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EDITORIAL

OJPH: New Editor-in-Chief, Enduring Public Health Challenges

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On behalf of the Ohio Public Health Association (OPHA) and the many individuals who have contributed to this issue, I am pleased to present Volume 4, Issue 2 of the *Ohio Journal of Public Health* (OJPH). As I write this editorial, the Omicron variant of coronavirus disease 2019 (COVID-19) has been identified in increasing numbers and in an increasing number of locations, including Ohio. Although there are many unknowns about Omicron, including typical seriousness of symptoms, level of protection offered by vaccination and boosters, and the range of feasible strategies for controlling the spread, it is clear to me and borne out by the papers published in this issue that while COVID-19 is a public health issue of profound importance and longevity, a range of other public health concerns continue to impact Ohioans. Some, including unequal access to health care and prevalence of mental illness, may be exacerbated by the pandemic and emergence of variants. That said, these and others—trends in chronic disease, shortage of care workers, substance abuse and misuse—comprised major public health concerns in Ohio before the pandemic and are likely to remain key concerns, including in some epidemiologist-suggested potential scenarios where COVID-19 transforms from pandemic to endemic.[1]

Like many others, I am doing my best to engage in behaviors that promote my mental and physical health, while at the same time I struggle with uncertainty and pandemic-associated weariness. One thing I look forward to in our post-COVID pandemic future, is the opportunity for public health professionals to critically reflect on *lessons learned* from multiple aspects of the pandemic, including environmental issues. I became concerned about the environmental impact of COVID-19 during the early days of the pandemic as I started to see masks, mostly disposable but sometimes reusable, scattered near the entrance of any location that overtly enforced mask-wearing. I took the cover photo during a walk on one of the sunny and pleasant days this fall and selected it due to the color contrast between the mask and leaves. Sadly, this was one of several discarded masks I saw and captured on that day walking around a geographically compact area. Ideally future public health professionals will find a way to balance ready availability of masks with sustainability, perhaps by using designs that have recyclable aspects and by increasing availability of appropriate disposal methods.

As I suggested previously, the papers in this issue reflect a range of topics of importance to public health practitioners, researchers, and educators. King and colleagues contributed the only COVID-19 focused manuscript in this issue in which they explored relationships among preexisting health diagnoses, risk perceptions, and self-reported compliance with social distancing recommendations. Schmiederer describes the public health value and critical need for home health aides, which is an issue of increasing importance, given that the proportion of Ohioans 60 years of age or over is projected to increase by 30% by the year 2030.[2] Substance abuse and misuse continue to be critical concerns in Ohio and comprise the focus of 3 papers, including a research brief about medication-assisted treatment. Acquavita and colleagues qualitatively considered the perspectives of law enforcement and treatment providers along with those of individuals with substance use disorders, while Jacobson and colleagues described the challenges in conducting a review of health care records to identify women who might benefit from integrated maternal health and opioid use disorder treatment during pregnancy. Other topics explored by authors in this issue include associations between socioeconomic factors and trends in chronic disease, how charity care practices in nonprofit hospitals in Columbus compare with those in peer cities, the development and potential value of the Ohio Equity Institute data portal to facilitate credible evaluation of services provided by community-based organizations, and disparate health outcomes among adults in Ohio who reflect sexual and gender minorities.

In closing my first editorial, I want to acknowledge the many sources of support that make this journal possible. Publication of OJPH is a team effort that involves invaluable contributions from the Ohio Public Health Association, the dedicated and motivated members of the journal editorial board, the online journal staff from The Ohio State University Libraries, and our amazing copy editor, Darlene Bowers. I also want to say a special thank you to Cheryl Davis from OPHA for her invaluable assistance provided to me during the processing of this issue. And, finally, I express my sincere gratitude to Dr. Amy Ferketich, founding editor-in-chief of OJPH, who started training me in early 2021 and has continued to be an exceptional source of information and support. Through the first 7 issues of OJPH, Dr. Ferketich established procedures from scratch while ensuring OJPH reflects a broad range of high-quality content of interest to public health practitioners, researchers, and educators in Ohio. It is both my honor and challenge to follow in her footsteps.

