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Impact of community health workers on diabetes management in an urban United States Community with high diabetes burden through the COVID pandemic

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ABSTRACT

Objective: Community Health Worker (CHW) interventions are promising approaches to increasing access to health care, garnering better health outcomes, and decreasing health inequities for historically marginalized populations. This study examines the impact of a health system-based CHW program embedded in the Diabetes Impact Project – Indianapolis Neighborhoods (DIP-IN), a large, place-based, multi-year intervention to reduce diabetes burden. We assessed the CHW program's effectiveness in managing glucose control and reducing diabetes-associated complications across the COVID timeline.
Methods: We examined the association between the CHW intervention and diabetes management in 454 CHW patients and 1,020 propensity score-matched comparison patients**.** Using electronic medical records for encounters between January 1, 2017, and March 31, 2022, we estimated the CHW program effect using a difference-in-difference approach through generalized linear mixed models.
Results: Participation was associated with a significant reduction (-0.54-unit (95 % CI: −0.73, −0.35) in glycosylated hemoglobin (A1C) on average over time that was beyond the change observed among comparison patients, higher odds of having $\geq$ 2 A1C measures in a year (OR = 2.32, 95 % CI: 1.79, 3.00), lower odds of ED visits (OR: 0.88; 95 % CI: 0.73, 1.05), and lower odds of hospital admission (OR: 0.81; 95 % CI: 0.60,1.09). When analyses were restricted to a pre-pandemic timeframe, the pattern of results were similar.
Conclusion: This program was effective in improving diabetes management among patients living in diabetes-burdened communities, and the effects were persistent throughout the pandemic timeline. CHW programs offer crucial reinforcement for diabetes management during periods when routine healthcare access is constrained.

1. Introduction

Community health workers (CHWs) working in healthcare settings are frontline public health workers sharing socioeconomic and cultural backgrounds with the community served. (Indiana Community Health Workers Association, 2021; Community Preventive Services Task Force, 2017) CHWs liaise between patients and providers, promoting and improving community-clinical linkages. (Centers for Disease Control and Prevention, 2014; Indiana Community Health Workers Association, 2021; U.S. Bureau of Labor Statistics, 2021) Shared life experiences

Abbreviations: A1C, Glycated Hemoglobin; CHW, Community Health Worker; DD, Difference-in-difference; DIP-IN, Diabetes Impact Project – Indianapolis Neighborhoods; ED, Emergency Department; EMR, Electronic Medical Record; FQHC, Federally Qualified Health Center; PS, Propensity Score; SD, Standard Deviation.

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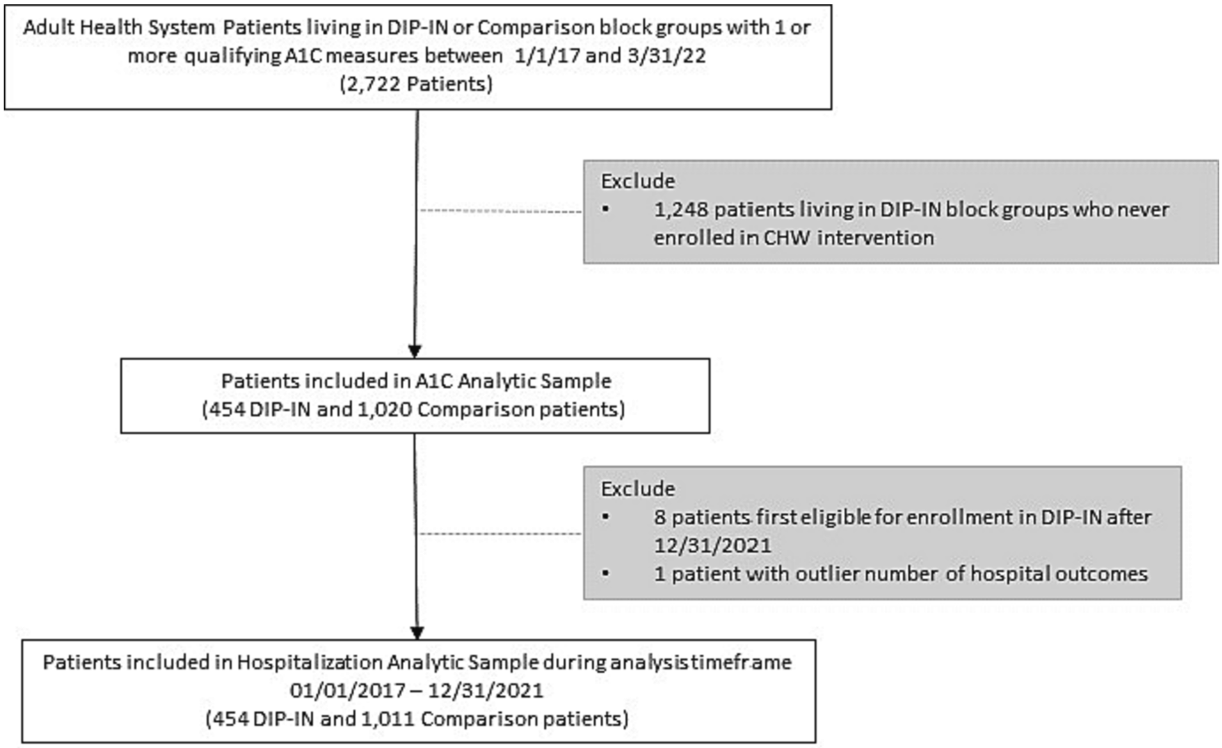

Fig. 1. Indianapolis health system patient analytic flowchart for A1C and hospital outcomes (2017–2022; Indiana, United States).

between CHWs and patients help build trusting relationships that foster success in influencing attitudes, addressing social drivers of health, and bolstering self-efficacy. (Indiana Community Health Workers Association, 2021; Edlind et al., 2018; Rodriguez and Ramirez, 2015) For patients with chronic disease, this trusting relationship with a CHW allows for open communication about needs and enables CHWs to better assist with disease management and healthcare system navigation. (Centers for Disease Control and Prevention, 2014;Feltner et al.,2017) Consequently, CHW interventions are a promising community-based approach (Lopez et al., 2017) to increasing access to health care, garnering better health outcomes, and decreasing health inequities for historically marginalized populations. (Rodriguez and Ramirez, 2015; Institute of Medicine (US) Committee on Understanding and Eliminating Racial and Ethnic Disparities in Health Care, 2003).

With U.S. societal costs of diabetes and pre-diabetes estimated to exceed $400 billion annually, (Staten et al., 2023) there is growing interest in expanding the CHW workforce to address prevention and control of type 2 diabetes. (Crespo et al., 2020) CHW interventions are cost-effective in improving self-management of diabetes through increased appointment attendance, medication adherence, behavioral change, and primary and preventive care, (Centers for Disease Control and Prevention, 2014; Institute of Medicine (US) Committee on Understanding and Eliminating Racial and Ethnic Disparities in Health Care, 2003; Jacob et al., 2019) and have demonstrated significant decreases in HbA1c (A1C) levels. (Community Preventive Services Task Force, 2017; Edlind et al., 2018; Feltner et al., 2017; Trump and Mendenhall, 2017).

