimate higher numbers (100,000) of CHWs, but the U.S. government estimates that in May 2021, 61,010 people met the definition of a CHW and earned a median annual wage of $47,780.[3,10,11]

CHWs have played a role in the U.S. healthcare system for over 50 years.[12] Efforts to standardize the CHW workforce through organization, training, and credentialing began in the early 1990s. Massachusetts, California, New Mexico, Arizona, and Kentucky were some states that were early adopters of CHW programming, training, education, and funding appropriation.[2,13] The National Community Health Advisor Study, released in 1998, was the first attempt to outline the CHW profile across the U.S. in order to provide guidance to policymakers and practitioners.[2,12,14] APHA's CHW Section recommended that common definitions and competencies be created for CHWs.[12] The United States (U.S.) Department of Labor recommended the establishment of a Standard Occupational Classification for CHWs in 2009, and in 2010, the Patient Protection and Affordable Care Act (ACA) included language that specifically identified CHWs as health professionals and authorized grant funding for the employment of CHWs for supporting the healthcare needs of medically underserved populations.[2,5,15] The ACA-directed grants for CHW work specified allotting funds toward "medically underserved communities, particularly racial and ethnic minority populations."[15,Section 5313] State-level choices in ACA implementation, specifically Medicaid expansion (**Figure 1.1**), impact opportunities for CHW reimbursement for services.[5] In 2014, the CDC recommended CHW policy initiatives, which included establishing state-level definitions.[3,12] The CHW Core Consensus Project (C3) looks at CHW roles and competencies, and published their most recent report in 2016.[12,16] A recent study outlined state-level definitions and roles of

CHWs in order to promote a groundwork for more consistency in CHW practices and identities.[12] Of recent note, in September 2022, the American Rescue Plan awarded $225 million to train over 13,000 CHWs. The Consolidated Appropriations Act of 2023 authorized $50 million to build CHW workforce capacity between state fiscal years 2023 to 2027.[17]

Figure 1.1. State action on Medicaid expansion, May 2021



Note. Citation[18]

Targeted development of the Indiana CHW workforce began in 2011. A CHW Coalition convened in 2012 and later became the currently titled Indiana Community Health Workers Association (INCHWA) in 2013. INCHWA has since developed a strategic plan that includes establishing CHW networks across the state, defining certification criteria and certifying bodies, and securing reimbursement for CHW services.[2] The Indiana Governor's Health Workforce Council convened a CHW

Taskforce in 2017 that was tasked with defining CHWs, developing the certification process, and determining reimbursement.[2,8] In May 2021, an estimated 1,610 CHWs were employed in Indiana, earning an annual mean wage of $43,110. The Lafayette-West Lafayette, IN, metropolitan area had the sixth highest concentration of CHW jobs and location quotients in the U.S.[4]

Diabetes Mellitus

Diabetes mellitus (hereafter diabetes) is a complex metabolic disorder that can be divided into four main types: type 1, type 2, gestational, and secondary or other types.[19,20] Diabetes is not one illness; rather, it is a group of chronic metabolic conditions stemming from the body's inability to produce insulin or resistance to use insulin effectively.[19,20] Insulin is a hormone that the pancreas produces for the purpose of allowing blood sugar into the body's cells to be used as energy.[21] When insulin is ineffectively produced or used, uncontrolled blood sugar can develop into a chronic disease that may lead to additional health issues.[21,22] Diabetes is of such concern not only because of the disorder itself, but because it increases the risk of severe complications, including: hypertension, cardiovascular disease, kidney disease, neuropathy, blindness, stroke, and lower-extremity amputation.[19,23]

Types of Diabetes

Type 1 diabetes is not preventable and is characterized by a lack of insulin production. It is considered an autoimmune disorder with risk factors that include family history, environmental factors, certain viral infections during childhood, and race (the white population has a higher prevalence).[19]

Type 2 diabetes develops when cells do not respond normally to insulin and the pancreas produces more insulin in an attempt to get cells to respond. This process eventually causes insulin resistance when the pancreas cannot keep up with insulin production and blood sugar rises.[19,21] Nonmodifiable risk factors for type 2 diabetes include age (risk increases with increasing age; those over 45 are most at risk), race and ethnicity (Black and Native American populations have a higher prevalence), family history, history of gestational diabetes, and low birth weight of the individual (there is a possible link between intrauterine conditions and metabolic disorders after birth).[19,21,24] Although age is a risk factor, a recent trend shows a higher than anticipated rate of type 2 diabetes (as well as obesity) incidence among children, teens, and young adults. More than 75% of younger patients with type 2 diabetes have a close relative who also have type 2 diabetes, which indicates risk based in genetics or shared lifestyle factors.[21] Modifiable, or lifestyle, risk factors for type 2 diabetes include a diet of poor nutritional quality, physical inactivity, body mass index (BMI) indicating overweight or obesity, hypertension, smoking, high cholesterol, stress, and alcohol consumption.[13,19,25] Environmental factors such as barriers to physical activity and social isolation, as well as factors like inadequate health insurance and a lack of understanding about the healthcare system, may contribute to type 2 diabetes.[13] Studies have shown that one can reduce their risk for type 2 diabetes by losing body weight (primarily through dietary changes) and exercising moderately 30 minutes a day, five days a week.[26,27] Notwithstanding, many risk factors for type 2 diabetes stem from deeply rooted SDOH, such as socioeconomic status, that are not mitigated by individual behavior.[6]

Gestational diabetes is glucose intolerance that impacts 2-4% of pregnancies annually.[28] Risk factors include: race and ethnicity (minority women have a higher prevalence), obesity, family history, and previous diagnosis of gestational diabetes. Women diagnosed with gestational diabetes have a 20-25% increase risk for later development of type 2 diabetes.[19] Other types of diabetes are caused by specific genetic defects, disease of the pancreas, or drugs or other chemicals.[19] Prediabetes is a precursor to a diabetes diagnosis in which blood glucose levels are elevated but do not meet diabetes diagnostic criteria.[19] While patients with prediabetes have a high risk for future type 1 or type 2 diabetes, not all who meet the definition will eventually develop diabetes.[20]

Diagnosis of Diabetes

Diabetes is often diagnosed through a blood test that measures glycosylated hemoglobin (Hb A1c, A1C from here), or average blood sugar, levels over the past three months.[20,21,26,29] Risk for diabetes and diabetic complications increases with higher A1C levels.[26,29] An A1C level ≥6.5% is recognized by the American Diabetes Association as the diagnostic threshold for diabetes.[20,26] Patients with prediabetes have an A1C level of 5.7%-6.4%, and an A1C below 5.7% is normal.[20,29,30] Diabetes can also be diagnosed through a fasting plasma glucose test (fasting blood sugar ranges: normal – 99 mg/dL or lower; prediabetes – 100-125 mg/dL; diabetes – 126 mg/dL or higher); an oral glucose tolerance test that measures blood sugar before and after a glucose drink is imbibed, following overnight fasting (2-hour blood sugar ranges: normal – 140 mg/dL or lower; prediabetes – 140-199 mg/dL; diabetes – 200 mg/dL or higher); or a non-fasting random plasma glucose test, which is usually given when diabetes symptoms are noted (diabetes range – 200 mg/dL or higher).[26,30]

Diabetes in the United States and Globally

Diabetes Incidence and Prevalence

Diabetes is a large contributor to excess morbidity and mortality in the U.S. and around the world.[19,22,27] Globally, an estimated 463 million adults (aged 20-79) have diabetes, half of whom have not been diagnosed.[31] Among American adults, there is an approximate 14.7% diabetes prevalence (or approximately 37 million people aged 18 or older), with an increasing prevalence with increasing age. This rate includes 8.5 million adults who meet the laboratory criteria for diabetes but are unaware of or do not report a diagnosis of diabetes.[32] Among those 65 and older, 29.2% of Americans and 20% of older adults around the world have diabetes.[31,32] Type 2 diabetes accounts for between 90-95% of cases both in the U.S. and worldwide.[19–22] In 2018, 1.5 million Americans were diagnosed with diabetes, and it is thought that up to 30% of cases are undiagnosed because symptoms may develop slowly over several years or be unnoticeable.[19,21,25] Although the majority (187,000) of the 210,000 children and adolescents under the age of 20 with diabetes have type 1 diabetes, the incidence of type 2 diabetes in this age group increased significantly between 2015 and 2018.[25] Additionally, in 2018, an estimated 88 million adults over the age of 18 met the criteria for prediabetes.[25]

Diabetes Prevalence by Social Determinant Factors

It is important to note that race and ethnicity are often used as a proxy for risk factors stemming from the root causes of many health inequities – including diabetes – seen among those from a historically marginalized population: structural and institutional racism.[33,34] While race and ethnicity have been and will be mentioned as "risk factors" in this document, this is an approximation of differences that arise as a result of these root causes.

As mentioned, race and ethnicity are nonmodifiable risk factors for diabetes. This risk can be seen in differences in prevalence by race and ethnicity for age-adjusted diabetes rates for American adults aged 18 or older for the years 2017-2018: Non-Hispanic American Indian/Alaska Native (14.7%); Hispanic (12.5%), Non-Hispanic Black (11.7%); Non-Hispanic Asian (9.2%); and Non-Hispanic White (7.5%).[25] Diagnosed diabetes prevalence also varies by education level, which is often used as an indicator for socioeconomic status: less than high school education (13.3%); high school education (9.7%); post-high school education (7.5%).[25] Globally, nearly 80% of adults with diabetes lived in low-and middle-income countries.[31]

The Cost of Diabetes

Diabetes is a significant contributor to healthcare costs for both healthcare systems and individuals.[19] Globally, at least $760 billion was spent on diabetes health expenditures in 2019.[31] In the U.S., an estimated one in every seven healthcare dollars is directed toward care of diabetes and its comorbidities, amounting to $327 billion in 2017; about 40% of which is estimated to have been incurred for direct medical costs.[19,22,25,35,36] Direct economic costs are generated by the treatment of diabetes and include services like hospital care, physician services, long-term care, and pharmacotherapy. Indirect costs include loss of societal productivity attributable to diabetes and include lost wages, disability, and premature death.[36] Cardiovascular events and stroke account for approximately 85% of medical costs associated with diabetes complications.[19] When accounting for demographic characteristics, people with diabetes spend 2.4 to 2.6 times more in medical costs than those without diabetes.[36] Patients with diabetes with higher A1C levels at diagnosis and those with more variation in annual A1C levels incur higher medical costs than patients with diabetes with lower or more consistent A1C levels.[19] The cost of diabetes is rising: between 2012-2017, excess medical costs per person increased from $8,417 to $9,601.[25]

Diabetes Hospitalization and Emergency Department Visits

In 2016, there were 16 million emergency department visits among adults over the age of 18 that contained diabetes as any listed diagnosis. Of those, 224,000 visits were for hyperglycemic crisis (a rate of 9.7 per 1,000 adult patients with diabetes) and 235,000 were for hypoglycemia (a rate of 10.2 per 1,000 adult patients with diabetes). A majority of the time (59%), the patient was treated and released from the emergency department, but over 35% were admitted to the hospital and 0.2% died.[25]

Diabetes Morbidity

Increased morbidity from diabetes stems from the ailment itself and exacerbated impacts of its associated comorbidities. Patients with type 2 diabetes have a higher prevalence of hypertension than the general population. At age 45, about 40% of patients with diabetes have been diagnosed with hypertension, a rate that increases to 60% by age 75.[23] An estimated 37% of adult patients with diabetes have chronic kidney disease. Diabetes is the leading cause of new cases of blindness among adults; an estimated 11.7% of adult patients with diabetes fall into this category.[25]

Diabetes Mortality

In 2019, diabetes was the cause of 4.2 million deaths worldwide.[31] In 2019, diabetes was the seventh leading cause of death in the U.S.; 87,647 death certificates listed diabetes as the underlying cause of death and 282,801 death certificates listed diabetes as an underlying or contributing cause of death.[37] Diabetes is likely to be underreported as a cause of death because of the myriad associated complications that may themselves ultimately lead to death.[19] The risk of death among patients with diabetes is nearly twice that of patients without diabetes of a similar age.[19] Two-thirds of patients with diabetes die of heart disease or stroke, and the risk for cardiovascular disease mortality is two to four times higher among patients with diabetes than patients without diabetes.[19]

Diabetes Management

Diabetes is managed primarily by the patient with support from a healthcare team that may include a primary care physician, nurse, podiatrist, dentist, optometrist, registered dietitian, pharmacist, and diabetes educator.[21,38] To tailor diabetes control efforts to the current disease state, patients with diabetes should get an A1C test at least twice a year. The typical A1C goal for diabetes management is 7% or less.[29] Pharmaceutical intervention for managing blood sugar and avoiding diabetes complications may include prescribed insulin, other injectable medications, or oral diabetes medicines.[21] Intensive pharmaceutical glucose control in newly diagnosed patients with diabetes is estimated to cost $35,300 over a lifetime per quality-adjusted life year gained; approximately 10.9% of adults diagnosed with diabetes began to use insulin within the first year of diagnosis.[25,36] Lifestyle interventions that aim to control blood sugar levels, blood pressure, and cholesterol have been shown to prevent or delay the onset of diabetes-related complications among patients with diabetes.[19] These interventions may focus on behaviors like healthy eating, active living, relaxation, and sufficient sleep.[21] One study found that tight control of blood pressure among patients with diabetes with hypertension led to a 32% reduction in diabetes-related mortality, 44% reduction of stroke, 56% reduction in heart failure, and 37% reduction in micro-vascular disease.[23]

Because of the high prevalence of diabetes, most people know someone with or something about the chronic disease, and the well-known complications often incite fear of getting a diabetes diagnosis. Acceptance of the disease at diagnosis is important for setting each individual's course of care in order to address these fears: for life, complications, work, family, and stigmatization.[39,40] Stigma includes both feeling judged and being blamed for having diabetes.[39] These fears directly correlate to the individualized care needed by patients with diabetes – needs for support; education about diabetes in general, its management, and how to look for complications; learning about treatment technique; lifestyle modifications; and clear communication.[40] In order to effectively treat the patient as a whole, someone on the diabetes care healthcare team should be focused on addressing these needs.

While each dollar invested in a diabetes self-management program yields a median $2 reduction in hospital costs, resources that could be devoted to diabetes control and prevention are often limited due to opportunity costs.[36] One example of opportunity cost in diabetes care comes from a Canadian study in which researchers found that limiting the number of government-funded glucose test strips provided to noninsulintreated patients with diabetes would allow for redirection of cost savings to other programs or interventions for patients with diabetes without compromising the care of patients.[41] The economic burden of diabetes, and therefore the cost-saving opportunities of diabetes care programs, is well-documented. Many of these studies do not include social costs (e.g., productivity losses and/or informal care), which may lead to the development of more equitable interventions.[35]

The economic burden of diabetes pharmaceutical control was mentioned briefly, but it is worth expanding on the topic. For many patients with diabetes, access to insulin is a matter of life and death.[42] The cost of insulin tripled in the U.S. between 2003 and 2013, forcing many patients with diabetes to ration or forgo this necessary treatment and leading to additional morbidity and mortality.[42–44] Many solutions to this devastating problem have been offered, including governmental overseeing of pricing, emergency access laws, and providers prescribing the lowest-priced insulin taking into account each patient's specific condition.[42,43] In response, Eli Lilly and Company (Lilly), one of the main manufacturers of insulin, created the Lilly Diabetes Solution Center, a collaboration between stakeholders aiming to address gaps in the healthcare system that do not sufficiently cover the cost of insulin care for patients with diabetes. As of January 2021, any user of Lilly insulin, regardless of insurance status, could purchase insulin for $35 each month.[45] More recently, in 2023, all major insulin manufacturers in the U.S. began efforts to reduce the cost of insulin, and cost-sharing limits on insulin were enacted in 22 states and Washington, D.C.[46]

Community Health Workers and Diabetes Management

The use of CHWs is considered a cost-effective strategy to help manage chronic disease in a home and community setting.[1,13,47] Because CHWs are a part of the community in which they work, the connections they develop with patients suffering from chronic disease allow for more open communication about patient needs, which leads to CHWs being able to improve health outcomes and the patient's ability to navigate the healthcare system, including its wrap-around services.[13] Evaluation, highlighted as an important method to rigorously demonstrate the outcomes of CHW programs, has shown positive outcomes for CHWs working with patients with diabetes.[14] CHWs have been studied and shown to be a successful, cost-effective intervention for diabetes control.[13]

Many barriers to patient care within a healthcare system, including for diabetes care, are rooted in the SDOH.[14] A challenge to diabetes management, particularly among historically marginalized populations, is improving basic SDOH, like socioeconomic status, health knowledge, education, access to healthcare, and stressors.[48] Where traditional medicine does not typically have success in addressing the SDOH, CHWs are better suited for this type of intervention.[14] The ACA aims to direct funds for CHWs to work with populations with high rates of chronic disease and SDOH linked to negative health outcomes, including the un- or underinsured and residents of communities designated as a health professional shortage area.[15] By addressing the SDOH, CHWs work to increase access to wraparound services like social services and reduce hospital visits, while improving outcomes for diabetes.[3]

Diabetes control often requires constant and consistent monitoring by the patients. CHW interventions among patients with diabetes have been shown to improve self-management of the chronic disease, which includes a significant decrease in A1C level after CHW intervention.[1,13,49,50] Decreased A1C levels are considered a primary indicator for longer-term glycemic control by the patient.[50] CHWs have been shown to improve self-management of diabetes through measures such as increased appointment attendance, adherence to medication routines, goal-setting, behavioral change, use of primary and preventive care, and decreased distress attributed to diabetes.[3,7,49,50] Because CHWs have been found to be effective in diabetes self-management care, the American Diabetes Association has developed a CHW Professional Membership and hosts various resources and trainings for CHWs specifically for those working with patients with diabetes.[51]