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COMMENTARY

Home Health Aides: The Burgeoning Backbone of the Health Care System

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By 2030, the entirety of the baby boomer generation will have shifted into the ranks of older adulthood (65 years old and older), making up 20.3% of the United States population. Older adults utilize more health care services than younger groups as the majority of them have at least one chronic condition that requires care.[1] The health care system is approaching a turning point: How will we care for our aging population?

Studies continuously show that keeping the elderly in their homes is the best option for improving health outcomes and lowering health care costs. It is also typically the desire of the patient. AARP estimates that nearly 90% of people over age 65 want to stay in their home for as long as possible.[2] Home health aides (HHAs), workers who provide assistance to patients with activities of daily living in the home, allow patients to age safely in place. The demand for in-home care is expected to increase with a 33% rise in job prospects.[3] With Ohio's elderly population growing 20 times faster than its general population, it is crucial that the health care system start taking the HHA occupation seriously.

I have been working as a part-time aide to a 90-year-old man for nearly a year. My tasks include helping him dress, preparing his medications, helping him get to and from his walker, and grocery shopping. My assistance is mostly companionship, conversation, and ensuring that his basic needs are met. I work as an HHA as a 'side-gig' because the wage is not sufficient to make a living with an average compensation of about $12.15 per hour.[4] Many of the HHAs that I work with are immigrants and work several jobs as well. We do not receive any benefits, nor do we have many opportunities for professional development.

The burgeoning issue is the lack of a home care workforce. The Ohio Department of Aging notes that workforce capacity is among "key issues facing Ohio's aging population" in its 2021 Annual Report. The Ohio Provider Resource Association similarly states that industry efforts to recruit HHAs in Ohio have proven futile, leaving the state "in crisis."[5]

An alternative option is caring for older adults in inpatient nursing care facilities, the cost of which are tremendous when compared to in-home services. The Ohio Association of Area Agencies on Aging estimates that inpatient facilities cost about $6361 per month while in-home services cost around $1225 per month.[6] Additionally, emerging legislation in the state called Esther's Law highlights the issue of abuse and neglect in inpatient settings.[7] In 2019, Ohio's nursing homes ranked among the nation's lowest in quality of care with 41% of the facilities earning a below-average Medicare rating.[8]

Luckily, under Governor Mike DeWine, the reimbursement rates to Medicaid for in-home and community-based health care services are set to increase beginning November 2021. This will impact the nearly 200 000 Ohioans on the program by increasing in-home care opportunities for such individuals.

Home health aides provide some of the most essential work for society by caring for the elderly in their homes; in many ways they are the backbone of the health care system. It is long overdue that the profession receive investment in the form of wage and benefit increases via greater reimbursement rates, opportunities for professional development, and general acknowledgement of the profession's importance by the public health system. The increase in reimbursement rates is a small step in the direction of improving the in-home care options for our nation's elderly.

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RESEARCH BRIEF

The Supply of Authorized Providers for Medication-Assisted Treatment in Ohio

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ABSTRACT

Background: Ohio experiences among the highest drug overdose rates nationally. The Drug Addiction Treatment Act (DATA) of 2000 permits qualified clinicians to use medication-assisted treatment (MAT) to treat opioid dependency. This study characterizes clinicians authorized to perform MAT and examines whether these clinicians are geographically collocated in areas with higher opioid burdens.

Methods: Data of DATA providers in 2019 came from the Substance Abuse and Mental Health Administration. Opioid overdose mortality rates were extracted from the County Health Rankings and Roadmaps to represent disease burdens in local areas. The DATA provider density is represented by the number of DATA-waivered providers per 100 000 population for each county. We used Pearson correlational tests to examine the correlations between the local DATA provider density and the opioid mortality rate.

Results: Most of the DATA providers were physicians (57%), followed by nurse practitioners (27%) and physician assistants (4%). The average waivered provider density was 13.90 per 100 000 population. The local density of DATA providers and local opioid overdose death rates are moderately correlated ($P < 0.001$).

Conclusion: Physicians still represent most waivered providers in Ohio. While DATA providers were located in some areas with high needs for opioid treatments, our data suggest that other areas with high opioid burdens likely have an inadequate workforce supply to reduce opioid burdens. Without an adequate DATA workforce, policies that focus on MAT care access to address the opioid epidemic may be in vain.