Despite the growing body of evidence supporting CHW interventions for patients with diabetes as cost-effective and promoters of positive health outcomes, (Community Preventive Services Task Force, 2017; Feltner et al., 2017; Trump and Mendenhall, 2017) gaps in the literature persist. Our study builds upon existing evidence by examining the impact of a corporate-funded, health system-based, multi-partner, multi-year CHW program implemented as one element of a larger intervention to reduce the diabetes burden in affected urban communities. (Staten et al., 2023) Additionally, due to the timing of implementation, our study serves as a natural experiment for COVID-19 outcomes within participants in an active CHW program. While prior studies have found diabetes to be a risk factor for more severe disease among those infected with COVID-19, (Floyd et al., 2023; Kastora et al., 2022) the impact of CHW interventions overlapping with the pandemic timeline on clinical outcomes among patients with diabetes has been reported in limited contexts. (Whitehouse et al., 2023) We aimed to assess the effectiveness of a health system-based CHW program at managing glucose control and reducing complications associated with diabetes in a population of patients residing in areas with a high burden of diabetes and contextual factors that may increase susceptibility to complications. We hypothesized that the CHW program would be associated with a reduction in uncontrolled glycemic levels and hospital emergency department visits and admissions among patients with diabetes.

2. Methods

2.1. Study setting and population

The Diabetes Impact Project - Indianapolis Neighborhoods (DIP-IN) is a community-engaged, multicomponent, multisector partnership led by the Indiana University Fairbanks School of Public Health and supported by Eli Lilly and Company that aims to reduce the disproportionately high diabetes burden in three Indianapolis (Marion County, Indiana) communities by implementing evidence-based strategies across the prevention continuum. (Staten et al., 2023) In 2019, these three communities, home to approximately 46,000 people, had an estimated diabetes prevalence (diagnosed and undiagnosed) of 23.3 % compared to 14.7 % nationally. (CDC, 2022; Prevalence of Both Diagnosed and Undiagnosed Diabetes | Diabetes | CDC, 2022) Compared to Marion County overall, these three communities have a higher proportion of people of color (72 %-94 % versus 44 %) and higher poverty rate (35 %-38 % versus 19 %). (Staten et al., 2023) The health system-based CHW component of DIP-IN was implemented within the largest public hospital system in Indianapolis, which serves diverse populations at

Table 1
Selected demographic composition of DIP-IN and Comparison groups by year (2019–2022): (A) Adult patients contributing to the A1C analytic sample, (B) Adult patients contributing to the hospitalization analytic sample (Indianapolis, Indiana, United States).

A. Patients contributing to the A1C analytic sample

	2019		2020		2021		2022	
	DIP-IN N = 398	Comp N = 567	DIP-IN N = 387	Comp N = 565	DIP-IN N = 392	Comp N = 668	DIP-IN N = 211	Comp N = 407
Mean Age in 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	35.68	32.80	36.69	37.35	38.01	38.77	37.44	35.38
Medicare	44.97	30.69	44.19	26.37	42.60	22.16	44.55	23.10
Other Government	0.75	4.41	1.03	4.42	0.77	3.89	0.47	3.19
Uninsured	5.78	16.58	6.46	15.58	6.12	17.81	4.74	21.38
Unknown	0.25	0.53	0.26	0.35	0.26	1.50	0.00	0.98
Private	12.56	14.99	11.37	15.93	12.24	16.17	12.80	15.97

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
Mean Age in 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

Abbreviations: A1C, Glycated Hemoglobin; DIP-IN, Diabetes Impact Project – Indianapolis Neighborhoods;
SD, Standard Deviation.
Note: Data above are presented in means (SD) or frequencies (column percents).

multiple Federally Qualified Health Centers (FQHCs). (Staten et al., 2023).

2.2. Intervention

DIP-IN utilizes CHWs as an evidence-based strategy to reduce complications and improve quality of life among people already diagnosed with type 2 diabetes and living within the three priority communities. This CHW program was designed as a quality improvement process with internal feedback loops to improve quality and continuity of care. Quarterly key performance indicators were monitored, with successes and barriers influencing program modifications. For instance, continual monitoring of patient enrollment resulted in the program expanding from three to five FQHCs in order to reach larger numbers of patients within DIP-IN communities. In addition, the protocol for frequency and duration of CHW-patient interaction evolved based on CHW caseload and patient outcomes. Prior to implementation, CHW workflows and documentation were incorporated into the electronic medical record (EMR) system to integrate CHWs into clinical care teams and ensure that information from CHW encounters was available to inform patient care. If the program proved effective among DIP-IN patients, integration into the EMR would make it easier to expand to patients beyond DIP-IN communities. In addition to theorized improvements in care delivery and sustainability, deployment of DIP-IN through a health system facilitates tracking and evaluation of the intervention's impact on healthcare use and diabetes management outcomes. (Staten et al., 2023) The study protocol was reviewed by the Indiana University Institutional Review Board and deemed exempt prior to implementation.

The public hospital system hired 6 CHWs (with funding shared by DIP-IN and the hospital) to serve patients with diabetes residing in the DIP-IN communities. Two CHWs were assigned to each area. After initial training within the healthcare system, CHWs completed CHW certification. CHW supervision was provided by a registered nurse clinical care manager with a Master of Health Administration degree. While funded by Eli Lilly and Company, the corporation did not provide additional medication or service support.

Patients with type 2 diabetes who met eligibility criteria (age $\geq$ 18 years; recent A1C measure $\geq$ 7.9 %; and home address in one of six DIP-IN ZIP Codes) were contacted by a CHW for potential enrollment in the program. (Staten et al., 2023) Enrollment began on April 1, 2019, and occurred on a rolling basis. There was no limit to the length of participation. Patients were disenrolled when they achieved successful glycemic control, were lost to follow-up, or at patient request. The program was designed for CHW visits to occur in-person, but most were by telephone during COVID. CHWs captured encounter data using assessment tools and worked closely with clinical care teams to ensure patients' needs were addressed. During encounters, CHWs provided diabetes management education and worked with patients to address social needs such as food insecurity, eviction, and transportation. CHWs made referrals as needed and encouraged patients to make those connections directly to increase self-efficacy (S. Zapata, oral communication, March 2023).