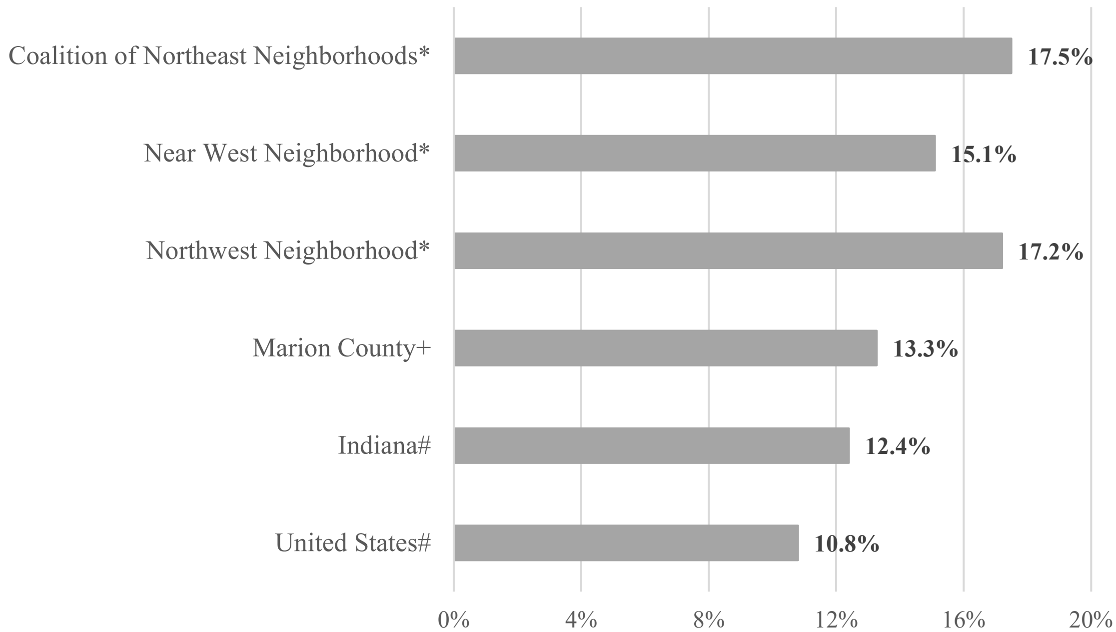
Even with the growing evidence base depicting the effectiveness of the CHW workforce in improving health outcomes among patients with diabetes, gaps in the literature remain. The CHW interventions included in the majority of studies are small, exclude rural settings, are funded by public grants, last a year or less, have more female than male participation, and deliver services in the home or community.[52]

Diabetes Impact Project – Indianapolis Neighborhoods

The Diabetes Impact Project – Indianapolis Neighborhoods (DIP-IN), which began in 2018, is a collaboration between the Fairbanks School of Public Health (FSPH – Dr. Lisa Staten, Principal Investigator) and Eli Lilly and Company (Lilly) that works to address the high prevalence of diabetes in three Indianapolis communities. Project partners include the Local Initiatives Support Corporation (LISC), the Marion County

Public Health Department (MCPHD), and Eskenazi Health (Eskenazi). DIP-IN is the first U.S.-based project to be funded through the Lilly Global Health program. The long-term goal of DIP-IN is to reduce diabetes-related complications and to ultimately reduce the rate of diabetes in three Indianapolis communities with a high prevalence of diabetes.[53] The three communities are the Northwest Neighborhood, the Near West Neighborhood, and the Coalition of Northeast Neighborhoods. In addition to high rates of diabetes, these communities also have higher risk factors for diabetes compared to other communities in Indiana. Place-based interventions, including those utilizing CHWs, can be effective at improving health equity in communities disproportionately impacted by factors influencing negative health outcomes.[54] **Figure 1.2** shows diabetes prevalence in the three DIP-IN neighborhoods, Marion County as a whole, Indiana, and the U.S. The 2016 overall Marion County rate of 13.3% was similar to the median county-level prevalence of diabetes across the U.S. of 13.1% for the same year (the U.S. prevalence in Figure 2 gives a more updated rate).[25] **Figure 1.2** only includes diagnosed diabetes; rates would be even higher if prediabetes or undiagnosed diabetes were included.

Figure 1.2. Diabetes prevalence by geographic location



*Indiana Network for Patient Care, Regenstrief Institute, 2013
+CDC, Behavioral Risk Factors Surveillance System, 2016
#CDC, Behavioral Risk Factors Surveillance System, 2019

DIP-IN initiatives work to address primary, secondary, and tertiary prevention of diabetes. Community engagement within the communities is a key element of the project, and the three neighborhoods have active community partnerships. Residential-led Steering Committees drive priority interventions for each neighborhood. While the development of the Lilly Diabetes Solution Center discussed in the Diabetes Control section above was established before DIP-IN began, conversations between the Steering Committee, the communities, project staff, and Lilly about the prohibitive cost of insulin as a barrier to diabetes management helped outline best practices for improvement in this area.

The three aims of DIP-IN are to: 1) reduce complications and improve quality of life of people living with diabetes, 2) increase awareness of risk factors for diabetes and encourage people at high risk to be screened so they can take action to prevent future complications, and 3) foster an environment (physical and social) that supports greater health and wellbeing for all residents. Diabetes CHWs stationed at Eskenazi Health (Eskenazi) Federally Qualified Health Centers (FQHC) in the three project communities help to address the first project aim. In an effort to promote long-term sustainability of the health system-based CHW intervention, Lilly funds three CHWs and Eskenazi funds an additional three CHWs. These CHWs provide support to patients having difficulties controlling their glucose levels, focus on SDOH (including ways to control the cost of insulin), and offer graduated support. Since implementation, visit locations have varied (based on COVID-19 restrictions and need) and have been held at patient homes, in clinic, as patient "porch" visits, and over the phone.[55]

DIP-IN Patients

Between April 1, 2019, and March 31, 2022, a total of 488 Eskenazi Health patients were enrolled in DIP-IN. Eskenazi patients qualified for enrollment if they had a recent A1C measures greater than or equal to 7.9%, were over the age of 18, and resided in a DIP-IN community ZIP Code (46226, 46218, 46205, 46208, 46202, and 46222) (complete list found in **Appendix Table A1**). Of those 488 enrolled, 34 appear to have been enrolled from outside a DIP-IN ZIP Code and have been excluded from this analysis. **Table 1.1** provides an overview of the area of patient residence at time of enrollment as well as the number of patients enrolled by project year.

Table 1.1. DIP-IN patient enrollment area and project year

Patient Enrollment (N=454)		
Area of Residence at Enrollment	**Frequency**	**Percent**
Northeast Community	55	11.27%
Near Westside Community	58	11.89%
Northwest Community	45	9.22%
DIP-IN ZIP Code	296	60.66%
Project Year of Enrollment		
1 *(April 1, 2019 – March 31, 2020)*	251	55.29%
2 *(April 1, 2020 – March 31, 2021)*	146	32.16%
3 *(April 1, 2021 – March 31, 2022)*	57	12.56%
Active Patients by Project Year		
1 *(April 1, 2019 – March 31, 2020)*	251	
2 *(April 1, 2020 – March 31, 2021)*	349	
3 *(April 1, 2021 – March 31, 2022)*	366	

Table 1.2 provides an overview of patient demographics. Most DIP-IN patients (78%) are Non-Hispanic Black or African American. DIP-IN patients are primarily (60%) in the 45-64 age category, with a mean patient age at enrollment of 55.75 years (SD = 12.21). There are more female (57%) than male patients, the largest subset of patients (33%) earned a high school diploma or equivalent, and most patients did not have a partner at baseline (70%).

Table 1.2. DIP-IN patient demographics

Demographics (N=454)		
Race and Ethnicity *(some groups have been collapsed)*	**Frequency**	**Percent**
Hispanic or Latino Black or African American, Other Pacific Islander, Unknown Race	10	2.20%
Hispanic or Latino Declined to State Race	28	6.17%
Hispanic or Latino White	17	3.74%
Non-Hispanic Black or African American, Unknown Ethnicity Black or African American	353	77.75%
Non-Hispanic Asian, Declined to State Race, Multiracial	6	1.32%
Non-Hispanic White	40	8.81%
Age Category at Enrollment		
18-44 years old	78	17.18%
45-64 years old	273	60.13%
65+ years old	103	22.69%
Gender		
Female	261	57.49%
Male	193	42.51%
Educational Attainment at Enrollment		
Less than high school	140	30.84%
High school diploma or equivalent	153	33.70%
Some college	82	18.06%
College or advanced degree	22	4.85%
Missing	57	12.56%
Marital Status at Enrollment		
Married/Partnered	137	30.18%
Unmarried/Not Partnered	192	42.29%
Widowed/Divorced/Separated	124	27.32%
Unknown	1	0.22%

DIP-IN Encounters

Six DIP-IN CHWs were originally based at three Eskenazi FQHCs. **Table 1.3** summarizes data about DIP-IN encounters. After implementation of the program, CHWs expanded to two additional Eskenazi FQHCs that also see patients from DIP-IN ZIP Codes. Over the three-year evaluation period, CHWs had a total of 5,660 encounters with DIP-IN patients, with an average encounter length of just over 20 minutes. DIP-IN patients were enrolled in the program for an average of 668 days and spent a total of over 254 minutes with their CHW on average.

Table 1.3. DIP-IN CHW encounter summary

Encounter measure	N	Mean	Standard Deviation	Min	Max
Number of encounters	5660	12.47	9.50	1	62
Length of encounter (minutes)	5460	20.90	14.51	5	60
Total time spent with CHW (minutes)	450	253.60	224.35	5	1720
Time enrolled in DIP-IN (days)*	454	667.70	301.04	0	1077

*Time enrolled in DIP-IN was calculated differently for those for whom disenrollment was noted and those for whom disenrollment was not noted. For those for whom disenrollment was noted, the number of days enrolled in DIP-IN was calculated using the number of days between the first and last CHW encounter. For those for whom disenrollment was not noted, the number of days enrolled in DIP-IN was calculated using the number of days between the first CHW encounter and the end of intervention Year 3 (March 31, 2022).

The clinical CHW intervention was designed for the predominant type of CHW encounter with patients to be in-person. Intervention design adapted to the changing climate of COVID-19 in the beginning of the second year when almost all CHW encounters became phone visits. This change in encounter type most likely impacted the amount of time spent with clients. **Table 1.4** highlights how long CHWs spent with clients by the type of interaction. **Table 1.4** is segmented to show both the overall time spent by encounter type as well as a summary of each year. Overall, CHWs spent more time on average per encounter during an in-person visit (M = 39.02 minutes, SD = 16.36) than a phone visit (M = 16.88 minutes, SD = 10.42). The shift to almost exclusive phone encounters in Year 2 (98.90% as compared to 47.59% in Year 1) corresponds to intervention changes due to COVID-19 restrictions. The total number of visits increased by year, but the average length of visits decreased by 37% between Year 1 and Year 2 and by 42% between Year 1 and Year 3 (Year 1: M = 28.78 minutes, SD = 18.22; Year 2: M = 18.02 minutes, SD = 12.26; Year 3: M = 16.62 minutes, SD = 8.90).

Table 1.4. DIP-IN CHW encounter times and types: Overall and by project year

	Length of encounter (min)						
Type of Interaction	**5**	**15**	**20**	**30**	**45**	**60**	**Total**
	N *Row %*						
Overall							
In person	26 2.62%	63 6.34%	73 7.35%	389 39.17%	132 13.29%	310 31.22%	993
Telephone	81 18.30%	2400 53.76%	726 16.26%	300 6.72%	102 2.28%	119 2.67%	4464
Mail	1 33.33%	1 33.33%	1 33.33%	0	0	0	3
Total	844	2464	800	689	234	429	**5460**
Frequency Missing = 200							
Year 1							
In person	8 0.89%	30 3.33%	59 6.54%	372 41.24%	127 14.08%	306 33.92%	902
Telephone	211 25.73%	402 49.02%	127 15.49%	54 6.59%	9 1.10%	17 2.07%	820
Mail	0	1 100%	0	0	0	0	1
Total	219	433	186	426	136	323	**1723**
Frequency Missing = 77							
Year 2							
In person	10 55.56%	4 22.22%	1 5.56%	2 11.11%	0	1 5.56%	18
Telephone	304 17.81%	891 52.20%	254 14.88%	126 7.38%	54 3.16%	78 4.57%	1707
Mail	1 100%	0	0	0	0	0	1
Total	315	895	255	128	54	79	**1726**
Frequency Missing = 58							
Year 3							
In person	8 10.96%	29 39.73%	13 17.81%	15 20.55%	5 6.85%	3 4.11%	73
Telephone	302 15.59%	1107 57.15%	345 17.81%	120 6.20%	39 2.01%	24 1.24%	1937
Mail	0	0	1 100%	0	0	0	1
Total	310	1136	359	135	44	27	**2011**
Frequency Missing = 65							

Note: Some lengths of encounters were provided in ranges (5-10 min, 60 min or greater). The lower end of the range was used in the calculation of encounter length (5, 60 min).

Health system-based CHWs ask a variety of questions during patient visits, though not all questions are asked at each visit. **Table 1.5** highlights responses to a few questions asked about diabetes management at time of enrollment by year of enrollment. Over time, fewer patients considered that they were managing their diabetes well or very well, reported taking their medications as prescribed, or owned a working blood glucose monitor.

Table 1.5. Self-reported health and diabetes management practices at time of enrollment by project year of enrollment

Question	Year 1	Year 2	Year 3
	N=251	N=146	N=57
		N (Col. %)	
"How well do you think you are managing your diabetes right now?"			
Not well at all	30 (11.95%)	17 (11.64%)	4 (7.02%)
Fairly well	100 (39.84%)	60 (41.10%)	21 (36.84%)
Well	78 (31.08%)	32 (21.92%)	14 (24.56%)
Very well	25 (9.96%)	9 (6.16%)	6 (10.53%)
Missing	18 (7.17%)	28 (19.18%)	12 (21.05%)
"Are you taking your medications as prescribed?"			
Yes	191 (76.10%)	100 (68.49%)	39 (68.42%)
No	42 (16.73%)	17 (11.64%)	7 (12.28%)
Missing	18 (7.17%)	29 (19.87%)	11 (19.30%)
"Do you own a working blood glucose monitor?"			
Yes	199 (79.28%)	102 (69.87%)	42 (73.69%)
No	32 (12.75%)	17 (11.64%)	3 (5.26%)
Missing	20 (7.97%)	27 (18.49%)	12 (21.05%)

Table 1.6 highlights the number of specified referrals by each year. Medical referrals include, but are not limited to, referrals for topics such as: dental issues, medication questions, and vaccinations. Basic needs referrals include, but are not limited to, referrals for topics such as: food pantry needs, social worker needs, and transportation issues. The number of medical referrals increased over time, and the number of basic needs referrals decreased over time.

Table 1.6. Number of specified referrals by project year

DIP-IN patients with at least one medical referral	
Project Year	**Frequency**
Year 1	146
Year 2	177
Year 3	202
DIP-IN patients with at least one referral for basic needs	
Year 1	104
Year 2	111
Year 3	92

Overview of the Dissertation

The first of three papers in this dissertation, presented in Chapter 2, uses policy surveillance to identify state-level CHW legislation that was passed before January 1, 2022. Regulations that did not provide substantive guidance to CHWs, such as executive orders honoring a named CHW, were excluded. I used a Boolean keyword search on Nexis Uni, and we included CHW synonyms that specified and met the definition of a CHW within the policy. A team of three coded the laws using a set of questions guided by best practices for CHW legislation. While searches have been completed on state CHW laws, this paper adds a longitudinal timeframe to the knowledge base, does not include synonyms that are not explicitly defined as a CHW would be, and adds later years of legislation that include more states that have adopted Medicaid expansion and COVID-19 policies.

The second paper (Chapter 3) estimates the effect of the health system-based DIP-IN CHW intervention on A1C and hospital outcomes. We derived a comparison group using propensity score matching and used encounter-level from Eskenazi's electronic medical record (EMR) system as the study's data source. The study used a difference-in-difference approach to compare changes in the CHW intervention group while disentangling secular trends in comparison group outcomes. We applied generalized linear mixed models in this study to gauge the outcomes of A1C, time between A1C measures, hospital emergency department visits, and hospital admissions. This paper adds to the knowledge base on CHW outcomes, but also adds in the outcome of time between A1C as an indicator of diabetes management best practices. While many CHW interventions include A1C testing as an activity, DIP-IN does not, so improvements in A1C might relate to improved self-management of diabetes by DIP-IN patients or strengthened community-clinical connections leveraged by CHW inclusion in the healthcare system.

The final paper, found in Chapter 4, estimates the association of the health system-based DIP-IN CHW intervention on COVID-19 hospital outcomes. This paper used the same comparison group and EMR described in the second paper. We used multivariable regression to determine if there was a difference in the odds of COVID-19 hospitalizations between DIP-IN and comparison group patients. We also used a multivariable negative binomial model to assess if there was a difference in incident rate of COVID-19 hospital length of stay between DIP-IN and comparison patients. This paper adds to a still-developing body of literature looking at the use of CHWs to improve or mitigate negative outcomes among those disproportionately at risk for COVID-19 morbidity and mortality.

Despite the growing number of published works on CHW interventions, gaps in knowledge still exist, some of which this dissertation aims to address. The assessment of state-level CHW policy over time adds to previous policy assessment with a rigorous legal mapping methodology and the inclusion of more recent legislation based on

Medicaid expansion and COVID-19. Contrary to typically public grant funded CHW interventions, DIP-IN is financed through private monies; the evaluation will add depth to the literature on CHW funding mechanisms. This dissertation also hopes to show sustainable improvements in health outcomes in a long-term CHW intervention, add context to the frequency and duration of CHW interactions with patients, and estimate the impact of utilizing community-clinic linkages to improve diabetes management among patients from historically underserved communities.