Keywords: Drug Addiction Treatment Act (DATA); Health care workforce; Medication-assisted treatment; Opioid use disorder

INTRODUCTION

Today, Ohio stands among the top 5 states for the highest mortality rates due to drug overdoses.[1] In the last 2 decades, the overall drug overdose rate in Ohio increased 9-fold compared to the national average increase of 3-fold.[2] To help tackle the opioid crisis, local and state governments pushed to expand medication-assisted treatment (MAT) with evidence of its ability to reduce drug overdose deaths.[3] Medication-assisted treatment utilizes medications, such as methadone, buprenorphine, and naltrexone, alongside counseling and behavioral therapies to treat substance use disorders, including opioid and alcohol use disorders.[1,4] Under the Drug Addiction Treatment Act of 2000 (DATA 2000), certain clinicians can obtain a waiver to prescribe MAT with buprenorphine or naltrexone outside of opioid treatment programs.[5] The DATA 2000 first only allowed physicians to be eligible for the waiver. The DATA waiver was later extended to other qualified clinicians under the Comprehensive Addiction and Recovery Act of 2016, such as nurse practitioners (NPs) and physician assistants (PAs), to also provide MAT.[6]

Despite policies to expand MAT treatment workforce, a national shortage in the availability of providers still exists. In 2017, approximately 46.4% of all US counties lacked an authorized clinician to prescribe MATs for opioid use disorders, a situation worse in rural counties (71.6%).[7] Over 30% of US counties did not have a single DATA waived provider in 2018.[8] Few physicians, 3% of all primary care physicians (PCPs) and 16% of all psychiatrists, have ever obtained the DATA waiver, and most of them practice in urban areas.[9] The severity of the opioid epidemic in Ohio demonstrates the urgency to examine whether DATA providers are geographically collocated in Ohio counties with higher opioid burdens. This information is critical for policy decisions that impact the allocation of state resources, workforce planning, and targeted interventions to reduce disparities. Without an adequate MAT provider workforce available, Ohio cannot possibly deliver vital treatments to the most vulnerable populations in need.

METHODS

Design

We conducted secondary data analyses with a cross-sectional design at the county level in Ohio to examine the correlation between DATA-waivered providers and opioid mortality rates.

Data and Study Sample

Waivered provider information was obtained from the 2019 SAMHSA buprenorphine waiver registration database.[10] The database contained detailed information about practitioners with a DATA waiver, including their credentials such as medical doctors (MDs), doctors of osteopathy (DOs), PAs, and NPs, as well as the contacting information of each provider. Providers registered under multiple practice locations in the same county were counted as 1 provider. Providers practicing in multiple counties were counted as a separate provider under each county. The study sample included 2075 DATA-registered providers.

Data to measure the opioid burden were taken from the County Health Rankings and Roadmaps program of the Robert Wood Johnson Foundation.[11] The 2015-2017 drug overdose deaths data in each Ohio county were used, which were based off a 3-year average, and these were the most updated data available during the study. The US Census Bureau data were used for the population counts.[12]

Measures/Outcomes

The DATA provider density was defined as the number of waivered providers per 100 000 population in a county. We calculated a provider density measure for total DATA providers in a county, including all provider types. We also calculated a density for each of the 3 major provider types (physician, NP, and PA), respectively. The opioid burden is represented by the drug overdose mortality rates, defined as the number of drug poisoning deaths per 100 000 population in a county.[11] Drug poisoning deaths are deaths from accidental, incidental, and undetermined drug poisoning for the aggregate annual population over a 3-year period (2015-2017).[11] The count of drug overdose deaths was utilized as an alternative measure of the opioid burden during robustness analyses. Four counties did not report any drug overdose deaths during the observation period and were coded as "0" in the drug burden measures.

Statistical Analysis

The DATA provider types were first characterized in each county. We studied the DATA provider distribution according to the drug use disease burden. The total DATA provider density was also ranked by counties. To gauge whether supply of MAT treatment workforce matches the local medical needs, Pearson correlation tests were applied to test the correlations between waivered provider density measures and opioid overdose rates. Strength thresholds picked for the Pearson correlational coefficient (R) were based on a scale commonly used in the social sciences.[13] A robustness test was conducted using the counts of opioid deaths in a county. A 95% confidence interval (CI) was used for all tests.