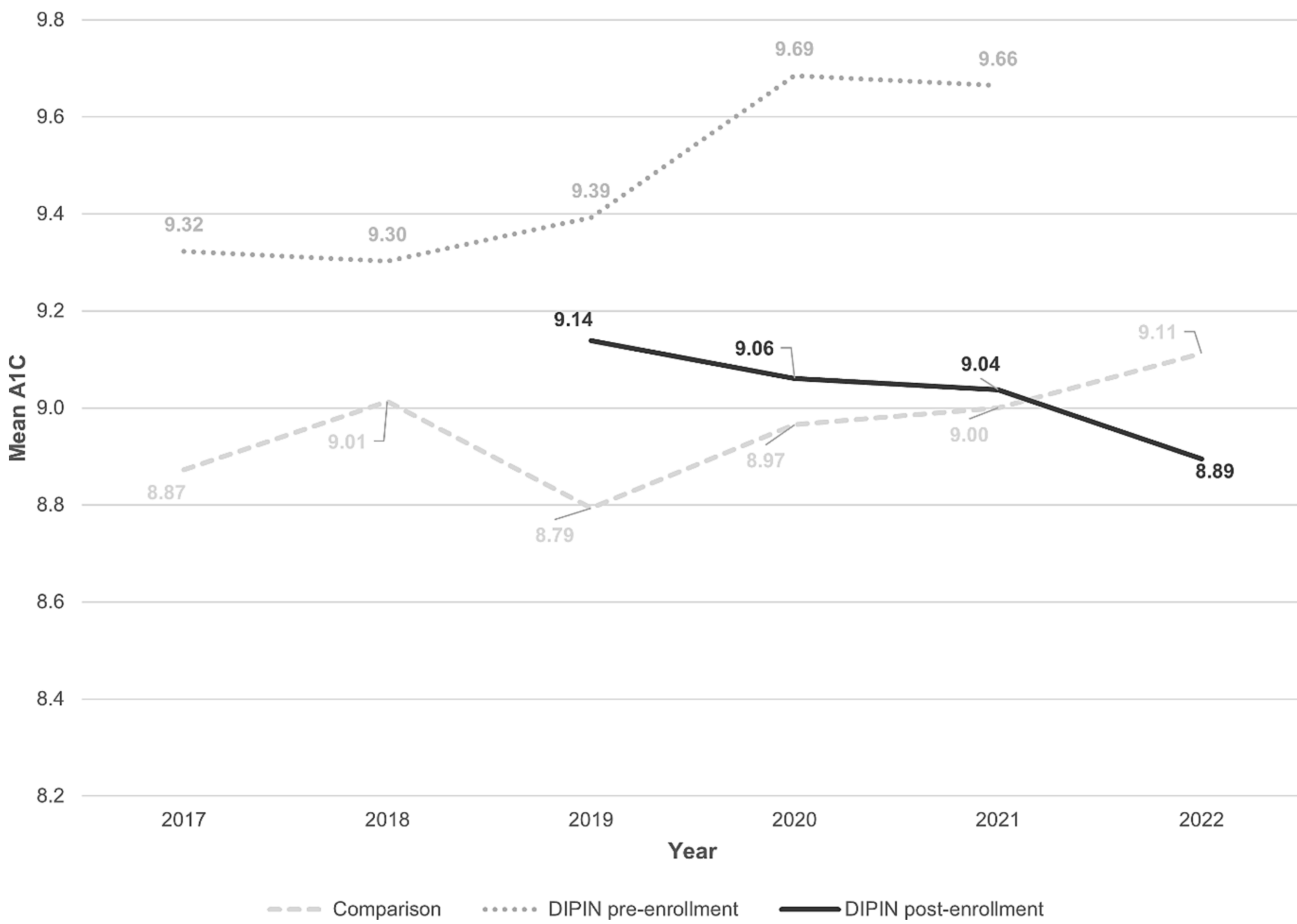

Fig. 2. Mean A1C by year (2017–2022) and analysis group (Comparison, DIP-IN pre-enrollment, DIP-IN post-enrollment) (Indianapolis, Indiana, United States).

2.3. Comparison areas

Recognizing the effects of place on health, independent of person-level characteristics, we identified comparison areas to match as closely as possible to the three intervention communities on key factors. (Hill-Briggs et al., 2020) Further, matching at the area-level versus individual level was prudent given that eligibility, recruitment, and deployment of DIP-IN-related activities are anchored to residence in certain geographic areas. Briefly, through area-level propensity score (PS) matching, census tract-level data on community sociodemographic profiles and diabetes burden were used to identify areas in Indianapolis comparable to DIP-IN areas (Appendix Table 1). We utilized the smaller geographic unit of block groups in the matching process to reduce further heterogeneity in the neighborhood environments between DIP-IN and comparison areas (N = 138 DIP-IN and 354 potential comparison block groups). We used logistic regression to estimate the probability of each block group being given a DIP-IN designation based on community contextual factors. Block groups were retained as comparators if they had a similar probability (or PS) of being a DIP-IN block group as $\geq$ 1 DIP-IN block group. Because DIP-IN communities were intentionally chosen based on high diabetes prevalence and socioeconomic factors, most 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 PSs, we sampled without replacement. With a caliper of 0.5SD, 45 total comparison block groups were matched to $\geq$ 1 of each of the 138 DIP-IN block groups While matching facilitated greater comparability between DIP-IN and other block groups in Indianapolis, DIP-IN block groups had comparatively higher socioeconomic deprivation, proportion Black residents, and diabetes prevalence.

2.4. Measures

This study leverages data extracted from the EMR, which includes variables at the patient level for all encounters occurring between December 1, 2016, and March 31, 2022.

Dependent Variables. 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 healthcare system in the analysis period. The occurrence of more than 1 ED visit or hospital admission within a 6-month-period was rare, thus hospitalization outcomes were dichotomized to 0 visits or 1 + visits to enable estimation in multivariable models. Additionally, we included descriptive data about COVID-19-related hospitalizations and in-hospital mortality during these hospitalizations. Any A1C result recorded with a greater than (>) or less than (<) symbol was rounded up or down to the nearest tenth of a decimal. Additionally, three A1C values were treated as missing due to recording error. At a given point in time, patients were categorized as adhering to best practices (Centers for Disease Control and Prevention, 2018; American Diabetes Association, 2021) if in addition to their current A1C measurement they had at least *one* other A1C measure in the past year. Beginning with the first six-month timeframe in the study period in which the patient interacted with the healthcare system, we created an additional variable categorizing the presence or absence of $\geq$ 1 ED visit or admission in six-month periods.