CHAPTER TWO: STATE-LEVEL POLICY SURVEILLANCE OF COMMUNITY HEALTH WORKER LEGISLATION

Introduction

Healthcare interventions that incorporate Community Health Workers (CHW) have been shown to be effective in increasing patient self-management of chronic illness while reducing healthcare costs.[13,55,56] The language describing CHWs, laws outlining the licensing and scope of work of CHWs, and reimbursement for CHW services vary by jurisdiction.[5,57] There is no single definition used consistently to describe CHWs, but they are typically considered trained public health frontline workers who are trusted members of the community they serve.[2,9] CHWs have many monikers, including community health representatives, *promotoras*, and lay health workers.[8,9,56] These inconsistencies make the development of replicable CHW intervention, evaluation, and reimbursement mechanisms for CHW services more difficult.[12] Understanding CHW interventions at the policy level would allow researchers, policymakers, and practitioners to better gauge the effectiveness of CHWs and potential factors that influence CHW programs. Understanding the core components of an effective CHW policy will facilitate efforts to create and maintain the most successful CHW workforce.[58]

Laws that influence public health can create sustainable, population-level improvements; the ten greatest public health achievements of the 20th century were all accomplished, in part, through policy change.[59,60] Public health laws can also have negative or unintended consequences, or they may fail to make intended population health changes.[59] To be able to better understand the impact of public health policy on outcomes, it is vital to monitor and evaluate laws and their changes across time, much like traditional public health surveillance of disease and events.[60,61] Policy analysis can be more difficult when considering public health policy than healthcare policy because it typically addresses the social determinants of health (SDOH) of a person, rather than focusing solely on medical care.[62] Various reports have synthesized information about regulations and roles of CHWs. The National Community Health Advisor Study, published in 1998, sought to provide guidance for policymakers on improving the field of CHWs.[14] The Centers for Disease Control and Prevention (CDC) developed fact sheets in 2012 and 2016 outlining different facets related to state laws regarding CHW infrastructure, professional identity, workforce development, and financing,[56,63] and CDC recently published the methods that produced these tools.[64] The National Academy for State Health Policy (NASHP) developed a snapshot of CHWs at the state level in 2015 that included elements like financing, education, and state legislation.[57] One recent study outlined state-level legislative definitions and roles of CHWs as a method of advocating more consistency,[12] and the Community Health Worker Core Consensus (C3) Project provides a list of CHW roles and competencies.[65] Because of the recursive nature of public health policymaking, it is important to have periodic updates on the status of public health laws over time, not only to evaluate the health impacts of regulations, but also to identify legal gaps that need to be addressed.[59,60] The importance of this method is noted in an assertion by Burris et. al that "legal mapping virtually always reveals some important discrepancy between what we think we know about the problem or the law and what the law is actually doing."[66] Policy surveillance is a legal mapping technique that is an "ongoing systematic, scientific collection and analysis of laws of public health significance."[60,67]

Enacted in 2010, the Patient Protection and Affordable Care Act (ACA) expanded reimbursement for certain healthcare services provided by health professionals, including CHWs.[5] In addition to Medicaid reimbursement, the ACA included additional opportunities for CHW expansion: inclusion in Medicaid Health Homes, grant opportunities through the Centers for Disease Control and Prevention, and funding for State Innovation Models, which may include CHWs.[68] Expansion was optional at the state-level, so the ACA implementation choices may significantly impact the ability of states to deliver CHW services.[5]

This paper applies policy surveillance as a tool to assess how CHWs are defined, funded, licensed, and certified, among other indicators, in the United States across the 50 states and D.C. This mapping paper adds a time-bound element to CHW policy literature, and it includes more recent years that have seen a change in CHW landscape through COVID-19 policy and increased awareness of this public health asset.

Methods

Data Sources

This paper used the legal mapping technique of policy surveillance to identify, compile, code, and look for patterns in state policies surrounding CHWs over time.[66] The researcher identified policies for inclusion on Nexis Uni, a centralized and current online repository of laws and legal sources, using a Boolean keyword search that included common synonyms of CHWs (complete list in **Appendix Table B1**)[58,69] and a timeframe before January 1, 2022. A state-level analysis was chosen over a narrower geographic area because legislation and financing of CHW programs are typically determined at the state level. The researcher reviewed the Nexis Uni categories of "statutes and legislation" and “administrative codes and regulations.” Resolutions, executive orders, or other legal documents in the search that did not provide substantive rulemaking for CHWs were excluded from analysis, as were policies that had not been enacted or adopted. Current information on states’ adoption of ACA’s Medicaid expansion was pulled from the KFF website,[18] and a broad internet search was conducted to find state or jurisdictional CHW organizations. No human subject data were used in this study, so IRB approval was not required.

Policy Surveillance Process

Legal mapping is an iterative process through which some steps are repeated in order to validate the final datasets.[59,61] Between March-November 2022, the researcher compiled a longitudinal set of individual state laws to be systematically analyzed and coded into a database. Each policy extracted by state was recorded on a research sheet, each amendment was recorded on an amendment tracker, and text for each policy was copied to a third document.[59] The researcher reviewed a total of 7,570 policies, and the coded dataset included 281 policies. One policy was excluded when the coders found it did not meet inclusion criteria, producing a final dataset of 280 policies. In addition to the exclusion criteria noted above, policies using CHW synonyms were only included if the term was defined in law and met the definition of a CHW. To track, code, organize, and visualize laws, three coders used a database called MonQcle, which is a software developed by Temple University’s Center for Public Health Law Research specifically for legal mapping methods. Two coders were master’s-level public health students, and one coder was a Public Health Associate at a local health department. The researcher extracted all relevant laws and policies and created an initial list of questions and variables for coding based on areas noted in previous literature as best practices for CHW legislation.[59] Variables and questions were edited, and previously coded states revised, through the iterative process that resulted from discussion between the researcher and coders. The final list included 17 dichotomous, categorical, or free text variables, including the definition of a CHW, funding mechanisms, and instructions for CHW training and/or certification. Using redundant coding, two coders independently coded each jurisdiction, chosen at random through a random generator in Excel. The researcher maintained rates of divergences and coder rationale for divergences. These rates of divergence never fell below 5%,[59] and the inter-rater reliability overall was calculated to be .85, slightly below the desired level of .90. Therefore, two coders independently assessed each policy coded in this project. After each round of coding, coders sent their responses so that divergences could be recorded by the researcher. Coders reviewed divergences and recorded why they maintained or changed divergent responses before a set meeting convened between the researcher and coders in which all parties discussed the results. All divergences were adjudicated through discussion between coders and the researcher and final coding was agreed upon by all.[59,66,70]

Measures

Dependent variables were primarily dichotomous markers indicating the presence or absence of regulations surrounding CHWs. Indicators that did not fall into this category, included a specified definition of CHWs, a list of CHW synonyms, and services to be provided by CHWs that were outlined in law.

State-level characteristics included the status of state ACA Medicaid expansion and the presence of a publicly searchable state or jurisdictional CHW organization, coalition, or other group.

Data Analysis

The researchers used Microsoft Excel 365 for data collection and R Studio version 1.4.1717 for data analysis. State analysis included frequencies of each variable over time, as well as mapping of specified variables by years of interest.

Results

Looking over time, most data are presented for three years: 1998, 2014, and 2021. The first analysis year serves as a baseline, as the 1998 National Community Health Advisor Study was the first major publication looking to educate policymakers about CHWs. Another major shift in CHW legislation came with Medicaid reimbursement models outlined in the ACA. While the ACA was enacted in 2010, the first states implemented Medicaid expansion in 2014,[18] thus creating the second year of analysis in this study. The third analysis year is the final year of the study, 2021.

To be concise, we will include D.C. as a "state" in reporting results. Therefore, frequency calculations presented are out of a total of 51 jurisdictions. From the 280 pieces of legislation analyzed in this study, all states (including D.C.) besides Alabama, Delaware, Georgia, Idaho, Montana, New Hampshire, Oklahoma, Pennsylvania, Tennessee, Utah, Vermont, Wisconsin, and Wyoming had at least one policy included in analysis. By 1998, seven states included CHWs, or a CHW synonym, in legislation. These early adopters of CHW legislation were Arizona, Florida, Indiana, Iowa, Kansas, New York, and Washington. That number increased to 24 by 2014 and 38 by 2021.

Figure 2.1 shows states with and without legislation across the three years used for analysis.

Figure 2.1. Mapping presence of CHW policies by state over time

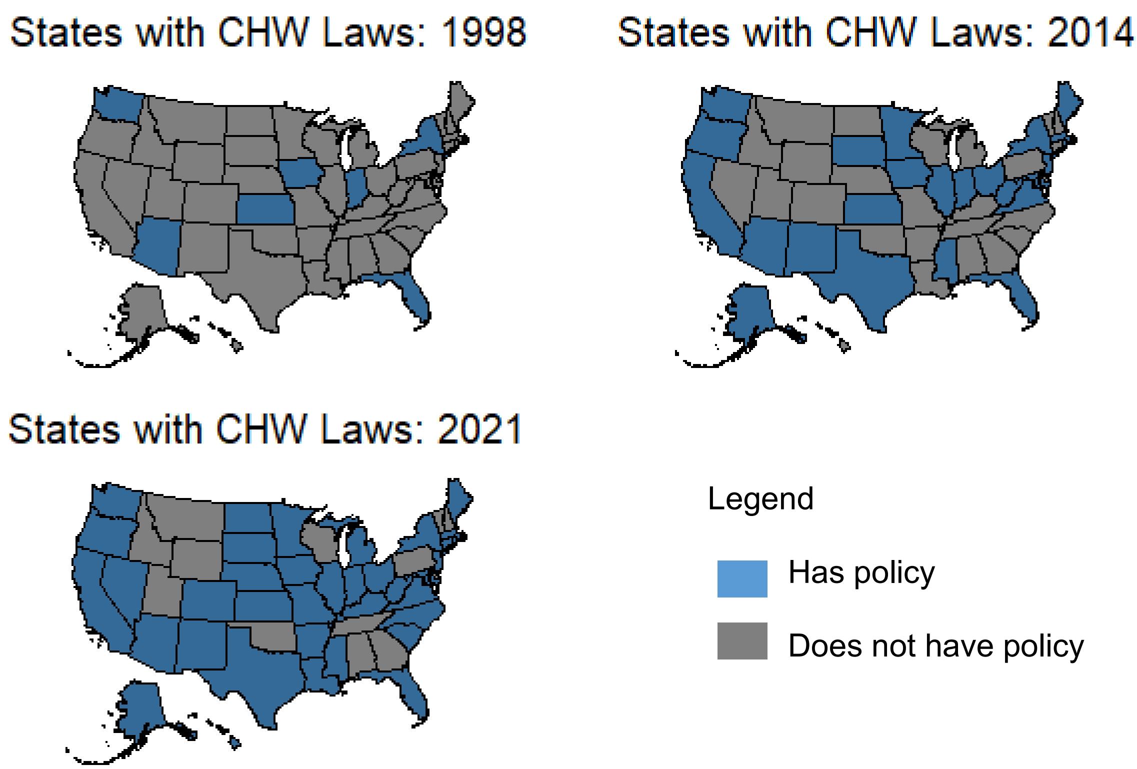


Table 2.1 outlines the findings of states that aligned with best practices over time. By 2021, fewer than a third of states defined CHWs in policy, a quarter of states outlined CHW training or certification, and a third of states outlined CHW employers or oversight. Some funding mechanism – Medicaid or otherwise – had been adopted for 61% of states by 2021. Within the timeframe of analysis (prior to 2022), 38 states and D.C. had adopted Medicaid expansion. Alabama, Florida, Georgia, Kansas, Mississippi, North Carolina, South Carolina, South Dakota, Tennessee, Texas, Wisconsin, and Wyoming had not adopted Medicaid expansion. Over half of the states defined a scope of

practice for CHWs by 2021. Seven states included CHWs in COVID-19 response policies. Finally, a broad internet search yielded a CHW organization or group at the state or more local level for all states besides Delaware, Wyoming, and North Dakota.

Table 2.1. State alignment with best practices for CHW policy over time

Legislative best practice	Number(%) of States[1] by 1998	Number(%) of States by 2014	Number(%) of States by 2021
Defined CHWs[2]	0(0%)	9(18%)	16(31%)
Specified funding mechanism for CHWs	5(10%)	21(41%)	31(61%)
Specified Medicaid as funding source	2(4%)	16(31%)	19(37%)
Adopted Medicaid expansion	N/A	27(53%)	39(76%)
Outlined primary CHW employer(s) or oversight	1(2%)	14(27%)	17(33%)
Defined CHW scope of practice	4(8%)	17(33%)	27(53%)
Outlined CHW training	1(2%)	7(14%)	14(27%)
Outlined CHW certification	0(0%)	7(14%)	13(25%)
Included CHWs in COVID-19 policies	N/A	N/A	7(14%)
Searchable CHW organization within state	N/A	N/A	48(94%)

[1]Includes D.C., total N=51
[2]Or CHW synonym

By 2021, 16 states and D.C. had passed policies that used CHW synonyms that were clearly defined within state law as some type of lay worker from or with unusual knowledge about a community; four states had passed CHW synonym legislation by 1998 and 11 by 2014. This study excluded some laws reported in other sources where a synonym like "outreach worker" was used in legislation but was not obviously someone employed for their unusual knowledge of or experience with the community served. **Table 2.2** shows that the most common synonym used was *promotora* or *promotore*, which was used in law from five states. Peer navigator was the second most common CHW synonym, appearing in legislation from four states.

Table 2.2 also outlines common CHW service areas defined in policy. Overall, 29 states included at least one CHW service area in legislation. Care coordination was the most common CHW service area defined; 22 states included this CHW service area in legislation. Maternal and child health (16 states) and health education (17 states) were also commonly cited as program or topic areas for CHWs.

Table 2.2. Overall frequencies of states with CHW synonyms or service areas included in state legislation

CHW Synonym	**Number(%) States**	**States Included**
Peer Navigator	4(8%)	CT, LA, RI, VI
Outreach Worker	1(2%)	IL
Promotora/e	5(10%)	CA, CO, NM, OR, TX
Health Paraprofessional	1(2%)	FL
Family Support Worker	2(4%)	IA, RI
Lay Health Worker/Visitor	2(4%)	AZ, NJ
Peer Educator	1(2%)	KS
Community Health Representative	1(2%)	ND
CHW Service Areas Defined		
Chronic Disease	10(20%)	IL, ME, MA, MS, NE, OH, OR, RI, TX, WA
Substance Use/Abuse	8(16%)	AR, CT, FL, IL, ME, MN, NM, OH
Maternal and Child Health	16(31%)	AZ, AR, CA, CT, DC, FL, IL, IN, IA, MN, NJ, NY, OH, OR, TX, WA
Health Education	17(33%)	AZ, CT, FL, IL, IN, KS, ME, MD, MA, MN, NV, NM, OH, OR, TX, WA
Care Coordination	22(43%)	AZ, AR, CT, DC, FL, IL, IN, IA, ME, MD, MA, MN, MS, MO, NM, NC, OH, OR, RI, TX, VA, WA
Mental Health	16(31%)	AZ, AR, CA, CT, FL, IL, IN, ME, MA, MN, NV, OH, OR, RI, VA, WA
Violence Prevention	1(2%)	IL
Cultural Competency	10(20%)	CT, FL, MD, MA, MN, NM, NY, OR, RI, TX
Emergency Healthcare Services	4(8%)	HI, KS, OR, TX
Sexual Health	1(2%)	KS
Health Screenings	3(6%)	MA, NM, TX
Oral Health	1(2%)	MN

Over time, the number of states with any type of reimbursement or funding mechanism for CHW services, recurrent or temporary, has increased. For overall reporting of funding mechanisms outlined in policy, states are included in a year if they had identified a funding mechanism or source up to the reported year. This may include temporary funding like grants, but this method gives an overall impression of states who had ever made CHW funding a priority. **Figure 2.2** depicts states with a stated CHW funding mechanism within each individual year (or condensed years for sequentially identical years).

Figure 2.2. Evolution of states with CHW funding mechanisms over time[1]

1991	92-93	94-95	96	97-99	2000	01	02-05	06	07-08	09	2010-11	12	13	14	15	16-17	18	19	2020	21
FL	FL	FL	FL	FL	FL	FL	FL	FL	FL	FL	FL	FL	CA	CA	CA	CA	CA	CA	CA	AR
KS	KS	IN	IN	IN	IN	IN	IL	IL	IL	IL	IL	IL	FL	FL	FL	FL	DC	DC	DC	CA
NY		KS	KS	IA	IA	IA	IN	IN	IN	IN	IN	IN	IL	IL	IL	IL	FL	FL	FL	CT
		NY		KS	KS	KS	IA	IA	IA	IA	IA	IA	IN	IN	IN	IN	IL	IL	IL	DC
					WA	MA	KS	KS	KS	KS	KS	KS	IA	IA	IA	IA	IN	IN	IN	FL
						TX	MA	NJ	MN	MA	MA	MD	KS	KS	KS	KS	IA	IA	IA	IL
						WA	TX	NM	NJ	MN	MN	MA	ME	ME	ME	ME	KS	KS	KS	IN
							WA	RI	NM	NM	MS	MN	MD	MD	MD	MD	ME	ME	ME	IA
								TX	RI	RI	NM	MS	MA	MA	MA	MA	MD	MD	MD	KS
								WA	TX	TX	OR	NM	MN	MN	MN	MN	MA	MA	MA	LA
									WA	WA	RI	NY	MS	MS	NE	MO	MN	MN	MN	ME
										WV	TX	OH	NM	NM	NV	NE	MO	MO	MO	MD
											WA	OR	NY	NY	NM	NV	NE	NE	NE	MA
											WV	RI	OH	OH	NY	NM	NV	NV	NV	MN
												TX	OR	OR	OH	NY	NM	NM	NM	MO
												WA	RI	RI	OR	OH	NY	NY	NY	NE
												WV	TX	TX	RI	OR	OH	ND	NC	NV
													WA	VA	TX	RI	OR	OH	ND	NM
													WV	WA	VA	TX	RI	OR	OH	NY
														WV	WA	VA	TX	RI	OR	NC
															WV	WA	VA	TX	RI	ND
																WV	WA	VA	TX	OH
																	WV	WA	VA	OR
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																				WV

[1]Duplicative years condensed

Discussion

The best available evidence suggests that state CHW policy has the potential to support the CHW workforce and thereby improve patient outcomes. Suggested policies that can bolster CHWs include: sustainable funding, workforce development, and occupational definitions and guidelines.[71] Over time, more states have included CHWs in legislation, thereby allowing more targeted workforce development and funding mechanisms. By 2021, only 13 states had not yet integrated CHWs into legislation in some meaningful way, and some of those states had CHWs on the docket for 2022 or 2023 legislative sessions. Once adopted into law, unless it referred to transient funding, states typically did not remove CHW legislation over time, indicating support for – or at least a lack of opposition to – CHW interventions. The inclusion of CHWs into seven states' COVID-19 recovery policies demonstrates that states are looking at different ways to use CHWs for a widening range of services.