RESULTS

Figure 1 presents the distribution of all DATA-waivered providers by profession across all counties. MDs and DOs were combined into 1 group to represent total physicians. Most of the DATA providers in Ohio were physicians (57%), followed by NPs (27%). In the DATA registry, 259 providers did not specify their profession but were included in the analysis of total waivered providers for each county. These practitioners were authorized to prescribe MAT (12%).

The average DATA provider density in a county, including all provider types, was 13.90 per 100 000 population (SD 9.9; 95% CI 11.7-16.1) with medium of 11.3 per 100 000 population. There was a substantial variation in waivered provider density statewide. Waivered provider densities ranged from a minimum of 1.89 per 100 000 to a maximum of 47.89 per 100 000 population.

A moderate, statistically significant positive relationship was observed between the density of providers in a county and county-level opioid overdose death rates ($r(76) = .40, P \leq .001$). This may suggest that eligible providers in high need regions were more likely to obtain the DATA waivers. However, the correlation was moderate and, in many counties with high drug overdose death rates, waivered providers did not locate where the potential patients were located.

Measures in counties with the highest and lowest overdose rates were examined and compared (Table 1). The 5 counties with the highest overdose rates had much higher mean provider densities (20.50 per 100 000) than the statewide average (13.90 per 100 000). Scioto County had the highest DATA provider density in Ohio. Montgomery County had the highest overdose rate in all of Ohio and had the 10th highest provider density compared to the sample average (26.11 versus 13.90 per 100 000 population). Yet most of the top overdose counties did not have the highest waivered provider densities that matched their disease burden ranking. Some of the top overdose counties even had DATA provider densities comparable to the provider densities of the lowest dis-

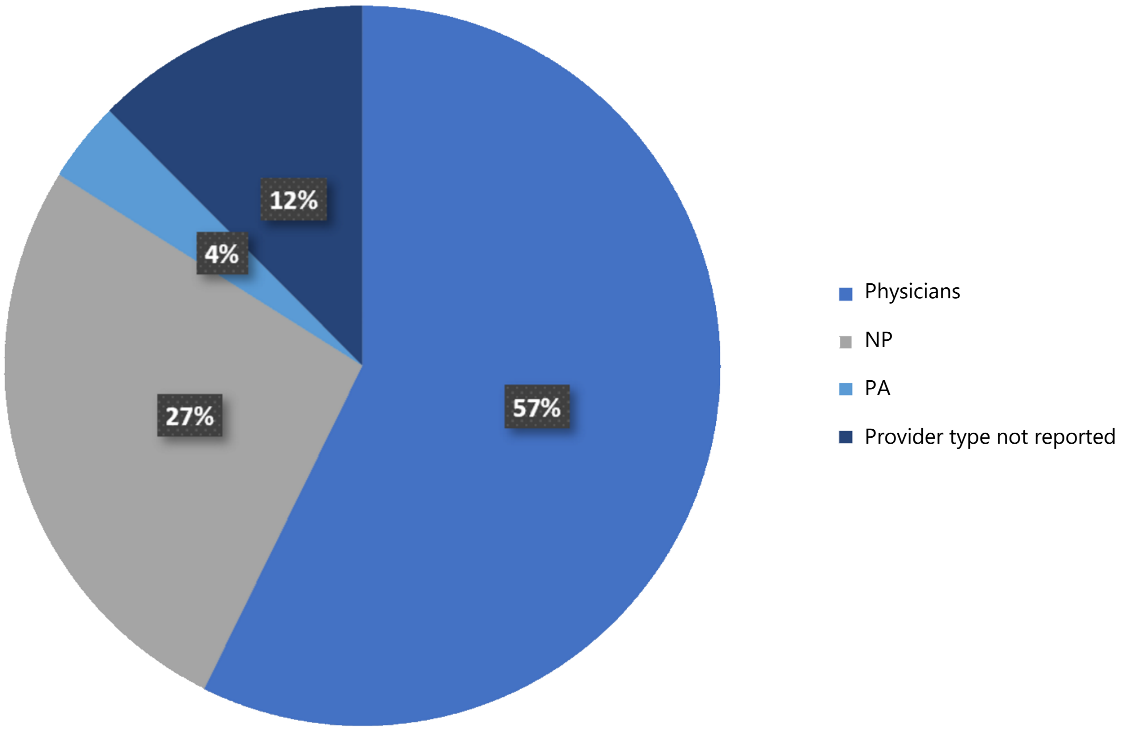

Figure 1. Distribution of DATA-Waivered Provider Types in Ohio

ease burden counties. This may raise some questions as to whether counties such as Clark, Butler, Trumbull and Brown, where the worse overdose death rates occurred, have an adequate supply of DATA-waivered providers to meet the disease burdens.