Independent Variables. Our time-varying exposure of interest was a dichotomous variable with a value of "1″ if the encounter occurred after the patient's enrollment (first CHW encounter) and "0" otherwise. As such, the exposure value was "0" for all comparison patients at all time

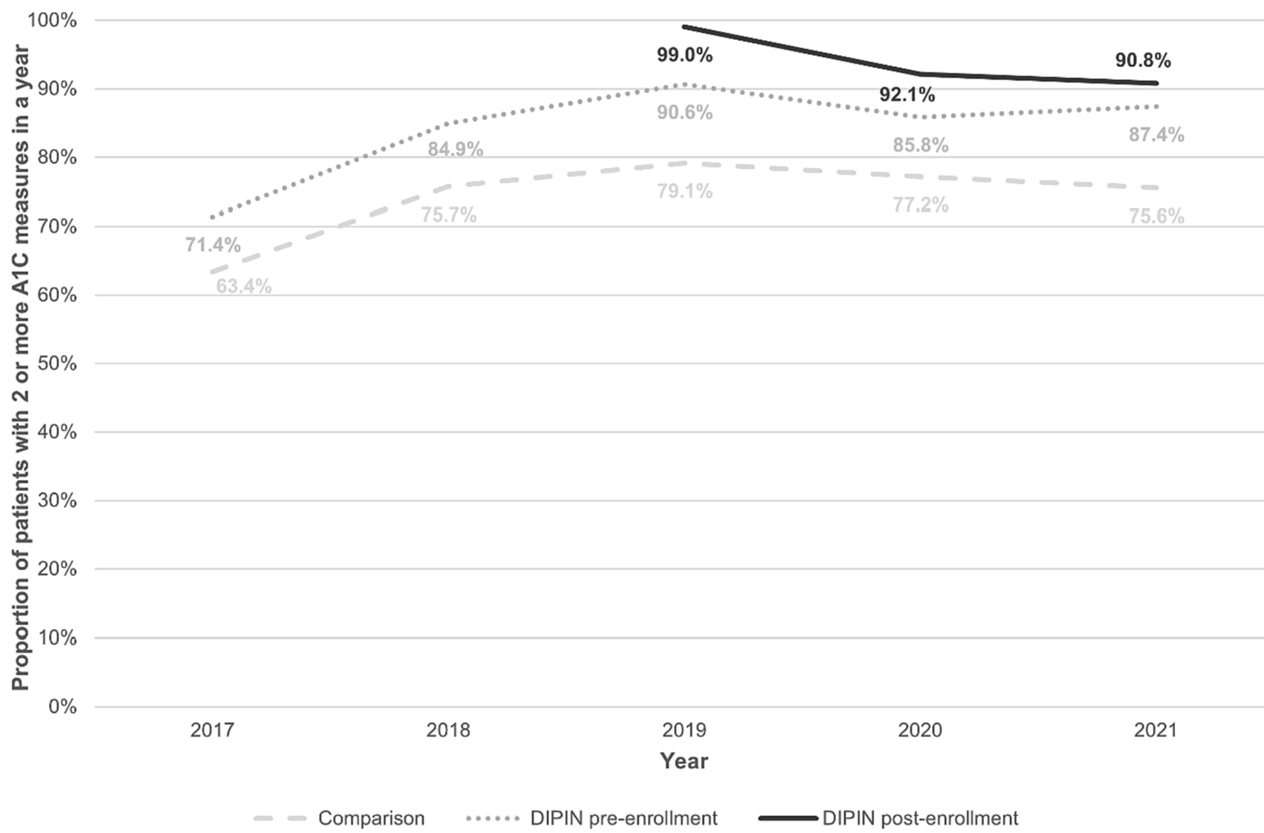

Fig. 3. Of Indianapolis health system patients included in study with at least 1 A1C[a], proportion with ≥ 2 A1C measures by year (2017–2022) and analysis group (Comparison, DIP-IN pre-enrollment, DIP-IN post-enrollment) (Indiana, United States) [a] Required to be in the A1C analytic sample.

points. When evaluating changes in A1C test values, to account for A1C being a three-month measure of blood glucose, DIP-IN patients were considered exposed 90 days after their first CHW visit (enrollment).

We identified confounders using a directed acyclic graph (Appendix Figure 1), (Greenland et al., 1999) created to reflect our assumed causal model and included patient gender, race and ethnicity, baseline payor, baseline marital status, age and quadratic age (continuous) at encounter, baseline ZIP Code of residence, encounter seasonality, and year of encounter. We considered the payor type and marital status captured closest to the first CHW visit (enrollment) 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.

2.5. Analytic approach

Analytic Sample. Analyses are limited to patients meeting enrollment criteria (Fig. 1). Of those patients living in a study block group (DIP-IN or comparison), 2,722 met the inclusion criteria for enrollment in DIP-IN, without considering place of residence. Within DIP-IN block groups, 1,248 patients were excluded from analysis because they were not enrolled in the program. The A1C analytic sample included 1,474 patients, and the hospital outcome analytic sample included 1,465 patients.

Statistical Analysis. We 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. GLMMs can be fit in the presence of missing data and provide unbiased estimates when data are missing at random. (MAR). Under MAR, we assume the missing outcome values depend entirely on the covariates in the model as well as outcome values at previous time points. (Schafer and Graham, 2002) The models incorporated fixed effects for the study group and year, time varying CHW exposure status, patient-level confounder variables, random intercepts for each unique patient, an unstructured covariance matrix, and robust standard errors. See Appendix Methods for additional details on our specified DD formula. As a robustness *check*, we re-estimated models for all four outcomes occurring before January 1, 2020, to assess the potential impact of the CHW intervention had COVID not occurred. Likewise, to assess the impact of CHWs in the context of the pandemic, all four models were re-estimated for outcomes occurring on or after March 1, 2020. Finally, models for all four outcomes were additionally re-estimated including the N = 1,214 individuals who resided in DIP-IN areas but never enrolled in the CHW program.

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.

3. Results

3.1. DIP-IN encounters

Between April 1, 2019, and March 31, 2022, CHWs reached 58 % of patients eligible for inclusion by telephone, 67 % of whom enrolled in DIP-IN. During this timeframe, 31 % of program participants disenrolled. Relative to patients who enrolled in DIP-IN, eligible patients who did not enroll were more likely to be men, White or Latinx, on Medicaid or uninsured, unpartnered, and younger on average (Appendix Table 2).

Over the first three years of the program, CHWs met with 454 DIP-IN patients an average of 12 times, for an average of 21 min per encounter.