CHW certification is of particular note in these results because of its utility as an indicator of competency or legitimacy to potential employers or payors.[71,72] Increased employer investment in CHWs can strengthen the overall workforce, and one recent study found CHW hourly wages to be $2.42 more in states with outlined CHW certification.[73] State CHW certification is considered a best practice for CHW policy, and has been shown to be cost-effective and improve outcomes like glycemic control among patients with diabetes and improved cancer awareness.[71] However, it is important to note that CHW organizations are concerned that too much regulation on certification may undermine the innate grassroots base of the role.[72] Defining a scope of practice, or outlining potential "setting, roles, functions, activities, and supervision requirements for

CHWs," is also considered a cost-effective best practice for CHW policy.[71] The C3 Project aimed to outline a standard set of core skills (and training) and roles (or a scope of practice).[65] The CHW organizations active in almost all states are well-suited to advise if that state is at risk for possible overregulation of CHWs. In these cases, CHW advocates can attempt to initiate policy at an organizational (e.g., state health department or CHW certifying organization) rather than legislative level.

Medicaid reimbursement is emphasized as a best practice because of its potential as a more sustainable funding source than short-term grants or annual budget allocations.[73] A current federal investment in CHWs through a 2022 $225 million American Rescue Plan award for funding CHW training and a 2023 $50 million Consolidated Appropriations Act award for building CHW workforce capacity may draw more attention to CHW funding, but these are still short-term investments.[17] A 2022 KFF state survey on Medicaid budget found that as of July 1, 2022, the majority of states that responded (29 of 48) allowed Medicaid payment for CHW services.[17] This compares to only 19 states that include Medicaid reimbursement as a funding mechanism for CHWs in state law. Future reviews can further explore this disconnect. Even when implemented, Medicaid as a funding mechanism falls short of covering all CHW services in some states; for instance, in Indiana, care coordination and arranging for or providing transportation are currently not covered CHW services.[74] In using this example, it is noteworthy that care coordination is included in Table 2 as a service legislated for Indiana. A regulation adopted in Indiana in 1994 allowing care coordination as a reimbursable service for pregnant women through Medicaid was later repealed. Sustainable investments in CHW funding can be outlined at the state legislative level; a deeper look at outcomes among states with different prescribed funding sources for CHWs would be of great value.

The evidence base for the effectiveness, both in terms of health outcomes and cost-savings, for community health workers is strong,[55] but no studies have directly linked CHW policy to health outcomes.[71] This research is needed to continue to make the case for CHW policy, especially when it comes to CHW funding. It may be more effective to search one best practice at a time, or present results in a longer format like a report so there is space to explain changes over time in more detail. Another relationship to explore is the landscape of state-level CHW workforces and state-specific CHW legislation, both as a method to determine strengths and impediments of CHW legislation (e.g., Do states with more CHW best practices outlined in legislation have more CHWs per capita? Do states with legislated certification standards have a CHW workforce more or less representative of the communities they serve?). One challenge to CHW policy analysis is accurate identification of CHWs in law. This is difficult to overcome with historical policies that lack solid definitions of CHWs or a CHW synonym, but advocates can request definitional clarity in CHW policy moving forward. However, researchers can capitalize on the variation in CHW legislation by state as a method to see differences in health outcomes and even CHW workforce composition.

Limitations

This analysis did not include policies outside of state statutes, legislation, and regulations. States may have funding or otherwise define CHWs through the state Medicaid office, health department, or other agency. To gain insight into differences between outcomes in states with CHW legislation versus CHW policies not mandated in law, future CHW policy exploration can broaden what is included in the dataset. While laws relevant to this study should have been included in Nexis Uni, it is possible that expanding to a second source like Westlaw would have captured additional policies. Policies in place before 1991 may not have been posted on Nexis Uni,[59] but the CHW regulations started coming into effect around that year regardless. Nexis Uni does not always show text for repealed laws, which means they would not appear in a Boolean keyword search, thereby limiting a complete analysis of change in policy over time.

Public Health Implications

CHWs are a cost-effective member of the public health workforce, and a growing body of literature suggests that CHW interventions have positive impacts on health and SDOH outcomes. CHWs are one of the most diverse – in terms of race, ethnicity, and linguistic skillset – sectors of the public health workforce, thereby qualifying CHWs to work with and relate to a wide range of community members. As such, CHWs are invaluable members of the public health workforce, filling gaps more traditional public health employees are less suited to fill.

State-level CHW policies can bring more apparent validity to potential employers and sustainable funding to the workforce. Specifically, policy-directed Medicaid funding through which an array of CHW services are reimbursable, a clear definition of what positions qualify as a CHW, and certification protocols that do not undermine the grassroots foundation of the CHW workforce can lead to a broadened and strengthened CHW workforce. This fortified CHW workforce can directly address SDOH among historically underserved communities, thereby improving health outcomes for all.

CHAPTER THREE: EVALUATION OF A HEALTH SYSTEM-BASED COMMUNITY HEALTH WORKER INTERVENTION AMONG HIGH-RISK PATIENTS WITH DIABETES

Introduction

Community health workers (CHW), trained frontline public health workers who are trusted members of or share socioeconomic and cultural backgrounds with the community served,[2,52] liaise between a patient and healthcare provider, thereby promoting and improving upon community-clinical linkages.[2–4] Shared experiences of CHWs with the community build trusting relationships that drive success in areas in which traditional healthcare or public health providers often have difficulties reaching patients, such as influencing attitudes, shifting social norms, addressing external barriers like the social determinants of health (SDOH), and bolstering self-efficacy.[1,2,5] Because of this unique, culturally appropriate skillset, CHW interventions are a promising place-based approach[54] to increasing access to healthcare and decreasing health inequities for historically marginalized populations.[5,7] CHWs are considered a cost-saving intervention for healthcare systems through implementation of a wide range of strategies and services that aim to assist patients in adopting health behaviors, including: outreach, care coordination, community education, informal counseling, social support, motivational interviewing, and advocacy.[1,2,4]

The use of CHWs is also considered an economical strategy to help manage complex chronic disease, like diabetes, in a home and community setting.[1,13,47] Barriers to successful disease management are often rooted in complex SDOH issues like access to healthcare and socioeconomic status.[6,14,50] Because CHWs are a part of the community in which they work, the connections they develop with patients suffering with chronic disease allow for more open communication about patient needs. Knowing the true barriers a patient faces, CHWs can better assist with navigating the healthcare system and disease management, including its wrap-around services like transportation, and thereby garner better health outcomes among patients.[3,13] Understanding the importance of addressing root causes of health inequities, the Patient Protection and Affordable Care Act (ACA) directed funds to CHWs to work with populations with high rates of chronic disease and SDOH linked to negative health outcomes, including the un-or underinsured and residents of areas designated as a health professional shortage area.[15]

Diabetes control often requires constant and consistent self-monitoring by patients. CHWs have been shown to improve self-management of diabetes through measures such as increased appointment attendance, adherence to medication routines, goal-setting, behavioral change, and use of primary and preventive care.[3,7] The literature shows an association with a significant decrease in HbA1c (A1C) level after CHW intervention.[1,13,50,52] Despite the growing body of evidence supporting CHW interventions for patients with diabetes as cost-effective and promoters of positive health outcomes,[13,50,52] gaps in the literature persist. Most CHW interventions are financed through public funding.[52] We will add to the knowledge base by looking at a CHW intervention that is funded through private dollars. Many CHW interventions are at the home or community level, and our study looks at health system-based CHWs, and can add information on frequency and duration of CHW-patient interactions.[52] This paper assesses the effectiveness of the Diabetes Impact Project – Indianapolis Neighborhoods (DIP-IN) health system-based CHW program, in relation to a comparison group, on reducing complications associated with diabetes and improving health outcomes for those enrolled in the health system-based CHW intervention. DIP-IN patients are considered to have a higher risk for diabetic complications and other health issues due to poorly controlled glycemic levels, which may be exacerbated by the sociodemographic environment of the areas in which they live. The research hypothesis that drives DIP-IN is that the CHW model will reduce complications (uncontrolled glycemic levels and hospital emergency department visits and admissions) for high-risk patients with diabetes served by the intervention.

Methods

Study Setting and Population

The Diabetes Impact Project Indianapolis Neighborhoods (DIP-IN) is a collaboration between the Indiana University Fairbanks School of Public Health (FSPH) and Eli Lilly and Company that aims to reduce diabetes-related complications and, ultimately, the incidence of diabetes in three neighborhoods with disproportionate rates of diabetes. In 2019, the three communities had a combined diagnosed and undiagnosed diabetes prevalence of 23.3%, as compared to a national rate of 14.7%.[32,75] As a whole, DIP-IN's theory of change for the patient-focused CHW intervention is based on the Social Cognitive Theory, which emphasizes the interconnectedness of behavior, personal factors, and the physical and social environment.[76] One element of the project is the employment of CHWs trained to work with high-risk diabetes patients at select Eskenazi Health (Eskenazi) Federally Qualified Health Centers (FQHC) within the target communities. Eskenazi is a public hospital system in Marion County, Indiana, providing cost-effective healthcare to a diverse population at multiple clinic sites.[77] This study leverages extracted data from Eskenazi's electronic medical record (EMR) system, Epic. Extracted data included variables at the patient level for all encounters occurring between December 1, 2016, and March 31, 2022.

Intervention

Health system-based DIP-IN CHWs are initially trained within the Eskenazi healthcare system. After a probationary period, the CHWs undergo Indiana's state-recognized CHW certification training. The cost of this certification is covered through employment. High-risk patients with diabetes meeting pre-determined criteria (Eskenazi patients 18 years and older with a recent A1C measure of 7.9% or higher who live in one of six DIP-IN ZIP Codes) are recruited for enrollment in the DIP-IN CHW program.[53] Enrollment into the health system-based DIP-IN CHW program began on April 1, 2019. Enrollment in the CHW intervention occurs on a rolling-basis, and patient disenrollment is based on individual patient needs rather than a set timeframe. During the study timeframe, CHWs were able to reach about 58% of patients contacted. Of all attempted contacts, there was an approximate 39% enrollment rate; among those with whom contact was made, the enrollment rate was about 67%. In the first three years of the intervention, about 31% of patients disenrolled. Patients were disenrolled for program compliance and glycemic control, two consecutive no shows to appointments, substance abuse issues, or decline of services, among other reasons. CHWs visit patients every two to four weeks, depending on the needs of each patient. CHWs track the encounters using assessment tools, often on paper to avoid a laptop as a possible distraction in the communication. Issues organically arise in the encounters, and CHWs aim to empower patients to increase self-sufficiency by giving information about referrals or assistance, but letting the patients attempt to make those connections (S. Zapata, oral communication, March 2023).

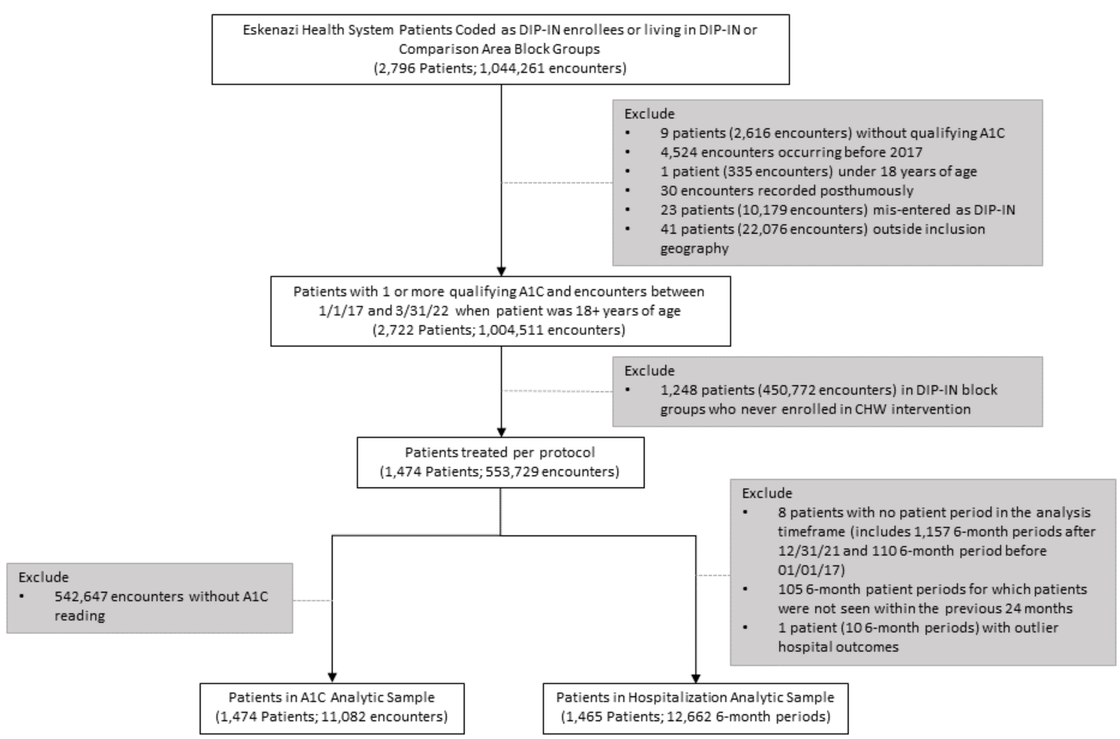
Comparison Areas

American Community Survey block group data (2019 5-year sample) and Behavioral Risk Factors Surveillance System (BRFSS) census tract level data (2017) were used to identify comparison areas in Marion County that were comparable to DIP-IN areas. We used logistic regression to estimate the probability of each Marion County block group being given a DIP-IN block group designation based on certain characteristics: racial and ethnic composition, percent of residents over the age of 45, diabetes prevalence, Area Deprivation Index[78] (ADI) rank of each block group, the average ADI rank of the block groups within each census tract, and ADI rank of the closest neighboring block group. The ADI takes into account "17 education, employment, housing-quality, and poverty measures" derived from the American Community Survey.[78] Comparison block groups were then retained if they had a similar probability (or propensity score) of being DIP-IN block group as one or more DIP-IN block group. Because DIP-IN communities were intentionally chosen for this intervention based on high diabetes prevalence and socioeconomic factors, the majority of DIP-IN block groups had >90% probability of being a DIP-IN block group. Due to minimal overlap between DIP-IN and non-DIP-IN block group propensity scores, we sampled without replacement, thereby allowing a non-DIP-IN block group to serve as a comparison block group for multiple DIP-IN block groups. We identified matches for 83/138 DIP-IN block groups at the recommended 0.2SD caliper (60% of matches) and were able to identify a match for all DIP-IN block groups with caliper of 0.5SD (N=45 total comparison area block groups). Matching facilitated greater comparability between DIP-IN block groups and other block groups in Marion County, though DIP-IN block groups have comparatively higher ADI, proportion Black residents, and diabetes prevalence (**Appendix Table C1**).

Analytic Sample

Our analyses are limited to patients meeting enrollment criteria for DIP-IN or meeting A1C enrollment criteria and living in a comparison block group. **Figure 3.1** outlines the patient analytic flowchart.

Figure 3.1. A1C and hospital outcomes patient analytic flowchart



Measures

Time-varying outcomes of interest included continuous A1C test values, duration of time between A1C test encounters (continuous days), and any emergency department (ED) visits or inpatient hospital admissions within the Eskenazi healthcare system in the past six months. Some A1C measures extracted from Epic contained a character value indicating a value greater than or less than a number value (e.g., <4.8). We modified these variables to remove character variables and maintain the value (the example would become 4.7). As a note, we are reporting A1C in a unit change rather than the notation of "%" so that changes are not interpreted as a percent change, rather than level change. In addition to calculating the continuous number of days between A1C test encounters, we also created a dichotomous variable to determine how many patients had an A1C within six months (182 days) of the previous recorded A1C measure.[26,29] We created dichotomous presence/absence variables for hospital ED visits and admissions. We defined presence as at least one hospital ED visit or admission for a patient in a six-month timeframe, beginning with the first six-month timeframe in which each patient had an interaction with the healthcare system within the analysis period. Our time-varying exposure of interest was a dichotomous variable that took on the value of "1" if the encounter occurred after the patient's first CHW encounter and "0" otherwise. As such, the exposure value was "0" for all patients residing in comparison areas at all time points. When evaluating changes in A1C test values, to account for A1C being a three-month measure of blood sugar, DIP-IN patients were considered exposed 90 days after their first CHW visit. We identified confounders using a directed acyclic graph (**Appendix Figure C1**),[79] created to reflect our assumed causal model and included gender (female, male), race and ethnicity (Black, Latinx, white, and other), payor (Medicaid, Medicare, private/employer, other governmental, uninsured, unknown), marital status (partner or married, previously partnered, single, missing), age and quadratic age (continuous), indicators for ZIP Code of residence, seasonality (winter, spring, summer, fall), and year of encounter. We calculated age at each encounter using date of birth. Epic provided the specific payor, so the evaluation team categorized and coded these to general payor types. We considered the payor type and marital status captured closest to the first CHW visit for DIP-IN patients or the date of a DIP-IN qualifying A1C for comparison group patients as baseline. We generated seasonality from each contact date. We considered dates in December – February as "winter," dates in March – May as "spring," dates in June – August as "summer," and dates in September – November as "fall."