Robustness Tests

A sensitivity test varied overdose death rates with the counts of overdose deaths to understand if the correlation between opioid burden and total waivered provider density held. A weaker but statistically significant positive relationship was also found between total waivered provider density and the number of overdose deaths across counties (r(76) = .31, P=.006; 95% CI .09- .50). Although this effect was weaker, a significant correlation further validates a likely positive relationship between the supply of waivered providers and opioid burden.

DISCUSSION

Alleviating the opioid crisis in Ohio through better access to MAT treatment is a vital public health policy. Our study found a positive association between where providers who are authorized to deliver the treatment are located and areas with high opioid overdose rates. This finding implies that overall, providers in an area with higher opioid burden are more likely to obtain DATA waivers to expand capacity to provide treatment. These results are consistent with literature documenting a positive relationship between areas of greater treatment capacity and a higher opioid burden nationally.[8] The average DATA provider density of 13.90 per 100 000 population in Ohio, was smaller than the national average of 14.3 per 100 000 person.[14] This places Ohio lower in provider supply compared to other states despite a more severe opioid epidemic, which demonstrates a necessity to expand MAT treatment provider workforce in Ohio.

Our study reveals that Ohio needs to improve the distribution of the MAT treatment workforce to serve drug dependency patients and to provide adequate care in areas where there is a high concentration of patients. Counties having the highest overdose rates did not possess high-ranking provider densities. This mismatch implies that having a high opioid burden may influence providers to obtain waivers in their county, but it has not strongly pushed providers to locate and practice where the highest needs are. The potential workforce shortages in Ohio will likely hamper the effectiveness of state or local policy efforts to expand the MAT treatment scale, leaving patients more vulnerable without sufficient care. Currently, Ohio is only able to treat 20% to 40% of the entire population abusing opioids or with drug dependence.[2] About 20% of Ohio office-based treatment clinicians are not actively prescribing and one half of them deny insurance for their services.[15] Our findings further add to the evidence base of provider maldistribution when poor accessibility prevents the ability to match treatment needs.

Furthermore, when understanding why providers did not obtain the DATA waiver in high need regions, it is possible that there has been a more severe shortage of clinicians in lower-income regions in general, as over one half of Ohio populations reside in areas with a shortage of primary care physicians.[16] Many of these areas have high opioid fatalities.

Table 1. Top Five Counties with Highest and Lowest Drug Overdose Death Rates

Counties with the 5 Highest Drug Overdose Rates	Overdose Death Rate per 100 000	DATA Provider Density per 100 000	DATA Provider Density Ranking*	DATA Physician Density per 100 000	DATA NP Density per 100 000	DATA PA Density per 100 000
1. Montgomery	70	26.11	10	13.52	7.33	1.31
2. Clark	62	15.60	25	8.17	3.72	2.23
3. Butler	60	14.65	28	8.11	5.75	0.78
4. Trumbull	57	12.08	35	7.55	3.52	0.50
Brown	57	6.88	61	2.29	4.59	0.00
5. Scioto	52	47.68	1	25.16	21.19	0.00
Counties with the 5 Lowest Drug Overdose Rates	**Overdose Death Rate per 100 000**	**DATA Provider Density per 100 000**	**DATA Provider Density Ranking***	**DATA Physician Density per 100 000**	**DATA NP Density per 100 000**	**DATA PA Density per 100 000**
1. Morgan	0	6.85	62	0	6.85	0
2. Vinton	0	7.61	55	0	7.61	0
3. Delaware	11	8.79	50	7.32	0.49	0.49
4. Auglaize	12	6.55	64	2.18	2.18	2.18
5. Putnam	13	8.89	49	5.92	2.96	0
Coshocton	13	8.19	52	5.46	2.73	0
Athens	13	19.75	16	13.67	4.56	0

*The waivered provider ranking assigns each county in order of the highest to lowest waivered provider densities (1=highest density, 88=lowest density).