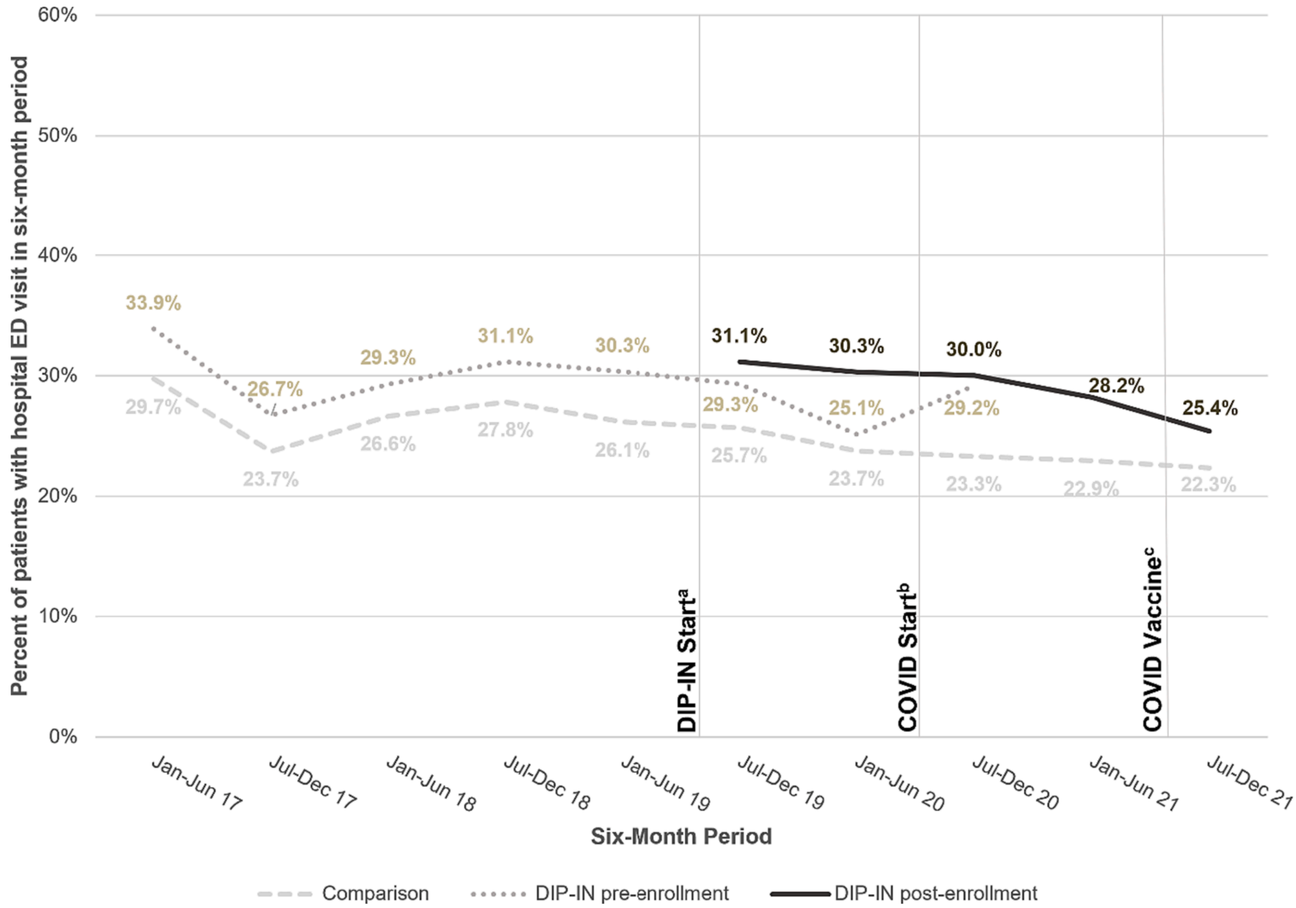

Fig. 4. Percent of Indianapolis health system patients included in study with hospital ED visit in six-month period (2017–2021) by analysis group (Comparison, DIP-IN pre-enrollment, DIP-IN post-enrollment) (Indiana, United States) [a] April 2019: Start of DIP-IN CHW program [b] March 2020: First COVID-19 case in Marion County, Indiana [c] April 2021: COVID-19 vaccine available for all adults in Indiana.

Patients were enrolled in DIP-IN for a median of 700 days (IQR 534 days). The majority (55 %) of patients were enrolled in the first year of the program, were Black (78 %), between 45 and 64 years old (60 %), and female (57 %). Though originally planned as an in-person program, due to COVID-19 restrictions implemented concurrently with the second year of the program, the majority (82 %) of encounters occurred by telephone and lasted about 15 min (45 %) over the three-year period.

3.2. Study population characteristics

The characteristics of patients contributing data for A1C and hospital outcomes stratified by group and year are presented in Table 1. In the first year of DIP-IN recruitment, relative to comparison patients, DIP-IN patients were on average slightly older, more likely to be women and/or Black, and less likely to be Latinx and/or uninsured. Over time, differences in the race and gender composition of study groups persisted while age differences further widened.

3.3. Clinical outcomes

In the first year of recruitment (2019), mean A1C levels for DIP-IN patients who had not yet experienced the intervention were higher than in comparison patients (9.39 % and 8.79 %, respectively; Fig. 2) while in the last year of follow-up (2022), mean A1C levels for DIP-IN patients post intervention were lower than those for comparison patients (8.89 % vs. 9.13 %, respectively). The proportion of patients with at least 2 A1C measures in a year was higher for DIP-IN patients, both before and after enrollment, for the duration of the observed study period (Fig. 3). Additionally, the proportion of DIP-IN patients without any A1C measures in a given year was consistently half that of patients in the comparison group (Appendix Table 3).

Figures 4 and 5 show a natural time variation for all-cause ED visits and hospital admissions for both groups. The figures include important dates, including the beginning of the DIP-IN CHW program (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, and a higher percentage of DIP-IN enrollees had an ED visit compared to those not yet enrolled (Fig. 4). There was a less consistent pattern between groups for hospital admissions, though DIP-IN enrollees had a higher peak of patients with an admission at the beginning of COVID-19 (Fig. 5).

3.4. COVID-19 hospital outcomes

ED visits and hospitalizations described in Figures 4 and 5 include all causes, including COVID-19. COVID was indicated as a diagnosis for < 3 % of ED visits among both groups (2.80 % for comparison and 2.66 % for DIP-IN). COVID was a diagnosis for more hospital admissions among DIP-IN patients (7.81 %) than comparison patients (3.90 %). The in-hospital COVID-19 mortality rate was 13.04 % for the overall analytic sample, 9.09 % for DIP-IN patients, and 14.89 % for comparison patients.