Statistical Analysis

We first tabulated sample characteristics (counts and proportions for categorical variables or means and standard deviations for continuous variables) overall and stratified by study group (DIP-IN or Comparison) and year. We then estimated the effect of DIP-IN's CHW intervention using a difference-in-difference (DD) approach. DD enabled us to compare pre-post changes in the CHW intervention group while "differencing out" secular trends in the outcomes in our comparison group. Briefly, we applied generalized linear mixed models (GLMM); a logit link was employed for dichotomous outcomes. The models incorporated fixed effects for the study group (DIP-IN or Comparison) and year, the time-varying CHW exposure status, confounder variables outlined above, random intercepts for each unique patient, an unstructured covariance matrix, and robust standard errors. Covariate referent groups were selected based on groups with known lower risk of diabetes: female,[32] white,[32,80] summer, private health insurance,[80,81] and married or partnered[82] were considered to be referent groups. We used the comparison group ZIP Code with the highest number of patients as the referent ZIP Code. As a robustness check, we re-estimated the effect of the CHW intervention on clinical outcomes when additionally adjusting for high blood pressure status at baseline (systolic measure > 130 units or diastolic measure >90).

We completed data analysis in SAS Enterprise Guide 8.3 (SAS Institute Inc., Cary, NC) and considered P values < 0.05 to be statistically significant.

Institutional Review Board

This study was approved through the Indiana University IRB as exempt protocol #1810153604A001.

Results

Patient Characteristics

The characteristics of patients contributing data for A1C and hospital outcomes stratified by group and year are presented in **Table 3.1**. In total, 454 DIP-IN patients and 1020 comparison group patients were included in the analysis. In the first year of recruitment for DIP-IN, relative to patients in the comparison group, DIP-IN patients were slightly older on average (and consequently more likely to be on Medicare), more likely to be women or Black, and less likely to be Latinx or uninsured. Over time, baseline differences in the race and gender composition of study groups persist while age differences (and consequently proportion on Medicare) further widen.

Table 3.1. Selected demographic composition of DIP-IN and Comparison groups by year: (A) Patients contributing to the A1C analytic sample, (B) Patients contributing to the hospitalization analytic sample

A. Patients contributing to the A1C analytic sample								
	2019		2020		2021		2022	
	DIP-IN N=398	Comp N=567	DIP-IN N=443	Comp N=565	DIP-IN N=454	Comp N=668	DIP-IN N=211	Comp N=407
Age (years) (SD)	55.08 (12.20)	53.34 (12.95)	56.34 (12.13)	53.13 (12.81)	56.63 (12.12)	52.93 (12.37)	57.08 (12.01)	53.55 (12.41)
Female Gender	57.04%	53.62%	58.66%	53.45%	56.38%	55.99%	54.50%	54.30%
Race/Ethnicity								
Black	77.39%	37.92%	77.00%	40.18%	77.30%	37.87%	78.20%	40.54%
Latinx	12.81%	37.39%	12.66%	37.35%	12.24%	40.42%	11.37%	39.56%
White	8.54%	21.87%	9.30%	18.76%	8.93%	17.66%	9.00%	16.95%
Other	1.26%	2.82%	1.03%	3.72%	1.53%	4.04%	1.42%	2.95%
Payor Type								
Medicaid	35.93%	32.28%	36.69%	36.64%	38.01%	38.17%	36.97%	34.40%
Medicare	44.72%	30.69%	43.93%	26.37%	42.35%	22.01%	45.02%	22.85%
Other Government	0.75%	4.76%	1.03%	4.60%	0.77%	3.89%	0.47%	3.44%
Uninsured	5.78%	16.75%	6.46%	15.93%	6.12%	18.11%	4.74%	21.87%
Unknown	0.25%	0.53%	0.26%	0.35%	0.26%	1.50%	0.00%	0.98%
Private	12.56%	14.99%	11.63%	16.11%	12.50%	16.32%	12.80%	16.46%

B. Patients contributing to the hospitalization analytic sample

	2019		2020		2021	
	DIP-IN N=414	Comparison N=652	DIP-IN N=443	Comparison N=741	DIP-IN N=454	Comparison N=852
Age (years) (SD)	54.82 (12.12)	52.93 (12.92)	55.57 (12.20)	52.80 (12.99)	56.55 (11.94)	52.77 (12.72)
Female Gender	57.28%	53.99%	57.73%	53.58%	56.92%	54.69%
Race/Ethnicity						
Black	77.18%	37.88%	78.18%	39.41%	77.55%	38.15%
Latinx	12.62%	36.50%	12.27%	36.84%	12.02%	39.32%
White	8.98%	21.93%	8.41%	20.11%	9.07%	18.54%
Other	1.21%	3.68%	1.14%	3.64%	1.36%	3.99%
Payor Type						
Medicaid	36.17%	33.59%	37.05%	35.22%	37.64%	37.44%
Medicare	44.17%	28.99%	43.18%	27.26%	42.86%	23.59%
Other Government	0.73%	5.37%	0.91%	4.99%	0.91%	4.23%
Uninsured	5.58%	16.10%	5.68%	16.06%	5.67%	17.37%
Unknown	0.24%	0.61%	0.23%	0.54%	0.23%	1.29%
Private	13.11%	15.34%	12.95%	15.92%	12.70%	16.08%

DIP-IN Encounters

Over the first three years of the intervention, health system-based CHWs met with 454 DIP-IN patients an average of 12 times each for an average of 21 minutes at each encounter. Patients were enrolled in DIP-IN for an average of 668 days. The majority (55%) of patients were enrolled in the first year of the intervention, were Black (78%), were between 45-64 years old (60%), and were female (57%). Though originally planned as an in-person intervention, due to COVID-19 restrictions implemented concurrently with the start of the second year of the intervention, the majority (82%) of encounters occurred by telephone and lasted about 15 minutes (45%) over the three-year period. DIP-IN CHWs feel like they are a valued member of the medical team within the FQHCs, and providers share concerns that they cannot address during medical visits (S. Zapata, oral communication, March 2023).

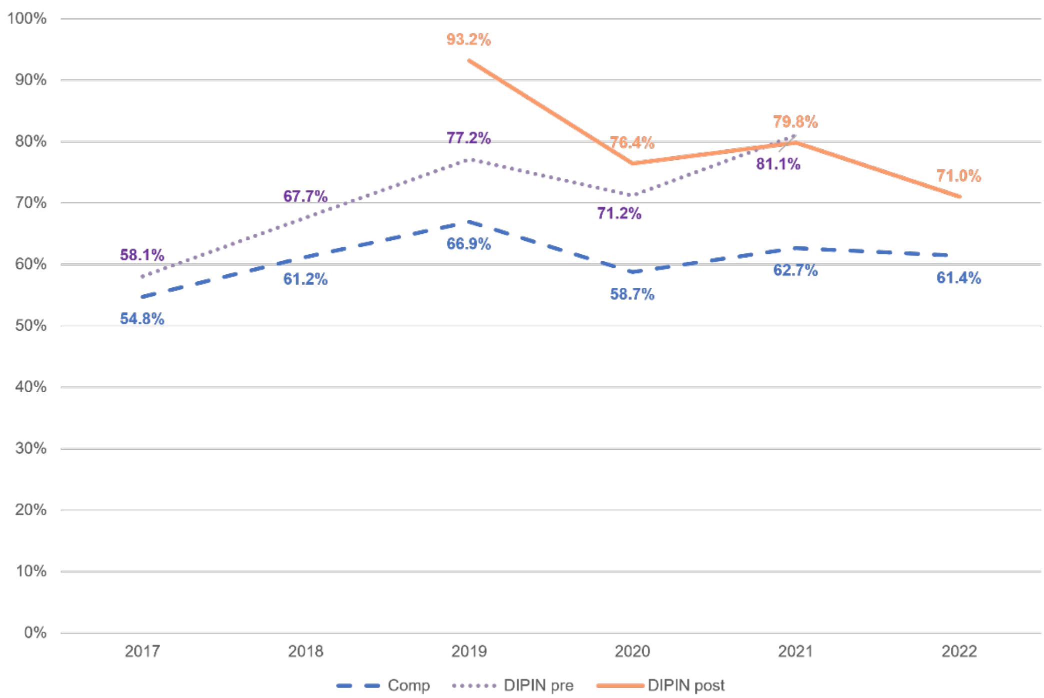
Clinical Outcomes

In the first year of recruitment (2019), the mean A1C levels for DIP-IN patients who had not yet experienced the intervention were higher than those for comparison group patients (9.39% and 8.79%, respectively; **Figure 3.2A**) while in the last year of follow-up (2022), the mean A1C levels for DIP-IN patients post intervention were lower than those for comparison group patients (8.89% vs. 9.13%, respectively). The proportion of patients with at least one A1C measure within six months of the prior measure was higher for DIP-IN patients in the first year of recruitment (58.1% vs. 54.8% for comparison group) and remained higher for the duration of the observed study period (**Figure 3.2B**).

Figure 3.2 also shows a natural time variation for ED visits and hospital admissions for both groups. To provide context, we added important dates to these figures, including the beginning of the DIP-IN CHW intervention (April 2019), the beginning of the COVID-19 pandemic (March 2020), and when COVID-19 vaccines were made available to all adults in Indiana (April 2021). The DIP-IN group tended to have a higher percentage of patients with an ED visit than the comparison group (**Figure 3.2C**). There was a less consistent pattern between the two groups for hospital admissions, though the DIP-IN group had a higher peak of patients with a hospital admission at the beginning of the COVID-19 pandemic (**Figure 3.2D**). COVID ED visits and hospitalizations contributed to these percentages. COVID was indicated as a diagnosis for approximately 3% of ED visits among both groups. COVID was a diagnosis for more (7.81%) hospital admissions among DIP-IN patients than comparison group patients (3.90%) (**Appendix Table C2**).

Figure 3.2. Clinical outcomes over time by analysis group: (A) Mean A1C by year, (B) Proportion of patients with at least one A1C measure within 6 months of prior measure by year, (C) Percent of patients with hospital ED visit in six-month period, (D) Percent of patients with hospital admission in six-month period

B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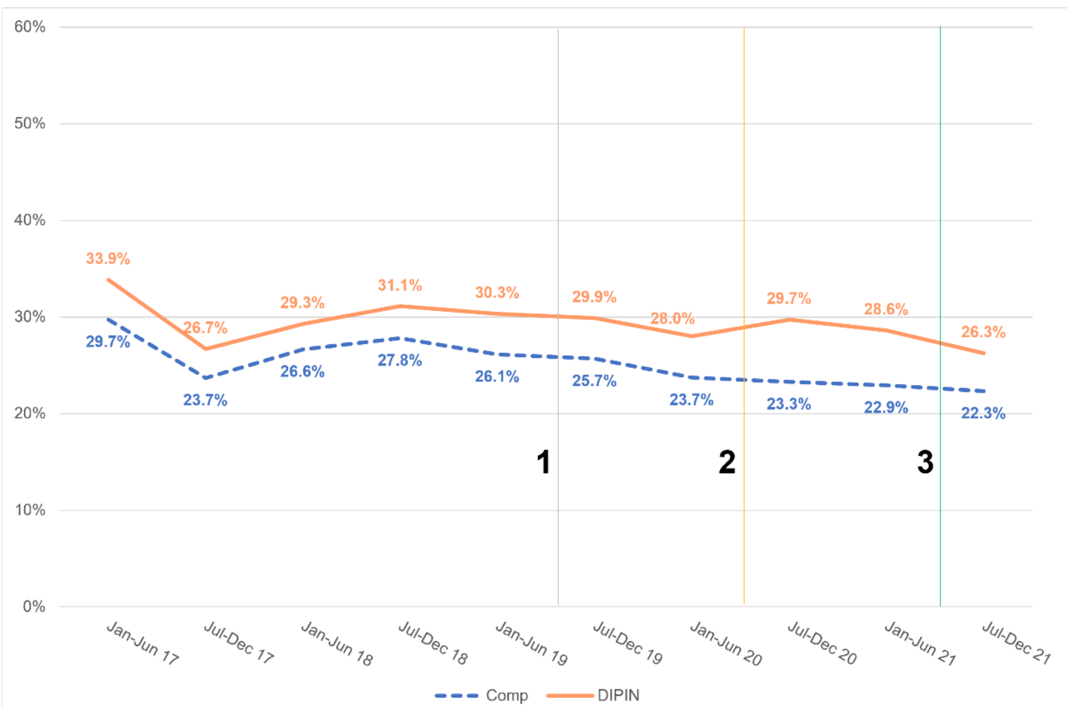
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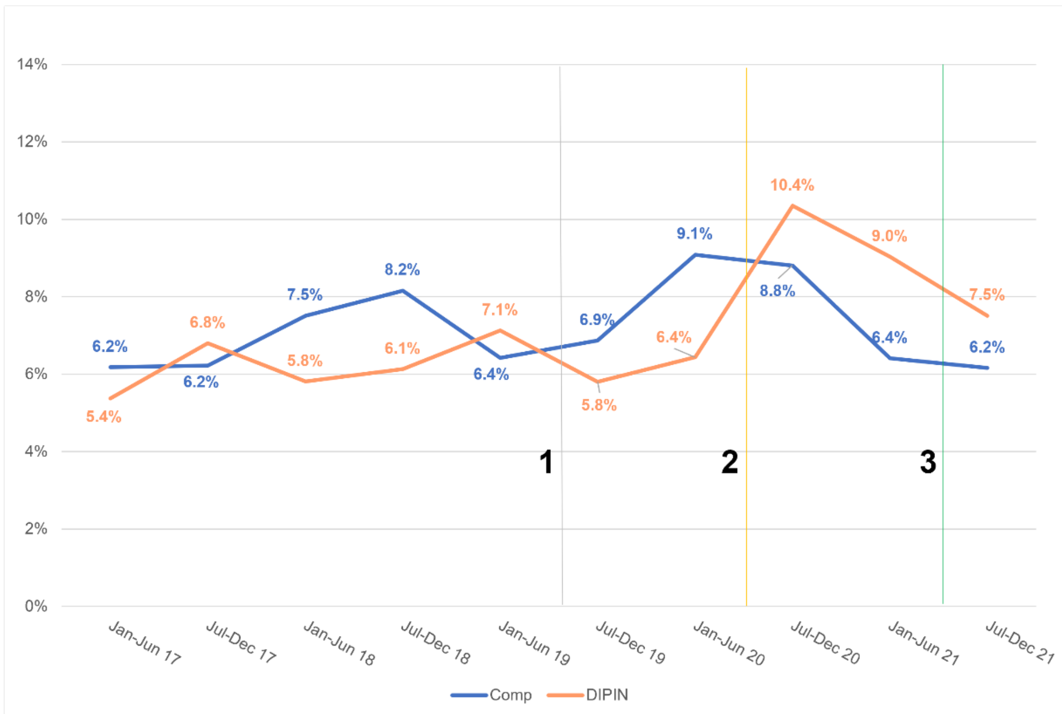


[1]April 2019: Start of DIP-IN CHW intervention
[2]March 2020: First COVID-19 case in Marion County, Indiana
[3]April 2021: COVID-19 vaccine available for all adults in Indiana

The Impact of DIP-IN CHW Intervention on Clinical Outcomes

Exposure to the health system-based DIP-IN CHW intervention was associated with a 0.55-unit (95% CI: -0.70, -0.30) reduction in A1C on average over time and a 34.48-day (95% CI: -44.52, -24.45) reduction in the number of days between A1C measures on average over time that was beyond the change observed among those who did not receive the DIP-IN CHW intervention during the same period (**Table 3.2**). Relative to the change observed over time in the comparison group, participation in the DIP-IN CHW intervention was associated with 12% lower odds of ED visits (OR: 0.88; 95% CI: 0.73,1.05) and 19% lower odds of hospital admission (OR: 0.81; 95% CI: 0.60,1.09). Estimates were robust to further adjustment for blood pressure with no appreciable change to direction, magnitude, or precision of the estimate (**Appendix Table C3**).

Table 3.2. Model-based estimated impact of DIP-IN CHWs over time relative to no CHW intervention on clinical outcomes

Outcome[1]	β (95%: CI)
1+ Mean A1C (points)	-0.55 (-0.70, -0.30)
1+ Mean Time between A1C Measures (days)	-34.48 (-44.52, -24.45)
Outcome[2]	**Odd Ratio (95%: CI)**
2+ ED Visit	0.88 (0.73, 1.05)
2+ Hospital Admission	0.81 (0.60, 1.09)

[1]Mixed effects linear regression models incorporated fixed effects for study group (DIP-IN or Comparison) by year, time-varying CHW exposure status, random intercepts for each unique patient, and robust standard errors. The model was additionally adjusted for season, residential ZIP Code, age, age-squared, gender, race and ethnicity, and baseline marital status and payor type
[2]Mixed effects logistic regression models incorporated fixed effects for study group (DIP-IN or Comparison) and year in 6-month intervals, time-varying CHW exposure status, random intercepts for each unique patient, and robust standard errors. The model was additionally adjusted for age, age-squared, gender, race and ethnicity, and baseline marital status and payor type

Discussion

Our findings provide results from a privately funded CHW intervention for high-risk patients with diabetes that is embedded within a healthcare system. These results show successful implementation and overall improvement in selected health outcomes, which underscores the ability to diversify CHW funding streams and improve clinical-community linkages through CHW interventions. We found that among high-risk patients with diabetes, the health system-based DIP-IN CHW intervention was associated with a significant decrease in mean A1C and mean time between A1C measures. Our findings on improvement in A1C among patients enrolled in a CHW intervention, in relation to a control group, is consistent with literature, including a 36-study systematic review.[50,52,83]

While not an outcome typically discussed in the literature for diabetes management interventions, the significant decrease in time between A1C measures among DIP-IN patients is important because best practices suggest patients with diabetes get an A1C test every six months to tailor glycemic management plans as needed.[26,29] When patients are not able to access care on a routine basis, it is difficult to adhere to that best practice. A shorter duration between A1C measures indicates that DIP-IN patients were better able to gain access to a provider as a part of diabetes management. Unlike many CHW interventions for patients with diabetes, DIP-IN protocol does not include a set schedule for A1C testing with CHWs for enrolled patients. Therefore, improvement in A1C measures in relation to the comparison group emphasizes that DIP-IN CHWs were able to build self-sufficiency among patients with diabetes.