Moreover, most waivered practitioners in Ohio were physicians, despite the federal policy that aims to expand prescribing capacity to include NPs and PAs. One reason may be that many steps are required before finally receiving the waiver such as qualification trainings[5,17] and certification trainings that lasts at least 8 hours for physicians and 24 for NPs/PAs.[17] Despite a physician shortage and a low supply of DATA providers in the state, Ohio currently has some of the most restrictive scope of practice laws in the country to limit the practice of NPs.[18] Without widening scope of practices for NPs and PAs, the low supply of DATA providers will likely continue in the state, posing a challenge to meet the care needs of the opioid epidemic. A few limitations are noteworthy. First, missing values in provider type for some providers in the SAMHSA database is a challenge to accurately describe provider demographics. Moreover, only data of listed waivered providers were available for this study, yet the local supply does not warrant MAT treatment appointments close to where patients live.[19] Additionally, as many as 70 000 opioid overdose deaths have been unreported or misclassified between 1999-2015.[20] Reporting inefficiencies could have influenced observed overdose deaths in Ohio counties and the magnitude of the opioid burden. Lastly, this study employed prepandemic data from 2019. The coronavirus disease 2019 (COVID-19) brought an unprecedented mental health crisis and a 30% increase in drug overdose deaths.[21] Future research may replicate this study utilizing postpandemic data to see if the pandemic changed the opioid burden in counties and the provider capacity necessary to address needs.

PUBLIC HEALTH IMPLICATIONS

The inefficiency of many waivered providers to practice where patients are in the most need may help inform future city planners and health systems to place a higher emphasis on high need regions when implementing new treatment programs and allocating funds. Strategies to recruit PCPs to health professional shortage areas may prove effective, as these regions often see higher opioid burdens. Moreover, county-level maldistributions between opioid burden and waivered provider supply demonstrate the presence of different mechanisms producing variabilities in opioid deaths. Providers and hospital systems should account for this variability by implementing community level initiatives that best serve their counties, as a one size fits all approach may not alleviate substance abuse. The lower supply of NPs and PAs as waivered providers suggests initiatives to encourage NPs and PAs to obtain a waiver may increase prescribing capacity among treatment programs and provide relief to both physicians and patients. Further reforming Ohio scope of practice agreements to enable NPs and PAs to treat patients without physician involvement and receive independent prescribing authority may reduce barriers to involve these clinicians in MAT. Ohio counties in this study that reported higher overdose rates (> 38.3 per 100 000) and lower provider densities (< 13.9 per 100 000) than the state average should be given special consideration when incentivizing the location of practices providing MAT. These regions may be eligible for special mental health professional shortage area (HPSA) designations and may leverage loan repayment programs to recruit providers.

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RESEARCH BRIEF

The High Cost of Opioid Use in Pregnancy

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ABSTRACT

Background: Numerous investigators have highlighted the need to integrate opioid use disorder (OUD) treatment with maternity care. Since data first became available in 2014, Montgomery County (Ohio) has experienced the highest rates of OUD and unintended opioid overdose deaths in the state. This paper examines the demographics and costs of medical treatment for pregnant women with OUD and their newborns with prenatal exposure to opioids (PEO).

Methods: The study involved a retrospective records review of all newborns born between May 1, 2016, and April 30, 2017, at a large, urban medical center. Newborns with PEO were matched with a control group by mother's type of insurance, race/ethnicity, method of birth, and maternal parity.

Results: Establishing which of the pregnant women should be diagnosed with OUD and be included in the study group was inordinately challenging. Ultimately, of the 3841 infants birthed during the study period, 131 (3.4%) were identified as being born to mothers with OUD. Significantly more mothers with OUD were White and on Medicaid. Only 25 (19.2%) mothers with OUD engaged in treatment for substance use. Compared to the control group, newborns with PEO were much more likely (71.4% versus 25.4%) to be admitted to the NICU and had much longer lengths of stay in both the NICU (mean of 14.4 versus 4.1 days) and hospital (16.9 versus 5.8 days), resulting in dramatic increases in health care cost.

Conclusion: These data underscore the need for a comprehensive, systematic approach to OUD and PEO and affirm the government as a major stakeholder in the care of infants born to these women.