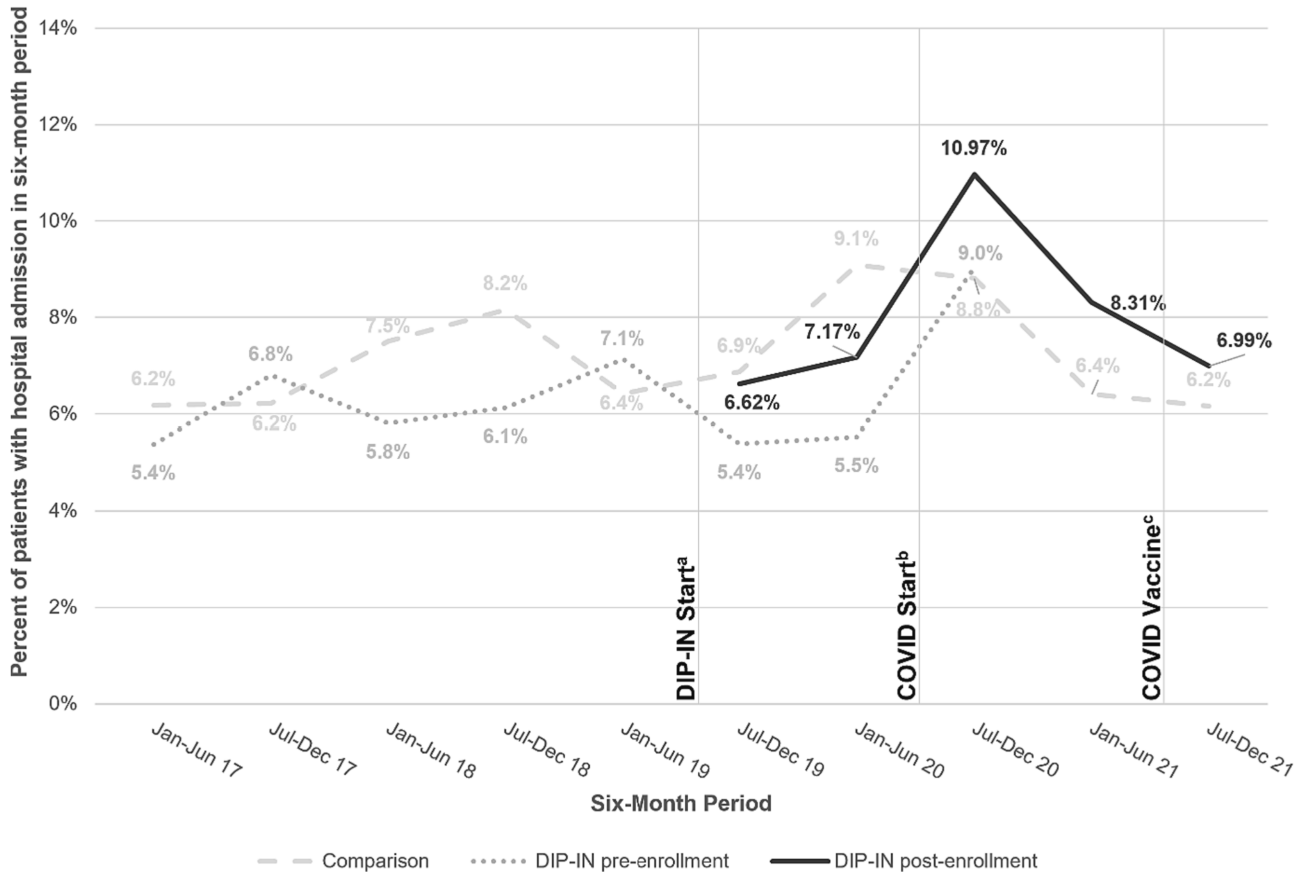

Fig. 5. Percent of Indianapolis health system patients included in study with hospital admission in six-month period (2017–2021) by analysis group (Comparison, DIP-IN pre-enrollment, DIP-IN post-enrollment) (Indiana, United States) [a] April 2019: Start of DIP-IN CHW program [b] March 2020: First COVID-19 case in Marion County, Indiana [c] April 2021: COVID-19 vaccine available for all adults in Indiana.

3.5. The impact of DIP-IN CHW program on clinical outcomes

Participation in the program was associated with a significant reduction (-0.54-unit (95 % CI: −0.73, −0.35)) in A1C on average over time that was beyond the change observed among those who did not receive the intervention during the same period (Table 2). Patients enrolled in DIP-IN had 2.32 times the odds (95 % CI: 1.79, 3.00) of having at least 2 A1C measures within a year. Though not significantly different from the comparison group, participation in the CHW program 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). When analyses were restricted to a pre-pandemic timeframe (01/01/2017 – 12/31/2019) and subsequently during the pandemic (03/01/2020 – 03/31/2022), the pattern of results were similar (Table 2). The largest estimated impact of CHWs on timing of A1C measures was observed prior to the pandemic (OR: 5.92 prior vs. 2.86 during the pandemic and 2.32 across the whole study), however, the largest estimated impact of CHWs on A1C values was observed during the pandemic (β: −0.82 during vs. −0.45 pre-pandemic and –0.54 across the whole study). Estimates were robust to further inclusion of eligible patients residing in a DIP-IN area who never enrolled in the CHW program.

4. Discussion

In using an evidence-based practice (CHWs), we hypothesized positive outcomes for a health system-based CHW program for people with diabetes that is part of an 8-year, multicomponent, community-based initiative to reduce the high diabetes burden in 3 urban communities. (Staten et al., 2023) This program was effective in improving key health outcomes among participants within a local health system with diabetes management challenges. We found that, among patients with diabetes, participation in the CHW program was associated with significant reductions in A1C and increased odds of having 2 or more A1C measures in a year. We likewise observed a greater reduction in hospital ED visits and admissions among DIP-IN participants relative to patients from comparison areas, though this finding was not statistically significant. Notably, these positive results persisted over the analysis period, which spanned the COVID-19 pandemic. For two years, CHW visits were constrained to occur largely by telephone rather than in person, indicating the CHW intervention may confer resilience within vulnerable populations despite external challenges to health and routine healthcare access.

Findings on improvement in A1C among DIP-IN enrollees, in relation to a comparison group, are consistent with the change in magnitude of A1C measures seen in the literature. (Community Preventive Services Task Force, 2017; Trump and Mendenhall, 2017; Mirhoseiny et al., 2019) We also report patients with 2 or more A1C measures in a year because best practices suggest patients with diabetes get tested at least twice annually to tailor glycemic management plans,(Centers for Disease Control and Prevention, 2018; American Diabetes Association, 2021) a practice difficult to adhere to when patients are unable to access care on a routine basis. Our results suggest DIP-IN patients were better able to access consistent diabetes management in healthcare. With a program that deferred to the usual standard of care for A1C testing, improvement in meeting the recommended A1C test frequency relative to the comparison group indicates that DIP-IN CHWs may have improved self-efficacy among patients with diabetes. Broadly, COVID disrupted clinical care, including primary care visits and the percent of patients meeting A1C testing guidelines, (Hooker et al., 2022) indicating

Table 2
Additional change in clinical outcomes over time (2017–2022) attributed to the DIP-IN CHW intervention as estimated in multivariable models (Indianapolis, Indiana, United States).

Analytic Sample	Outcome			
	Mean A1C (points)[a,b]	≥2 A1C Measures in 1 Year[c]	ED Visit[d]	Hospital Admission[d]
	β (95 %: CI)	Odd Ratio (95 %: CI)		
Enrolled residents of DIP-IN Areas & all residents of comparison areas (N = 1474)				
Complete Analysis Time Frame	−0.54 (-0.73, −0.35)	2.32 (1.79, 3.00)	0.88 (0.73, 1.05)	0.81 (0.60, 1.09)
01/01/17 – 12/31/19 Timeframe	−0.45 (-0.79, −0.12)	5.92 (1.42, 24.57)	0.89 (0.60, 1.31)	0.87 (0.43, 1.78)
03/01/2020—–03/31/2022 Timeframe	−0.82 (-1.10, −0.54)	2.86 (2.01, 4.07)	0.91 (0.68, 1.22)	NA[e]
All residents of DIP-IN Areas & comparison areas (N = 2688)				
Complete Analysis Time Frame	−0.42 (-0.60, −0.25)	2.85 (2.24, 3.62)	0.82 (0.71, 0.94)	0.65 (0.53, 0.81)
01/01/17 – 12/31/19 Timeframe	−0.40 (-0.74, −0.07)	6.85 (1.65, 28.46)	0.82 (0.70, 1.00)	0.60 (0.47, 0.76)
03/01/2020—–03/31/2022 Timeframe	−0.35 (-0.45, −0.25)	3.15 (2.44, 4.07)	0.88 (0.67, 1.15)	0.77 (0.52, 1.15)

Abbreviations: A1C, Glycated Hemoglobin; CHW, Community Health Worker; DIP-IN, Diabetes Impact Project – Indianapolis Neighborhoods; ED, Emergency Department; NA, Not Applicable.