A decrease in the odds of hospital ED visits and admissions among DIP-IN CHW patients was not significant, results that are consistent with literature.[52] In consideration of these hospital trends, DIP-IN patients had more risk factors for negative health outcomes based on factors like historic marginalization, Area Deprivation Index score, and living in communities with higher overall diabetes prevalence rates than the comparison group. In a national study, diabetes-related ED use was found to be three times higher among Black patients than white patients,[84] and multiple studies have found racial differences in ED-level outcomes (i.e., triage times, admission rates, mortality rates) that highlight the potential of racial bias within the ED.[85–87] The DIP-IN group had a much higher percentage of Black patients overall than the comparison group (78% versus 39%), so it is plausible that the reduction in ED visits among the DIP-IN intervention group may underestimate the results at a population level.

It is important to note that COVID-19 changed the way the intervention was originally planned; for nearly two years, CHW visits shifted from in-person to virtual or limited contact porch visits. The authors' hopes were that including one year of routine intervention and two years of varying COVID-19 protocol intervention would better reveal the intervention's effectiveness. Some analyses are intertwined with COVID-19. For instance, because of a low number overall, the analysis of hospital ED visits and admissions did not exclude those hospital visits due to COVID-19. COVID-19-specific hospital admissions will be analyzed in a later manuscript, but this paper does not distinguish COVID-19 outcomes. While the increased risk of COVID-19 morbidity and mortality among high-risk DIP-IN patients may impact these results, the authors felt it better to leave the larger sample size in the analyses.

Limitations

This study was not without limitations. With an approximate 39% recruitment rate of all patients with whom CHWs attempted to contact, factors related to those missed patients may present some selection bias of those enrolled in DIP-IN if these patients represent a demographic with more barriers to diabetes management that put them at a high risk for complications, such as those with unstable housing. The use of EMRs as a main data source for an observational public health study left gaps in our ability to account for some time-varying confounding. We were not able to include comorbidities or a poverty indicator (though Medicaid as the baseline payor is an imperfect proxy for poverty) in these analyses due to the nature of what data were included in and pulled from Epic. Within the hospital outcomes modeling, we used the logit link due to convergence issues. Because odds ratios overestimate relative risk, the estimated hospital outcomes may be more liberal than actual outcomes. This study only includes EMR records from one healthcare system within a large city; we assumed non-differential bias due to patients from both analysis groups seeking care elsewhere. Using a comparison group derived through propensity score matching is a strength of the study, though we cannot exclude the possibility of residual confounding. Because the DIP-IN population faced many barriers to care and successful diabetes management, these positive results should be generalizable to broader groups with high A1C levels. We also did not account for dosage of the intervention in this study. Another strength of the intervention is the integration of DIP-IN CHWs into Eskenazi's FQHC model, which may allow a more effective route to address this SDOH both through the existing community-clinical linkage and the ability of the CHW to both see the patient's medical records and confer with other providers. It would be useful for future analyses to be able to track outcomes like in-network routine care with providers for the intervention group.

Conclusion

A health system-based, CHW intervention can be successful in improving outcomes and increasing self-sufficiency among high-risk patients with diabetes in relation to a comparison group. Integration into a healthcare system and medical team supportive of the CHW team and intervention aids in creating clinical-community linkages through which patients can be treated for medical and SDOH needs.

CHAPTER FOUR: ASSOCIATION OF A COMMUNITY HEALTH WORKER INTERVENTION FOR PATIENTS WITH DIABETES ON COVID-19 HOSPITAL OUTCOMES

Introduction

As of March 2023, there have been nearly 104 million COVID-19 cases and over 1.1 million COVID-19 deaths in the U.S.,[88] and a link between diabetes and COVID-19 morbidity and mortality was identified within a month of the first reported case.[48,89,90] Prior studies, including a meta-analysis, found diabetes to be a risk factor for more severe disease among those infected with SARS-CoV-2.[91,92(p19)] Type 2 diabetes and COVID-19 share risk factors, including increased age, race and ethnicity (or more accurately, racism[33]), and those with overweight or obesity.[19,93,94] The risk of incident diabetes is associated with COVID-19 infection; one meta-analysis calculated a risk ratio for studies within the U.S. of 1.77 (95% CI: 1.41, 2.22).[95] Because of the increased risk of COVID-19 morbidity and mortality for patients with diabetes, diabetes management by an integrated care team that includes interventions aimed at preventing COVID-19 infection is crucial to preventing worse outcomes.[48,89,96]

Community Health Workers (CHWs), or frontline workers who share a background with the community in which they serve, are a part of the team that might assist in reducing the risk of contracting COVID-19, managing care if a diabetes patient contracts COVID-19, and offering support and advice on emerging topics like vaccines.[1,2,96,97] Management of diabetes through glycemic control may be helpful in mitigating severe COVID-19, and CHW interventions have been successful in this type of care.[1,13,29,48,50] CHWs are trained to serve clients holistically by addressing the social determinants of health (SDOH), so they are positioned to assess socioeconomic contextual information that may increase the risk of COVID-19 morbidity and mortality for patients with diabetes.[14] Complex challenges of diabetes management related to SDOH that may have been impacted by COVID-19 restrictions and the overall context of the pandemic include maintaining a healthy diet, getting exercise, adhering to medication regimen, getting social support, continuing routine primary care, and getting culturally and linguistically appropriate information on COVID-19 prevention.[96,98] Emerging studies have looked at CHW intervention for patients with diabetes during COVID-19. One utilized CHWs as a low-to no-cost solution to home delivery of medication to patients with diabetes, thus allowing the client to avoid the higher-risk environment for contracting COVID-19 at the pharmacy. This model also provided an opportunity for CHWs to screen patients and their households for symptoms of COVID-19 and other health and social risks.[97] Another study integrated Spanish-speaking CHWs at various tiers of care to assist Spanish-speaking COVID-19 patients with isolation, telehealth follow-ups, food delivery, and other social services.[98]

There is a body of literature supporting the use of CHWs to improve outcomes related to health and access to care,[55] and preliminary studies have demonstrated a positive impact of CHW interventions through the initial phases of COVID-19.[97–99] This paper adds to the knowledge base by looking at longer-term COVID-19 hospital outcomes among patients with diabetes. In this study, we assess if enrollment in the Diabetes Impact Project – Indianapolis Neighborhoods (DIP-IN) health system-based CHW intervention was associated with COVID-19 hospital admissions and length of stay (LOS). Patients enrolled in DIP-IN are at a higher risk for diabetic complications due to uncontrolled glycemic levels that may be exacerbated by the socioeconomic context of their residential environment. We hypothesized that DIP-IN patients, relative to a comparison group, would have a lower risk for COVID-19 hospitalizations and would experience shorter hospital lengths of stay if admitted for COVID-19 infection.

Methods

Study Setting and Sample

DIP-IN is a collaborative project that works to improve diabetes outcomes and reduce the incidence of diabetes in neighborhoods identified as having high rates of diabetes. In 2019, the three DIP-IN communities had a combined estimated diabetes prevalence of 23.3%, as compared to the overall U.S. rate of 14.7%.[32,75] This project identifies high-risk patients with diabetes within three Indianapolis neighborhoods who are Eskenazi Health (Eskenazi) Federally Qualified Health Center patients and recruits them for enrollment in a CHW program.[53] Eskenazi is a large, multi-site public hospital system in Marion County, Indiana, serving a diverse population with cost-effective healthcare.[77] This study utilizes data extracted from Eskenazi's electronic medical record (EMR) system, Epic. Patient-level data include all encounters that occurred between March 6, 2020, and March 31, 2022, for the analytic samples. March 6, 2020, was selected as the analytic start date because it was the date of the first known COVID-19 case in Marion County, Indiana. The overall study population includes Eskenazi patients who reside in DIP-IN or comparison census block groups and meet DIP-IN enrollment criteria as described below.

Intervention

Certified CHWs recruit Eskenazi patients into the DIP-IN program. DIP-IN CHW patients must meet enrollment criteria: Eskenazi patients 18 years and older with a recent A1C measure of 7.9% or higher who live in one of six DIP-IN ZIP Codes. DIP-IN's enrollment rate among those with whom contact was attempted is approximately 39% (67% among those with whom contact was made), and the disenrollment rate is approximately 31%. Those who disenrolled were in the program for an average of 465 days. During encounters, health system-based DIP-IN CHWs focus on addressing SDOH, in addition to working with patients on diabetes self-management. The DIP-IN CHW program began enrollment on April 1, 2019, so it functioned for one year before COVID-19 restrictions began in earnest. The program continued through COVID-19 restrictions, but some modes of the intervention adapted to meet the changing environment. For instance, home visits were transitioned mainly to phone appointments during times with the most stringent restrictions. In addition to diabetes encounters, CHWs also addressed SDOH needs by delivering food boxes to Eskenazi patients upon identification of a need or by request and pulse oximeters to DIP-IN CHW and other Eskenazi COVID patients after hospital discharge (S. Zapata, oral communication, March 2023).

Comparison Areas

DIP-IN communities were selected on block group socioeconomic factors in addition to high rates of diabetes, thereby necessitating specific characteristics of comparison block groups. To identify comparison block groups, we used logistic regression to find block group-level propensity score estimates. Propensity scores considered racial composition, diabetes prevalence, and residents over the age of 45. We also included the Area Deprivation Index[78] (an index of 17 census measures) ranking of every block group and its closest neighboring block group, as well as the average rankings of block groups within each census tract. The high diabetes prevalence rates and socioeconomic factors associated with DIP-IN communities meant that most DIP-IN block groups were highly likely (>90% probability) to be a DIP-IN block group. Probabilities – or propensity scores – were subsequently used to identify block groups outside of the DIP-IN communities that were most comparable to block groups in one or more of the DIP-IN communities. DIP-IN and non-DIP-IN block group propensity scores overlapped only minimally, so a non-DIP-IN block group was permitted to serve as a comparison block group for more than one DIP-IN block group by sampling without replacement. At the recommended 0.2SD caliper (60% of matches), we found matches for 83/138 DIP-IN block groups. Using a 0.5SD caliper, we identified matches for each DIP-IN block group, which resulted in 45 total comparison area block groups. The matching process created better comparability between DIP-IN block groups and other Marion County block groups. However, DIP-IN block groups have higher ADI, a greater proportion of Black residents, and higher prevalence of diabetes than block groups selected for the comparison group (**Appendix Table D1**).

Outcomes

Outcomes of interest included experience of COVID-19 hospitalization (yes/no) and LOS in days for those hospitalized with COVID-19. Presence or absence of one or more COVID-19 hospitalization was identified in the EMR using the following ICD-10 codes: U07.1, U09.9, and J12.82. In-hospital COVID mortality and ventilator use during COVID-19 hospitalization are secondary outcomes not included in the analytic models.

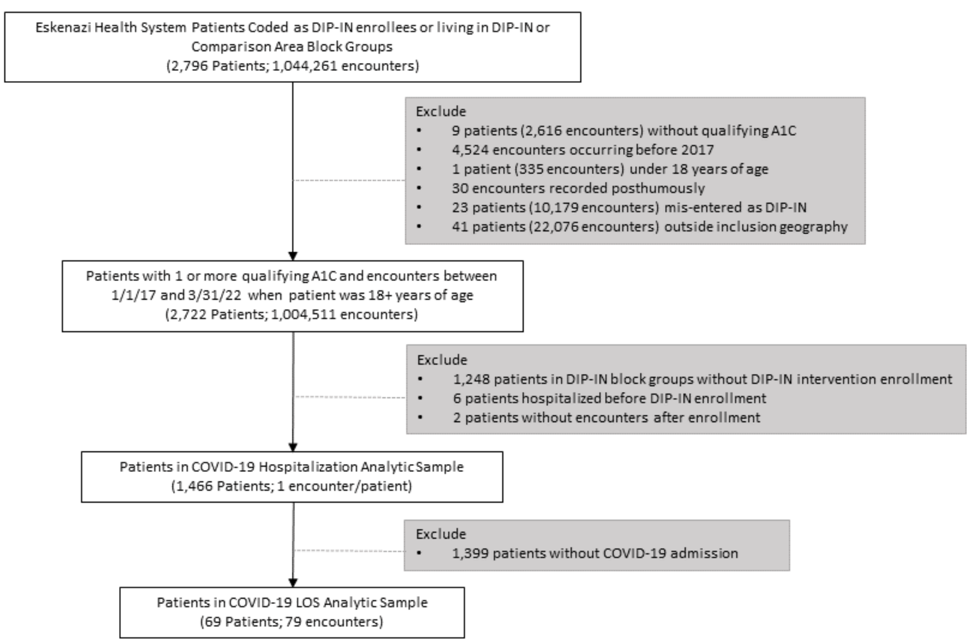
Potential Confounders

We developed a directed acyclic graph (**Appendix Figure D1**)[79] to identify potential confounders for our causal models. Potential confounders available in EMR included: race and ethnicity (Black, Latinx, white, other), payor (Medicaid, Medicare, private/employer, other governmental, uninsured, unknown), marital status (partner or married, previously partnered, single, missing), and gender (female, male), age and quadratic age (continuous), as well as the season (winter, spring, summer, fall), and year the patient entered our analytic sample. Insurance status data provided was the specific payor, so the authors developed payor categories and coded the payors to more general payor types. The payor type and marital status captured closest to the first CHW visit for DIP-IN patients or the date of a DIP-IN qualifying A1C for comparison group patients was considered baseline. We created a variable for seasonality based on encounter date. Encounters in December – February are coded as "winter," encounters in March – May are coded as "spring," encounters in June – August are coded as "summer," and encounters in September – November are coded as "fall."

Analytic Sample

Of the 2,796 patients who resided in a DIP-IN or comparison area, 2,722 had one or more qualifying A1C between January 1, 2017 – March 31, 2022 (**Figure 4.1**). For patients in DIP-IN areas, follow-up began when patient was officially enrolled in DIP-IN; follow-up initiation for those enrolled prior to March 6, 2020, was set to March 6, 2020 (N=1,248 residing in DIP-IN areas excluded for not being enrolled by March 31, 2022). Two patients without an encounter after DIP-IN enrollment were excluded from the sample. To make our denominator better reflect patients who would likely have been in-network to be admitted to Eskenazi's hospital had they been admitted during our study period, we restricted to patients with one or more encounter on or after March 6, 2020, or whose last encounter was within 24 months of their last encounter – no patients in either analysis group were excluded during this step. Patients were followed until whichever came first of the following: first COVID-19 hospitalization, 24 months after their last encounter, or March 31, 2022; six DIP-IN patients who experienced their first COVID-19 hospitalization prior to enrollment were excluded from analysis, thereby leaving 1,466 patients to assess odds of COVID-19 hospitalization. To assess LOS, the sample was further restricted to 69 patients with one or more COVID-19 hospitalization (79 total hospitalizations).

Figure 4.1. COVID-19 outcomes patient analytic sample flowchart



Statistical Analysis

To determine similarities or dissimilarities between our two analytic groups, we first generated sample characteristics and COVID-related hospital outcomes (counts and proportions for categorical variables or means and standard deviations for continuous variables) overall and stratified by study group (DIP-IN or Comparison). We used multivariable logistic regression modeling to determine if there was a difference in the odds of COVID-19 hospitalizations between DIP-IN patients and comparison group patients and a multivariable negative binomial model to determine if there was a difference in LOS for a COVID-19 hospital admission between DIP-IN and comparison group patients. Because we risked overfitting the models with too many variables due to the low number of patients in the analytic sample with a COVID-19 hospital admission, we used an iterative selection process to determine the most pertinent confounders. Using basic models without confounders, we first considered each candidate variable independently. We then added each candidate confounder to the basic model based on the strength of change of exposure effect, retaining variables inciting a ≥ 10% change in the estimated exposure effect. The iterative process continued until all variables meeting the ≥ 10% change metric were included in the models in the presence of new variables added.[100] The LOS model additionally incorporated random intercepts for each unique patient and an estimation of robust standard errors. We subsequently performed three robustness checks. First, we re-estimated associations of interest when including all potential confounders. Second, we re-estimated associations including DIP-IN patients regardless of their enrollment status (N=454). Third, we re-estimated LOS model when excluding a single patient who was admitted for 226 days.

We completed data analysis in SAS Enterprise Guide 8.3 (SAS Institute Inc., Cary, NC) and considered exclusion of 1 from the 95% CI to be statistically significant.

Institutional Review Board

This study was approved through the Indiana University Institutional Review Board as exempt protocol #1810153604A001.

Results

Patient Characteristics

Patient characteristics of those contributing to COVID-19 outcomes stratified by analysis group are presented in **Table 4.1**. A total of 446 DIP-IN patients and 1020 comparison group patients were included in the overall COVID-19 hospital admission analysis, and 22 DIP-IN patients and 47 comparison group patients were included in the COVID-19 hospital LOS analysis. Relative to patients in the comparison group, DIP-IN patients included in the hospital admission analysis were slightly older (and therefore more likely to be enrolled in Medicare), more likely to be women or Black, and less likely to be uninsured or Latinx. Most of these trends persist among those hospitalized for COVID-19, though slightly more women in the comparison group were hospitalized for COVID-19. Only Black or Latinx DIP-IN patients were hospitalized for COVID-19.