Keywords: Prenatal; Opioid; Ohio; Cost; Case control

INTRODUCTION

Since 2014 (when the Ohio Department of Health first published these data), Montgomery County (Ohio) has experienced the highest rates of OUD and unintended opioid overdose deaths in the state.[1-6] Nationally, between 1999 and 2014, the prevalence of maternal OUD more than quadrupled from 1999 (1.5 per 1000 hospital deliveries) to 2014 (6.5 per 1000).[7] By 2017, the incidence had climbed to 8.2 per 1000 hospital deliveries, and 7.3 per 1000 newborns were diagnosed with neonatal abstinence syndrome (NAS).[8] Furthermore, investigators have found that the prevalence of OUD in pregnant women is systematically underestimated.[9] Numerous investigators have highlighted the critical need to integrate opioid use disorder (OUD) treatment with maternity care.[10, 11] Pregnancy complications such as fetal growth restriction, abruptio placentae, fetal death, and preterm labor are common with OUD.[12] Additionally, untreated OUD has increased high-risk sexual activity, exposure to sexually transmitted infections, violence, and criminal activity.[12] Many of the pregnancies complicated by OUD are often also found to be complicated by comorbid mental health conditions.[12, 13] Finally, the rates of follow up postpartum visits to assure the care of the couplet is substantially decreased for persons with substance use disorders. This affects evaluation, identification, and treatment of postpartum mood disorders and future rates of unintended pregnancy, specifically.[12, 14]

Accurate diagnosis of OUD in persons receiving prenatal care is notably difficult. The American College of Obstetrics and Gynecology (ACOG) has provided recommendations for screening for OUD during prenatal care since 2012.[15] However, issues surrounding OUD continue to abound, as evidenced in the updated ACOG guidelines from 2021, which includes stronger language and specific screening modalities.[12] In Ohio, a volunteer survey of women who delivered in 2017 showed that of those receiving prenatal care, 82% were screened for substance use.[16] However, the variable rates of appropriately timed prenatal care among persons with OUD who are pregnant is a noted challenge to improving care for this population.[12] In addition, due to the lack of standardized practices for in-hospital treatment of infants born opioid-exposed, the cost of care and length of stay varies widely. Specifically, variation in identification of prenatal exposure to opioids (PEO), as well as location and level of care for PEO infants, nonpharmacologic treatment, and type of medication utilized (if appropriate), all affect length of stay and the overall cost of care.[17]

This paper examines the demographics and cost of care of PEO in all neonates born at a large southwest Ohio hospital during a 1-year period, with particular attention to identification procedures and care that was offered/received both to the neonates and to their birthing parent.

METHODS

This is a case-control study of PEO in neonates. After approval by the Wright State University institutional review board, retrospective chart review was conducted of all newborns born between May 1, 2016, and April 30, 2017, as well as the charts of their birthing parent, at a large hospital in southwest Ohio which is home to a Level 3 neonatal intensive care unit (NICU). A diverse research team convened regularly to develop the study. As described below, determining inclusion in the study group proved to be a time-consuming and challenging task and was ultimately determined by team consensus after review of many data points.

Of the 3841 neonates born during the study period, 131 (3.4%) were identified with PEO. Each of the 131 newborns identified with PEO were matched, based on type of insurance, race/ethnicity, method of birth delivery, and maternal parity, with a control group of 131 neonates born to women without OUD.

Measures/Outcomes:

The primary measures included timing of the first, and the total number of, prenatal visits, engagement of the mother in medication-assisted treatment (MAT), length of stay of each newborn in hospital and NICU, and cost of hospitalization.

RESULTS

Demographics

Of this sample of neonates, 131 (3.4%) were born to mothers with OUD. For the entire cohort of 3841 infants born during the study period, 66.5% were classified as White, 24.0% were Black, 1.5% were Asian, and 0.2% were Native American. In comparison, for the sample of 130 mothers with an OUD, the proportion of White mothers was disproportionately high (84.4% of those in the study group), while Blacks (13.4%) and Asians (0.4%) were much lower than their representation in the general population.

Similarly, the type of insurance coverage differed significantly for the group of infants with PEO compared to the entire cohort of 3841 neonates. Whereas 93.9% of the mothers with OUD and their infants received Medicaid/Medicare insurance coverage, only 47.9% of those in the entire cohort had Medicaid/Medicare insurance and 46.9% had private insurance.

Of the 262 births in the study (cases and controls), 32 were from first pregnancies. Sixteen of these first-time pregnancies were in the OUD group.