[a] 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.

[b] We are reporting A1C in a unit change rather than the notation of "%".

[c] Mixed effects logistic regression models incorporated fixed effects for study group (DIP-IN or Comparison) and year, 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.

[d] 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.

[e] Outcome rare, insufficient sample size for model convergence.

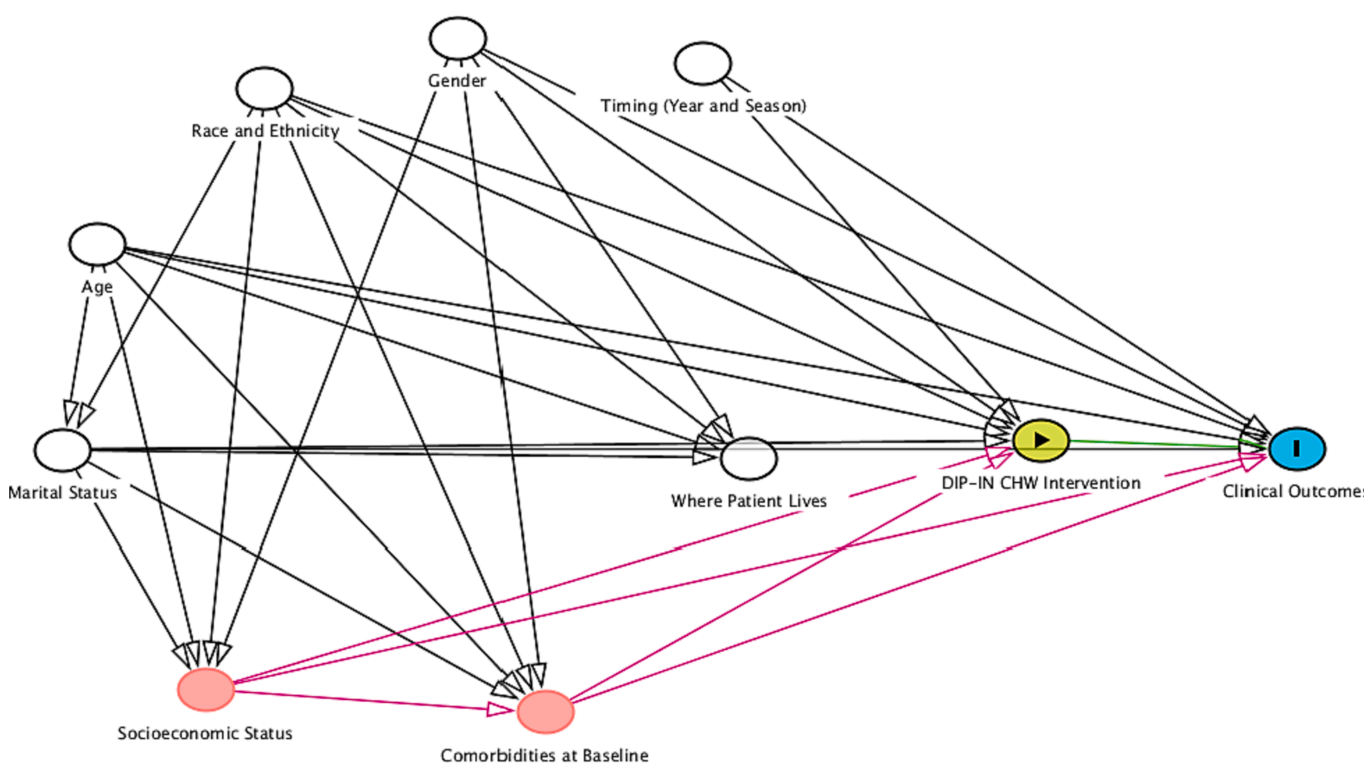

Fig. A1. Directed acyclic graph[a] identifying confounders for A1C and hospital outcome analytic models (Indianapolis, Indiana, United States). Abbreviations: A1C, Glycated Hemoglobin; DIP-IN, Diabetes Impact Project – Indianapolis Neighborhoods. [a] Directed acyclic graph created using: Johannes Textor, 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. [b] 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.

our results may have been greater without changes in care due to COVID. In our sensitivity analysis restricted to outcomes that occurred before COVID, we observed consistent reductions in mean A1C and hospitalizations but a more dramatic improvement in adherence to biannual A1C screening recommendations.

While DIP-IN patients initially had a greater burden of hospital ED

Table A1
Propensity score matching to DIP-IN treatment block groups with a caliper width of 0.5 Standard Deviation (Indianapolis, Indiana, United States).

Contextual Parameters used in Propensity Score Estimation[a]	All Comparison Block Groups (N = 354)	Matched Comparison Block Groups (N = 45/354)[b]	DIP-IN Treatment Block Groups (N = 138)
	Mean (SD)		
ADI Rank (block group)	68 (21.2)	74.8 (23.4)	84.7 (19.1)
ADI Rank (nearest neighbor)	68.4 (21.4)	74.8 (21)	81 (23)
ADI Rank (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, %	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, %	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)

Abbreviations: ADI, Area Deprivation Index; AI/AN, American Indian/American Native; NHOPI, Native Hawaiian and Other Pacific Islander; SD, Standard Deviation
[a] Contextual data sources used in the creation of census tract block group propensity score matching included the American Community Survey (ACS) block group data (2019 5-year sample) and Behavioral Risk Factors Surveillance System (BRFSS) census tract data (2017). Variables included: racial and ethnic composition, percent of residents over the age of 45, diabetes prevalence, Area Deprivation Index (Kind and Buckingham, 2018) (ADI) rank of each block group, average ADI rank of the block groups within each census tract, and ADI rank of the closest neighboring block group. (Kind and Buckingham, 2018).
[b] 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 the remaining 55 DIP-IN block groups with caliper of 0.5SD (N = 45 total comparison area block groups).

Table A2
Indianapolis health system patients included in study baseline demographics by analysis group (Comparison, DIP-IN pre-enrollment, DIP-IN post-enrollment) (Indiana, United States).