Table 4.1. Selected demographic composition of DIP-IN and Comparison group patients contributing to COVID-19 outcome analyses: (A) Patients contributing to the COVID-19 admission analytic sample, (B) Patients contributing to the COVID-19 admission LOS analytic sample

A. Patients contributing to the COVID-19 admission analytic sample		
	DIP-IN N=446	Comparison N=1020
Age (years) (St Dev)	55.94 (12.18)	52.03 (12.84)
Female Gender	57.40%	53.82%
Race/Ethnicity		
Black	77.80%	39.31%
Latinx	12.11%	37.25%
White	8.97%	19.22%
Other	1.12%	4.22%
Payor Type		
Medicaid	37.00%	38.14%
Medicare	43.50%	24.02%
Other Government	0.90%	4.51%
Uninsured	5.61%	16.37%
Unknown	0.22%	1.67%
Private	12.78%	15.29%
B. Patients contributing to the COVID-19 admission LOS analytic sample		
	DIP-IN N=22	Comparison N=47
Age (years) (St Dev)	59.41 (13.65)	55.66 (10.70)
Female Gender	45.45%	46.81%
Race/Ethnicity		
Black	86.36%	31.91%
Latinx	13.64%	44.68%
White	0%	21.28%
Other	0%	2.13%
Payor Type		
Medicaid	31.82%	42.55%
Medicare	50.00%	31.91%
Other Government	4.55%	4.26%
Uninsured	9.09%	14.89%
Unknown	0%	0%
Private	4.55%	6.38%

DIP-IN Encounters

After the first COVID-19 case was reported in Indianapolis, Indiana, on March 6, 2020, 416 DIP-IN patients were seen by health system-based CHWs. During this timeframe, the average number of patient encounters was 10, and visits lasted an average of 17 minutes. During the first year of the DIP-IN CHW intervention (April 1, 2019 – March 31, 2020), the majority (52%) of encounters occurred in-person. During the second and third years of the health system-based DIP-IN CHW intervention (April 1, 2020 – March 31, 2022), almost all (98%) of encounters occurred over the phone. Medical providers consider CHWs to be the eyes and ears of the healthcare system outside the clinic walls, and CHWs work closely with providers to ensure continuity in what is known about patient lives. All care team members, including CHWs, chart and view visit notes in Epic (S. Zapata, oral communication, March 2023).

COVID-Related Hospital Outcomes

Descriptives of COVID-related hospital outcomes are listed in **Table 4.2**. The percent of patients with a COVID-19 hospitalization was similar for our overall analytic sample (4.71%) and when stratified by analysis group: DIP-IN (4.93%) and comparison (4.61%). The average LOS is presented both with and without the patient with the outlier LOS. The average LOS (17.72 days) for COVID-19 hospitalizations was longer and the proportion of patients using a ventilator during a COVID-19 hospitalization (22.23%) was greater among DIP-IN patients than comparison patients (7.65 days and 19.15%, respectively). The in-hospital mortality rate was greater within the comparison group (14.89%) than DIP-IN group (9.09%). Estimates from robustness checks are found in **Appendix Table D3**.

Table 4.2. COVID-related hospital outcomes: Overall and by analysis group

Measure	Overall Analytic Sample	DIP-IN	Comparison
COVID-19 Hospitalization	4.71%	4.93%	4.61%
COVID-19 Hospitalization LOS *Mean (SD)*	10.84 (26.23)	17.72 (44.98)	7.65 (8.00)
COVID-19 Hospitalization LOS: Patient with outlier LOS removed *Mean (SD)*	9.83 (10.91)	9.04 (12.10)	7.65 (8.00)
In-Hospital COVID-19 Mortality	13.04%	9.09%	14.89%
Ventilator Use during COVID-19 Hospitalization	20.29%	22.23%	19.15%

Association between Enrollment in DIP-IN CHW Intervention and COVID-Related Hospital Outcomes

When compared to patients with diabetes residing in similar census block groups, patients residing in DIP-IN communities who were enrolled in the CHW intervention had 45% greater odds of a COVID-19 hospital admission (OR: 1.45, 95% CI: 0.84, 2.51; **Table 4.3**). When admitted to the hospital for COVID-19, DIP-IN patients stayed significantly longer than patients in the comparison group (IRR: 1.90, 95% CI: 1.07, 3.35). Robustness check model estimates are presented in **Appendix Table D1**. DIP-IN generally remained positively associated with COVID-19 hospitalization and LOS regardless of model specification; magnitude of association was largest when adjusting for all potential confounder (OR for COVID-19 hospitalization: 1.52; IRR for LOS: 1.82). Inclusion of DIP-IN patients who had not yet been enrolled in the CHW intervention by the time of COVID-19 hospitalization or who had no encounters after enrollment in DIP-IN substantially attenuated hospitalization association (OR: 1.05; 0.63, 1.75).

Table 4.3. Association between enrollment in DIP-IN CHWs and COVID-19 hospitalization and COVID-19 hospitalization length of stay (LOS), Eskenazi Health March 6, 2020, to March 31, 2022

Outcome	Model 1
	Odds Ratio (95% CI)
1+ COVID Hospital Admission	1.45 (0.84, 2.51)[1]
	Incidence Rate Ratio (95% CI)
1+ COVID Hospitalization LOS	1.90 (1.07, 3.35)[2]

[1]Logistic regression model minimally adjusted for variables eliciting a 10% change in the estimated association between DIP-IN and COVID hospitalization: season, age, and age-squared

[2]Multivariable negative binomial model with robust standard errors minimally adjusted for variables eliciting a 10% change in the estimated association between DIP-IN and COVID hospitalization: race and ethnicity and baseline payor type

Discussion

The health system-based DIP-IN CHW intervention did not have a protective association for COVID-19 hospitalization or LOS, as hypothesized. There was no significant difference in the odds of being hospitalized for COVID-19 between analytic groups. Among patients who were hospitalized for COVID-19, the LOS was significantly longer for DIP-IN group patients than comparison group patients. Contextualizing the two analysis groups, patients in the DIP-IN group were more at risk for negative COVID-19 outcomes, so those who were hospitalized in the intervention group were most likely sicker. DIP-IN patients hospitalized for COVID-19 were older, slightly more likely to be male, and all were part of a historically marginalized race or ethnicity. Because of these differences in patient demographics between the groups, it is possible that the weak to moderate positive associations were an indication of improvement from worse outcomes DIP-IN patients would otherwise have seen without intervention. It is also possible that being enrolled in DIP-IN gave patients an advocate within the healthcare system through the CHW, who may have suggested DIP-IN patients seek medical care when they otherwise would not have. In this case, a COVID-19 hospitalization may have improved subsequent health outcomes associated with COVID-19 for these patients because they sought needed medical care.

COVID-related hospital outcomes have been staggering. Between March 1, 2020, and March 31, 2022, in Marion County, Indiana, 20,773 unique patients were hospitalized with COVID-19, 4,380 of whom were admitted to an intensive care unit (ICU) and 2,411 (12%) of whom died in the hospital. Approximately 1% of Indiana residents overall died as a result of COVID-19.[101] Notably, our DIP-IN analysis group had a lower in-hospital mortality rate than everyone – with or without the complication of diabetes – hospitalized with COVID-19 in the county during this time. Among all Marion County positive COVID-19 cases, 3.95% were among patients with diabetes, and patients with diabetes accounted for 21.24% of COVID-19 hospitalizations and 25.49% of COVID-19 ICU stays. The average LOS for COVID-19 hospitalization was 15.0 days, and the average LOS in the ICU for COVID-19 was 10.6 days. About 37% of patients hospitalized for COVID-19 in Marion County were Black, and about 59% were white, with data not available by ethnicity.[101] While our study only includes a subset of Eskenazi patients, Marion County is a large urban county and therefore contains many hospitals from which these overall COVID-19 data were extracted. Notwithstanding, the comparison group population in this study had a shorter average LOS than all patients hospitalized for COVID-19 in the county, and the DIP-IN group had a longer average LOS. Our study did not include an indicator variable for ICU admission. Of those in Marion County hospitalized with COVID-19, without ethnicity data available, it is difficult to ascertain how many were Latinx. Overall hospital demographics could align with the comparison group depending on how those data disaggregate by ethnicity. Again, all DIP-IN patients hospitalized with COVID-19 were Black or Latinx, which is extremely disproportionate to overall county rates.

Because we did not have access to all COVID test results for our analytic samples, it was not possible to determine general COVID-19 rates within our study groups. Looking at county-wide data as a proxy, during the study timeframe, Marion County residents case rates per 100,000 population were: white: 17,671; Black: 15,892; and Latinx: 19,691. COVID-19 mortality rates per 100,000 population were: white: 256; Black: 236; Latinx: 93; and Asian: 70.[102] Because of the increased COVID-19 risk factors among our study population, these data trends may vary in the geographic areas in which the study's patients reside. However, case and death data are not available in smaller geographies than county-level. While we do not have mortality data for patients outside of those that occurred at Eskenazi, the mortality rates of our analytic sample, both in DIP-IN and the comparison groups, are disproportionately high among Black and Latinx residents as compared to whole-county mortality. If the estimates for in-hospital mortality can be generalized to our overall analytic samples, this may have led sampling bias in our hospitalization analysis, thereby disproportionately overestimating the number of eligible comparison group patients without a COVID-19 hospitalization.

In a separate overall analysis of the DIP-IN program, the change in A1C over time between the DIP-IN and comparison groups was measured. We found a 0.55-unit (95% CI: -0.70, -0.30) decrease in A1C value associated with the CHW intervention, as well as 12% lower odds of ED visits (OR: 0.88; 95% CI: 0.73,1.05) and 19% lower odds of all (COVID and other) hospital admissions (OR: 0.81; 95% CI: 0.60,1.09). The structure of the CHW intervention was forced to shift from an in-person model due to COVID restrictions, but that these improvement in clinical outcomes remained through phone visits is consistent with some studies that showed positive outcomes of CHW phone or telehealth interventions.[103,104] That said, because DIP-IN patients did see improvements in other areas, the mode of intervention delivery may not have influenced COVID-19 hospitalization outcomes.

Limitations

One limitation to the study was the small number of COVID-19 hospitalization events within our sample population. A survival analysis may have been useful for evaluation hospital admission, but we could not account for patient deaths due to COVID-19 that occurred outside of the Eskenazi healthcare system, and the low number of COVID-19 deaths in-hospital at Eskenazi limited our ability to consider this outcome. We also could not account for the variability in ventilator usage and availability throughout the pandemic, so we decided to exclude this analysis from the association modeling as well. We were not able to consider variability due to pandemic conditions, such as hospital diversions, vaccination availability, or in-hospital COVID-19 testing processes. This most likely led to patients from both of our analysis groups receiving care outside of the Eskenazi healthcare system, which may have led to measurement bias for the hospitalization outcome and selection bias for the LOS outcome. However, it is possible patients in the DIP-IN intervention would be more likely to seek care within the Eskenazi healthcare system due to increased trust instilled by working with the CHWs. A strength of the study was the use of a comparison group that was developed through propensity score matching. The data pulled from the EMR could not account for some time-varying confounders like comorbidities; therefore, we cannot definitively assume no residual confounders exist between analysis groups. Because of what we know about the sociodemographic composition of our two analytic groups, we would assume the DIP-IN group to be more at-risk for additional comorbidities, which supports the notion that our DIP-IN group was sicker irrespective of COVID and that our results may be artificially amplifying the association. We also did not include a dosage factor from the DIP-IN intervention in the analysis. Because the DIP-IN CHWs are embedded within FQHCs, a strength of the intervention in relation to COVID-19 outcomes is the community-clinical linkage continuum. The FQHCs provided COVID-19 testing and vaccines, which the CHWs promoted, and the CHWs liaise between patients and providers.

Conclusion

We did not find a positive association between the health system-based DIP-IN CHW intervention and COVID-19 hospitalization or COVID-19 hospitalization LOS. DIP-IN patients hospitalized with COVID-19 were more at risk for negative outcomes due to COVID-19; they were older and more likely to be male, and every DIP-IN patient hospitalized with COVID-19 at Eskenazi was part of a historically marginalized race or ethnicity. However, we did find that a smaller proportion of DIP-IN patients died in-hospital, indicating that DIP-IN patients sought needed medical care that prevented or lessened subsequent negative outcomes.

CHAPTER FIVE: CONCLUSION

Community health workers are a growing subset of the public health workforce. The collective addition to what is known in CHW research that this dissertation provides is timely here in Indiana given the focus on improving the public health infrastructure and developing sustainable, effective funding[105] – which may include the use of CHWs. Overall, these three papers add to what is known about CHW policy and intervention outcomes. Specially, Chapter 2 outlined a state-level policy surveillance exploring prevalence of CHW best practice legislation. Chapter 3 evaluated the effect of DIP-IN on A1C and hospital outcomes. Finally, Chapter 4 estimated the association of DIP-IN on COVID-19 hospitalization and length of stay.

Legislation is one way to effect change in the public health system, either within or across jurisdictions. While some work has been completed to assess CHW policies by state, there are gaps in what is known in the CHW policy landscape over time. The aim of Chapter 2 was to complete a policy surveillance to assess how best practices for CHW policies were implemented through legislation across the 50 states and D.C. All jurisdictions but 13 had enacted at least one piece of legislation impacting the CHW workforce. There was variation in how CHWs were defined, funded, certified, employed, trained, funded, and in what services they could provide. There may be a fine line for CHW legislation between supporting the growth of and adding credibility to the workforce and undermining the grassroots element that makes CHWs so unique. More research is needed to look more closely at each best practice individually, integrate health outcomes or workforce composition into analyses, and search policies that are not at the state legislative level.

CHW interventions have been shown to improve outcomes for patients with diabetes. Most studies include shorter-duration interventions, and many are home- or community-based. In Chapter 3, I explored outcomes of the health system-based DIP-IN CHW intervention, which does not have a set duration for enrollment and is embedded within a healthcare system. Using a difference-in-difference approach, I found that the DIP-IN CHW intervention was associated with a significant decrease in mean A1C and mean time between A1C measures. I also found that the DIP-IN intervention was associated with a decrease in the odds of a hospital ED visit or admission. These findings were largely consistent with previous studies; however, there is limited information available on time between A1C measures. This indicator is important to add to the evidence base because it shows adherence to diabetes management best practices.

The health system-based DIP-IN CHW intervention model changed from in-person visits to telephone visits due to COVID-19 restrictions that were implemented concurrently with the start of the second year of the program. Throughout COVID restrictions, CHWs did see their patients during home deliveries of food boxes or pulse oximeters, but the typical assessments were completed virtually. While there were fluctuations in the proportion of patients – in both analytic groups – who had at least one hospital admission during six-month periods at the beginning of the COVID pandemic, we also saw an improvement in glycemic control among DIP-IN patients during the same period. CHWs were able to see success among their patients despite the changing landscape of the program and added stressors of delivering services during a pandemic of a novel virus.

It has been only three years since COVID-19 was declared a pandemic. With only this short timeframe in which researchers could collect and assess data, less is known about the association between CHWs and COVID-19 outcomes. In Chapter 2, I found that a handful of states (7) had incorporated CHWs into COVID-19 response legislation, indicating support to find novel ways to utilize CHWs within the public health workforce. As described previously, health system-based DIP-IN CHWs adapted to COVID-19 restrictions and continued delivery of the intervention. CHWs also added additional services to assist with pandemic-induced stressors, including food insecurity. In Chapter 4, I used clinical data for DIP-IN and comparison group patients to assess if there was an association between the CHW intervention and COVID-related hospital outcomes. I found that DIP-IN patients had greater odds of being hospitalized with COVID-19 in relation to the comparison group, and that when hospitalized, they had a longer length of stay. Differences between sociodemographic composition may have influenced these results, as DIP-IN patients had more risk factors for COVID-19 morbidity and mortality. A lower proportion of DIP-IN patients had an in-hospital COVID-19 death, indicating that it is possible that having the CHW advocate within the healthcare system encouraged these patients to seek medical care when needed. More studies and data on the CHW association with COVID-19 hospital outcomes will emerge over the next few years and build upon our findings.

Collectively, the papers in this dissertation show that it is possible for a diversification of funding sources – beyond the typically studied public grants – to support the development of a successful CHW intervention. Additionally, a CHW program integrated into a healthcare system can be successful at achieving improved health outcomes among patients and can promote meaningful community-clinical linkages, particularly when the CHW is viewed as a vital member of the care team and all providers have access to the same charting system. This work could be used by CHW organizations to gauge how CHWs are legislated across the country and identify ways that CHW laws may be beneficial or impede work within their own states or jurisdictions. Funders can use this work as a success story to continue or begin funding of CHW interventions. Healthcare systems – including local health departments – can use this work to support the integration or expansion of the CHW workforce within their systems. Success of the health system-based DIP-IN CHW intervention prior to these results has already led to the adaptation and expansion of Eskenazi's CHW program, and other local healthcare systems are taking note of the program. As more organizations place an emphasis on addressing the SDOH and health equity within their target populations, CHWs can be a value-added asset to improve health outcomes and help to diminish inequities.

APPENDIX A

CHAPTER ONE SUPPLEMENTAL MATERIAL

Table A1. DIP-IN health system-based community health worker intervention patient enrollment criteria

Adults 18+
Assigned to “Diabetes Registry”
Have been seen within the past 365 days
Have a ZIP Code of 46202, 46205, 46208, 46218, 46222, or 46226
A1C greater than or equal to 7.9%
Diabetes Management Score <5 (1 point for each of the following) • Blood pressure <140/90 • Prescribed a statin • A1C < 8.0% • Non-smoker • Prescribed/taking daily aspirin
Eskenazi Risk Score 0-19 (ranges from 0-77, lower is better) • Factors in number of comorbidities and risk factors

APPENDIX B

CHAPTER TWO SUPPLEMENTAL MATERIAL

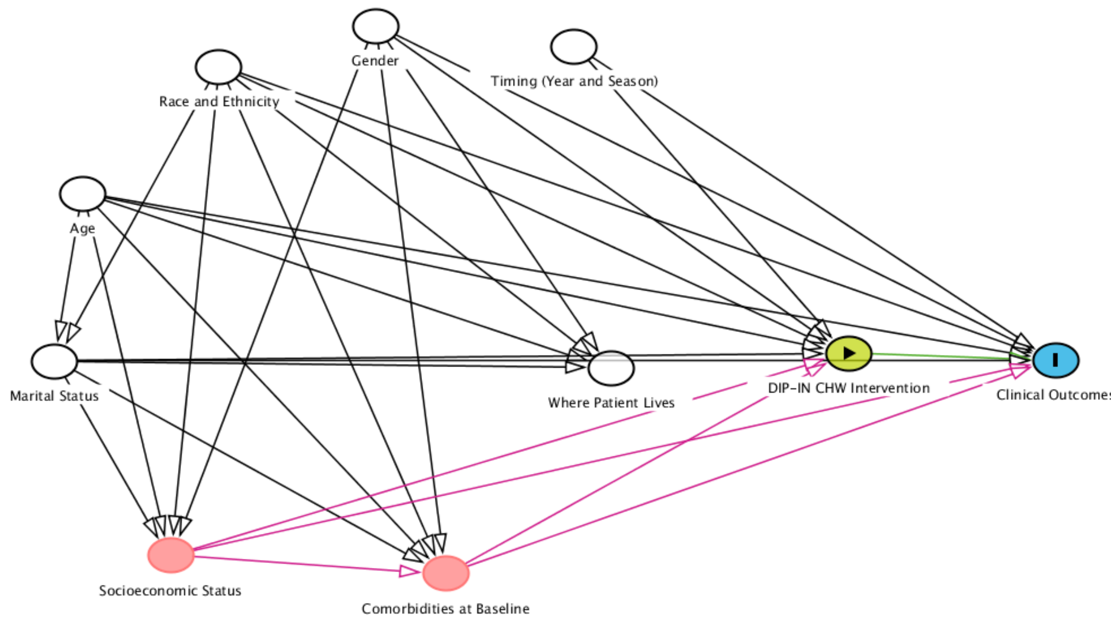
Table B1. Boolean keyword search terms used in Nexis Uni for policy surveillance

community health worker	OR
case work aide	OR
community care coordinator	OR
community connector	OR
community health a	OR
community health educator	OR
community health outreach worker	OR
community health promoter	OR
community health representative	OR
community navigator	OR
community resource specialist	OR
community services specialist	OR
community specialist	OR
family support worker	OR
health coach	OR
lay health *	OR
neighborhood health advisor	OR
outreach specialist	OR
outreach worker	OR
patient navigator	OR
peer educator	OR
peer health promoter	OR
peer navigator	OR
peer support worker	OR
promotor*	OR
public health aide	

APPENDIX C

CHAPTER THREE SUPPLEMENTAL MATERIAL

Figure C1. Directed acyclic graph[1] identifying confounders[2] for A1C and hospital outcome analytic models



[1]Directed acyclic graph created using: Johannes Textor, Benito van der Zander, Mark K. Gilthorpe, Maciej Liskiewicz, George T.H. Ellison. Robust causal inference using directed acyclic graphs: the R package 'dagitty'. International Journal of Epidemiology 45(6):1887-1894, 2016.

[2]The exposure is a green oval with an arrow inside, and the outcome is a blue oval with a vertical line inside. Adjusted variables are depicted with white ovals. Ancestors of the exposure and outcome are depicted with a salmon oval – in this study, these are unobserved variables. A causal path is indicated with a green line, and a biasing path is indicated with a pink line. Race and ethnicity are a proxy for racism and marginalization. While we did include payor type in our models as an indicator of socioeconomic status, we assume too much residual confounding remains.

Table C1. Propensity score matching to DIP-IN treatment block groups with a caliper width of 0.5 Standard Deviation

	All Control Block Groups (N=354)	Matched Control Block Groups (N=45)	Treatment Block Groups (N=138)
	Mean (SD)		
ADI[1] (block group)	68 (21.2)	74.8 (23.4)	84.7 (19.1)
ADI[1] (nearest neighbor)	68.4 (21.4)	74.8 (21)	81 (23)
ADI[1] (census tract)	68 (19.8)	74.1 (21.5)	84 (18.6)
% White	71.5 (23.3)	54.6 (27)	33.5 (25.7)
% Black	19 (20.1)	32.3 (23.8)	56.9 (28.1)
% AI/AN[2]	0.2 (0.9)	0.4 (1.4)	0.4 (1.5)
% Asian	3.4 (6.9)	1.9 (3.7)	1 (2.6)
% NHOPI[3]	0.1 (0.5)	0.1 (0.4)	0.1 (0.6)
% Other Race	2.9 (5.7)	7 (10)	5.4 (9.9)
% Multiple Race	3.1 (3.2)	3.8 (3.3)	2.8 (3.2)
% Diabetes	11.1 (2.5)	13.4 (2.6)	17.7 (4.4)
% Hispanic	9.5 (11.6)	17.9 (15.8)	12.7 (14.5)
% Over 45	38.9 (12.4)	34.6 (12.5)	37.5 (14)

[1]Area Deprivation Index (ADI)
[2]American Indian/American Native (AI/AN)
[3]Native Hawaiian and Other Pacific Islander (NHOPI)

Table C2. COVID ED and hospital admission counts and percent of total by analysis group

Outcome	Analysis Group	Number (% total)
COVID ED Visits	Comp	120 (2.80%)
COVID Hospital Admission	Comp	54 (3.90%)
COVID ED Visits	DIP-IN	59 (2.66%)
COVID Hospital Admission	DIP-IN	31 (7.81%)

Table C3. Model-based estimated impact of DIP-IN CHWs over time relative to no CHW intervention on selected hospital outcome measures – including blood pressure

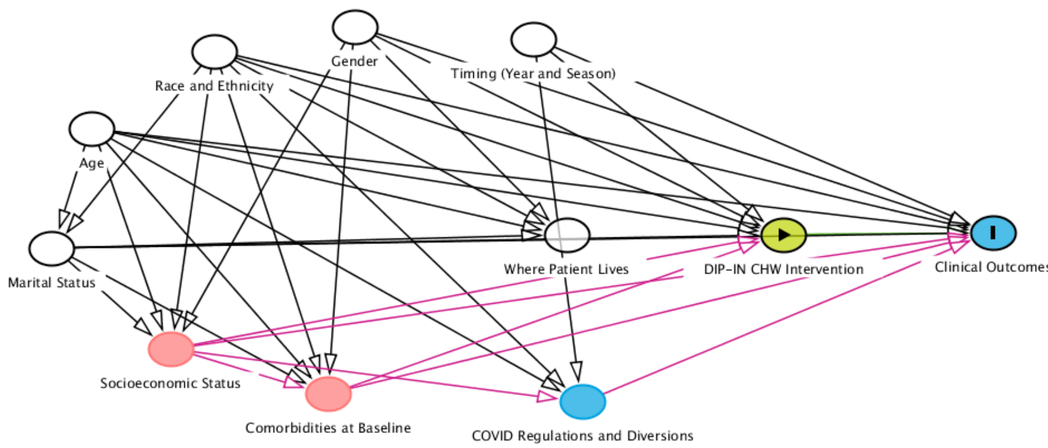
Outcome	Model 1[2]	Model 2[3]
	OR (95%: CI)	
1+ ED Visit	0.88 (0.73, 1.05)	0.88 (0.73, 1.04)
1+ Hospital Admission	0.81 (0.60, 1.09)	*Did not converge

[1]Mixed effects logistic regression models incorporated fixed effects for study group (DIP-IN or Comparison) and year in 6-month intervals, time-varying CHW exposure status, random intercepts for each unique patient, and robust standard errors.
[2]Adjusted for age, age-squared, gender, race and ethnicity, and baseline marital status and payor type
[3]Adjusted for everything in Model 1 and baseline high blood pressure

APPENDIX D

CHAPTER FOUR SUPPLEMENTAL MATERIAL

Figure D1. Directed acyclic graph[1] identifying confounders[2] for COVID-19 hospitalization outcome analytic models



[1]Directed acyclic graph created using: Johannes Textor, Benito van der Zander, Mark K. Gilthorpe, Maciej Liskiewicz, George T.H. Ellison. Robust causal inference using directed acyclic graphs: the R package 'dagitty'. International Journal of Epidemiology 45(6):1887-1894, 2016.
[2]The exposure is a green oval with an arrow inside, and the outcome is a blue oval with a vertical line inside. Adjusted variables are depicted with white ovals. Ancestors of the outcome are depicted with a blue oval, and ancestors of the exposure and outcome are depicted with a salmon oval – in this study, these are all unobserved variables. A causal path is indicated with a green line, and a biasing path is indicated with a pink line. Race and ethnicity are a proxy for racism and marginalization. While we did include payor type in our models as an indicator of socioeconomic status, we assume too much residual confounding remains.

Table D1. Propensity score matching to DIP-IN treatment block groups with a caliper width of 0.5 Standard Deviation

	All Control Block Groups (N=354)	Matched Control Block Groups (N=45)	Treatment Block Groups (N=138)
		Mean (SD)	
ADI[1] (block group)	68 (21.2)	74.8 (23.4)	84.7 (19.1)
ADI[1] (nearest neighbor)	68.4 (21.4)	74.8 (21)	81 (23)
ADI[1] (census tract)	68 (19.8)	74.1 (21.5)	84 (18.6)
% White	71.5 (23.3)	54.6 (27)	33.5 (25.7)
% Black	19 (20.1)	32.3 (23.8)	56.9 (28.1)
% AI/AN[2]	0.2 (0.9)	0.4 (1.4)	0.4 (1.5)
% Asian	3.4 (6.9)	1.9 (3.7)	1 (2.6)
% NHOPI[3]	0.1 (0.5)	0.1 (0.4)	0.1 (0.6)
% Other Race	2.9 (5.7)	7 (10)	5.4 (9.9)
% Multiple Race	3.1 (3.2)	3.8 (3.3)	2.8 (3.2)
% Diabetes	11.1 (2.5)	13.4 (2.6)	17.7 (4.4)
% Hispanic	9.5 (11.6)	17.9 (15.8)	12.7 (14.5)
% Over 45	38.9 (12.4)	34.6 (12.5)	37.5 (14)

[1]Area Deprivation Index (ADI)
[2]American Indian/American Native (AI/AN)
[3]Native Hawaiian and Other Pacific Islander (NHOPI)

Table D2. Model-based estimated impact of DIP-IN CHWs on COVID-19 hospitalization and COVID-19 hospitalization length of stay (LOS), Eskenazi Health March 6, 2020, to March 31, 2022 – additional analyses

Outcome	Model 1	Model 2	Model 3
		Odds Ratio (95% CI)	
1+ COVID Hospital Admission	1.52 (0.84, 2.79)[1]	1.05 (0.63, 1.75)[2]	
		Incidence Rate Ratio (95% CI)	
1+ COVID Hospitalization LOS	1.82 (1.02, 3.25)[3]	1.57 (0.87, 2.83)[4]	1.75 (1.02, 3.0)[5]

[1]Logistic regression model fully adjusted for year, season, age, age-squared, gender, race and ethnicity, and baseline marital status and payor type
[2]Sensitivity analysis logistic regression model including all DIP-IN patients regardless of intervention exposure minimally adjusted for variables eliciting a 10% change in the estimated association between DIP-IN and COVID hospitalization: season, age, and age-squared
[3]Negative binomial model with robust standard errors fully adjusted for gender, race and ethnicity, age, age-squared, and baseline payor type
[4]Negative binomial model removing patient with outlier LOS with robust standard errors minimally adjusted for variables eliciting a 10% change in the estimated association between DIP-IN and COVID hospitalization: race and ethnicity and baseline payor type
[5]Sensitivity analysis negative binomial model (without outlier patient) including all DIP-IN patients regardless of intervention exposure with robust standard errors minimally adjusted for variables eliciting a 10% change in the estimated association between DIP-IN and COVID hospitalization LOS: gender, race and ethnicity, age, age-squared, and baseline payor type

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CURRICULUM VITAE

Elinor Alice Hansotte

EDUCATION

Doctor of Philosophy
Health Policy and Management
Indiana University

Master of Public Health
Social and Behavioral Sciences
Indiana University

Bachelor of Science
Biology
Bachelor of Arts
Spanish
Indiana University

PROFESSIONAL EXPERIENCE

Epidemiologist, Marion County Public Health Department, Indianapolis, IN, November 2017-Present

Hazardous Materials Specialist, Marion County Public Health Department, Indianapolis, IN, October 2012-November 2017

Home Visiting Program Coordinator, Indiana State Department of Health, Indianapolis, IN, September 2011- July 2012

Environmental Health Specialist, Marion County Public Health Department, Indianapolis, IN, June 2009-September 2011

PEER-REVIEWED PUBLICATIONS

Hansotte E, Bowman E, Gibson PJ, Dixon BE, Madden VR, Caine VA. (2021). Supporting Health Equity Through Data-Driven Decision-Making: A Local Health Department Response to COVID-19. *American Journal of Public Health, 111*, S197-S200.

Hansotte E, Gahan E, Vaughn S, Lindstrom KE, Cummings S. (2021). Sodium Reduction in Distributive Meals Through Speed-Scratch Cooking. *Preventing Chronic Disease, 18(E75)*.

Stone C, Bochenek A, Redenz A, **Hansotte E**. (2020). Methods to conduct a Health Impact Assessment Learning Collaborative. *Chronicles of Health Impact Assessment,5(1)*.

Hansotte E., Payne S., & Babich S. (2017). Positive postpartum depression screening practices and subsequent mental health treatment for low-income women in Western countries: A systematic literature review. *Public Health Reviews, 38*(3).

CONFERENCE ORAL PRESENTATIONS

Prentice B, Irwin K, **Hansotte E**. Assessing, Addressing and Improving the Indiana Public Health Association's Equity, Diversity and Inclusion Practices. *American Public Health Association, Annual Conference*, Boston, MA, November 2022.

Hansotte E. Environmental Health Equity. *Indiana Environmental Health Association, Fall Conference*, Evansville, IN, September 2018.

Hansotte E. and Hilton-Dennis H. Indiana's Maternal, Infant and Early Childhood Home Visiting Program. *Indiana Joint National Public Health Week Conference*, Indianapolis, IN, April 2012.

CONFERENCE POSTER PRESENTATIONS

Hansotte E, Andrea SB, Weathers TD, Stone C, Staten LK. Tertiary prevention intervention to control diabetes in Central Indiana. *American Public Health Association, Annual Conference*, November 2022.

Lindstrom KE, **Hansotte E**, Vaughn S. Child & Adult Care Food Program and Summer Food Service Program Cold Storage Meals: A Strategy to Increase Access to Lower Sodium Meals by City Parks Food Program. *Indiana Public Health Association Conference and Annual Meeting*, Virtual Event, April 2021.

Lindstrom KE, **Hansotte E**, Vaughn S. Child & Adult Care Food Program and Summer Food Service Program Cold Storage Meals: A Strategy to Increase Access to Lower Sodium Meals by City Parks Food Program. *Food and Nutrition Conference & Expo*, Virtual Event, October 2020.

Lindstrom KE, **Hansotte E**, Vaughn S. RDN Collaboration with Food Service Management Company (FSMC) Reduces Sodium in Senior Meals. *Food and Nutrition Conference & Expo*, Philadelphia, PA, October 2019.

Lindstrom KE, Kennedy M, Sheck J, **Hansotte E**, Vaughn S. Out of School Time: Healthy Food and Nutrition Environment. *Indiana Annual School Health Conference*, Indianapolis, IN, June 2019.

Maher K, Vaughn S, **Hansotte E**. Sodium Reduction Initiatives: Successes, Challenges, and the Important Role of Partnerships. *National Network of Public Health Institutes Annual Conference*, Noblesville, IN, May 2019.

Biviji-Sharma R, **Hansotte E**, Kirbiyik U. Effectiveness of mind-body therapies on reducing prenatal stress, anxiety, or depression: A systematic review and meta-analysis. *American Public Health Association Annual Conference*, Chicago, IL, November 2015.

Hansotte E, Deardorff J, Kushi LH, Hiatt RA. Associations between Familial Context, Psychopathology, and Girls' Overweight. *Society for Research on Adolescence*, Chicago, IL, April 2008.

TEACHING EXPERIENCE

Teaching Assistant

Introduction to Public Health (P510), IUPUI, Spring 2022

Guest Lecturer

IUPUI: Careers in Public Health, November 2022, February 2023
IUPUI: Health Services Management, April 2022
Montana State University: Research Design and Analysis, November 2018, 2020, 2021
IUPUI: Public Health and Emergency Preparedness, June 2020, 2021
IUPUI: Introduction to Community Health, September 2018, January 2019
IUPUI: Medical Humanities 201, April 2018

PROFESSIONAL MEMBERSHIPS AND ACTIVITIES

Indiana Public Health Association

Board President, 2021-present
Board President-Elect, 2020-2021
Board of Directors, 2019-present
Member, 2019-present

American Public Health Association

Member 2012-present
Annual Conference Abstract Reviewer, 2020-present

Indiana University Fairbanks School of Public Health Alumni Board
Member, 2018-present

American Cancer Society Young Professionals Leadership Council of Indianapolis
Member 2019-2021

Indiana Environmental Health Association
Chair, Committee on Professional Education and Development, 2017-2019
Chair, General Public Health Services Committee, 2015-2017
Member, 2013-2019

Ad Hoc Reviewer
Preventing Chronic Disease
Ethnicity and Disease

HONORS AND RECOGNITION

Indiana University Fairbanks School of Public Health Dean's Public Health Impact Award, May 2023
Tony and Mary Hulman Local Health Department Exceptional Achievement Award, October 2018
Delta Omega, Honorary Society in Public Health, Inducted 2010