	DIP-IN (n = 454)	Comparison (n = 1,020)	DIP-IN area residents who qualify but are not enrolled (n = 1,214)
Mean Age in Years (SD)	55.75(12.21)	51.92(12.84)	53.72 (14.59)
Female Gender, %	57.49	53.82	53.21
Race/Ethnicity, %			
Black	77.97	39.31	59.39
Latinx	12.11	37.25	24.96
White	8.81	19.22	12.93
Other	1.11	4.22	2.72
Payor Type at baseline, %			
Medicaid	37.89	34.71	39.62
Medicare	42.95	21.67	33.20
Other Government	0.88	7.16	3.21
Uninsured	5.95	19.22	10.13
Unknown	0.22	1.67	1.48
Private	12.11	15.59	12.36
Marital Status at baseline, %			
Partner	30.40	37.35	29.24
Previous Partner	25.99	18.43	19.28
Single	43.17	43.82	51.15
Missing	0.44	0.39	0.33
Mean A1C at baseline (SD)	9.58 (2.30)	9.80 (2.17)	9.79 (2.29)

Abbreviations: A1C, Glycated Hemoglobin; DIP-IN, Diabetes Impact Project – Indianapolis Neighborhoods; SD, Standard Deviation

visits and admissions relative comparison patients, we observed a greater reduction in these visits over time after enrollment in DIP-IN. We leveraged PS matching to identify suitable comparison areas, however, by virtue of their identification as priorities for programming, DIP-IN areas were still comparatively contextually different. Consequently, there were differences in the sociodemographic composition of patients residing in each area. For example, patients from DIP-IN areas were disproportionately Black (78 % vs. 39 % in comparison areas). One national study found diabetes-related ED use to be three times higher among Black patients than White patients, (Uppal et al., 2022) and multiple studies have found racial differences in ED-level outcomes (i.e., admission rates and mortality rates). (Zhang et al., 2020; Schrader and Lewis, 2013; Sonnenfeld et al., 2012) Importantly, a strength of the DD design is that the model enables us to account for time-invariant differences between patients from DIP-IN and comparison areas. Additionally, our observed insignificant but greater reduction in odds of hospital ED visits and admissions among DIP-IN patients relative to comparison patients is consistent with the literature. (Community Preventive Services Task Force, 2017) Within the context of COVID, it is notable that, despite a higher percentage of hospital admissions stemming from COVID, DIP-IN patients had a lower in-hospital mortality rate (9 %) than the comparison group (15 %) and all Indianapolis hospitals (12 %). (Institute, 2021) This suggests that the connection to the healthcare system afforded by the CHW may have enabled DIP-IN patients to seek timely medical care.

Table A3
Proportion of Indianapolis health system patients included in study with 0 A1Cs collected in a given year (2019–2022) (Indiana, United States).

Time Period	DIP-IN	Comparison
4/1/2019 to 3/31/2020	11.10	21.80
4/1/2020 to 3/31/2021	18.80	37.80
4/1/2021 to 3/31/2022	16.30	36.40

Abbreviations: A1C, Glycated Hemoglobin; DIP-IN, Diabetes Impact Project – Indianapolis Neighborhoods.

5. Limitations

Our study is not without limitations. First, DIP-IN enrollees represent a subgroup (39 %) of the total eligible patient population, as 42 % of potential patients could not be reached and 33 % of those reached declined to participate. Therefore, selection bias may have occurred; those who enrolled could have had fewer barriers or more barriers to diabetes management overall than those who did not enroll. However, our secondary analysis including all eligible residents of DIP-IN areas irrespective of their participation in the CHW intervention as an additional control group yielded results consistent with our main findings. Second, while our analytic approach enabled us to account for differences in patient factors that did not change during our study period (e.g., genetic factors) between patients residing in DIP-IN and comparison areas, reliance on EMR data limited our ability to thoroughly account for confounding factors that change over time, such as socioeconomic status. As such, we relied on payor type as an imperfect proxy for socioeconomic status. Additionally, we could not include comorbidities in the model as we did not have access to dates and codes added to patients' histories. Consequently, we likely cannot completely assume MAR in the estimation of our results. Third, because this study only includes EMR records from one healthcare system within a large city, patients could have experienced ED visits and hospital admissions during our study period at other hospitals. Because DIP-IN and comparison areas are geographically interspersed with each other and the available healthcare systems, we suspect differential measurement error may contribute to an underestimation of the true impact of the CHW intervention on hospitalization-related outcomes since those in the CHW program may be more likely than those in comparison areas to return to the same health system for care. (Vasan et al., 2020) Fourth, the goal of this analysis was to assess the impact of the CHW intervention on diabetes-related outcomes, and patients enrolled in DIP-IN were included regardless of how briefly they engaged or the modality in which they engaged. Additionally, COVID-19 changed the way the program was implemented. For nearly two years, CHW visits shifted from in-person to phone or limited-contact visits. However, disaggregating outcomes by COVID and non-COVID timeframes enabled us to further appraise the robustness of the intervention to evolving encounter modalities.

6. Conclusion

A health system-based CHW program can be successful in improving outcomes among patients with diabetes in relation to a comparison group. Our study provided a natural experiment to assess outcomes of a CHW program for patients with diabetes during a time with significant external stressors, and we found the persistence of benefit of the program through the COVID-19 pandemic.

CRediT authorship contribution statement

Elinor Hansotte: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation. **Sarah B. Andrea:** Writing – review & editing, Visualization, Methodology. **Tess D. Weathers:** Writing – review & editing, Project administration, Methodology, Conceptualization. **Cynthia Stone:** Writing – review & editing, Writing – original draft. **Alisha Jessup:** Writing – review & editing, Supervision, Resources, Conceptualization. **Lisa K. Staten:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Funding acquisition, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Appendix Figures

Fig. A1

Appendix Tables

Appendix Methods

Difference-in-Difference (DD) Model Specification & Interpretation

Our reduced form DD equation was as follows:

$Y_{igt=}\beta_0 + \beta_1 DIPIN_g + \beta_2\ ExpCHW_{igt} + X_{igt} + \alpha_g + \gamma_t + \varepsilon_{igt}$.

Where Y_{igt} is the outcome for patient i in group g at time t, *DIPIN* is a binary variable taking on the value of "1″ for residents of DIP-IN areas and "0" for residents of comparison areas and *ExpCHW* is a binary variable taking on the value of "1" upon enrollment in the CHW intervention and "0" otherwise. All patient-level confounder variables in the ***Methods*** are captured in the vector X_{igt}. ZIP Code fixed effects α_g account for unmeasured time-invariant differences in patients' experiences based on ZIP of residence, year fixed effects γ_t account for state-level variation in outcomes over time, and ε_{igt} is a random error term. Models included an unstructured covariance matrix, and robust standard errors. β_2 is the coefficient of interest, representing the DD estimated average impact of the CHW intervention during the designated study period, and is the value reported for each model in the ***Results*** along with 95 % Confidence Intervals (CI). Covariate referent groups were selected based on groups with known lower risk of diabetes; female, (Prevalence of Both Diagnosed and Undiagnosed Diabetes | Diabetes | CDC, 2022) white, (Gold et al., 2021; Prevalence of Both Diagnosed and Undiagnosed Diabetes | Diabetes | CDC. Published September 21, 2022) summer, private health insurance, (Baicker et al., 2013; Gold et al., 2021) and married or partnered. (Ford and Robitaille, 2023) We used the comparison group ZIP Code with the highest number of patients as the referent ZIP Code.

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