Impact of OUD on Prenatal Care

Similar to data reported by Clemans-Cope and colleagues,[10] women with OUD who were pregnant in this study experienced delayed prenatal care and had significantly fewer postpartum visits than women in the control group, $t\,(250) = 2.75$, $p = .006$. Only 25 (19.2%) of the 130 women with OUD received MAT with methadone or buprenorphine at any time during the pregnancy. The percentage of women with OUD who were engaged in MAT was even lower for those pregnant for the first time: only 1 of 16 (6.2%) received MAT.

Length of Hospital (and NICU) Stays

Compared to the control group, newborns with PEO had longer hospital lengths of stay (LOS) after birth and higher NICU admission rates, corroborating additional data from Clemans-Cope et al.[10] Babies born to mothers with OUD spent significantly more time in the hospital after birth (mean = 16.9 days) than those born to mothers without OUD (mean = 5.8 days), $t\,(255) = -6.44$, $p <$ 001. Significantly more neonates in the PEO group spent time in the NICU than the newborns in the control group. Of the 131 infants in the PEO group, 71.4% went to the NICU, compared to 25.4% of the 131 newborns in the control group $X^2(\text{df}=1, n=252) = 57.31$, $p < .001$. Neonates whose birthing parent had OUD spent more than 3 times longer in the NICU, $t\,(250) = 6.16$, $p < .001$, a mean of 14.4 compared to 4.1 days controls.

Financial Burden of PEO

A lack of prenatal care has been associated with significant increases in maternal and newborn morbidity and cost of care,[8, 12] which proved to be the case in this study. In aggregate, 90 neonates with PEO were treated in the NICU, leading to aggregate costs of $1 918 388, while 32 newborns in the control group incurred $623 598 in NICU with charges.

To examine cost differences between neonates with PEO and those without PEO, a more detailed analysis was conducted. Typical

NICU care for most infants costs between $1000 and $50 000. In our study there were 5 neonates (3 in the control group and 2 in the PEO group) whose NICU costs exceeded $50 000 each. It was discovered that the inordinately high cost for these 5 outliers were, in each case, due to diagnoses unrelated to PEO. Because this study is attempting to determine differences in cost caused by PEO, these 5 outliers were removed from the analysis. After this was done, a significant difference was observed between the NICU costs for PEO and control infants, t (115) = -2.65, p = .009. Mean NICU cost per baby in the PEO group was $19 204 as compared to $13 323 for controls.

DISCUSSION

One of the more important findings of this paper was that establishing a diagnosis of maternal OUD and/or PEO in newborns was an enormous undertaking. Without a uniform standard for screening for or documenting substance use in pregnancy, no single component of the medical chart proved to be a fully reliable source. For example, while some have called for universal drug testing,[18] it is well known that urine testing is not sufficient in and of itself for identification of OUD. However, in our study, urine drug testing was frequently utilized as one of the (and sometimes the only) tool(s) for identifying PEO. Further, it was used without uniformity. For example, of the 130 women found to have OUD, 33 underwent this testing once, 19 twice, 16 three times, and 25 four or more times during the prenatal period. Because of these types of inconsistencies in the medical record, in order to identify infants with PEO, many different, unique searches of both maternal and neonatal records had to be utilized. Searches of maternal records included searching problem lists, admission diagnoses, records of maternal complications, results of urine screens, social history, and medication lists. Likewise, newborn charts were *scrubbed* for diagnoses, medications, admission to the NICU (and diagnoses at NICU admission), and neonatal abstinence syndrome scores. Ultimately, a *manual read* of the maternal admission history and physical proved to be 1 of the most informative sources. The final decision for whether or not a newborn and its parent were in the study group was made by a consensus of the entire research team after reviewing all available data points.

In spite of these efforts, we may not have captured all neonates with PEO. As studies have pointed out, traditional screening methods underestimate PEO and allow a significant percentage of persons with OUD who are pregnant or who have just given birth, and their newborns, to go untreated.[9] Given that the incidence of maternal OUD in our study was only 3.3%, which is less than half the national average, we believe that the incidence of PEO was higher than what we were able to determine, given the lack of consistency in identifying these dyads, and the lack of consistent documentation when OUD or PEO was identified.

Although the data for this study is from the years 2016-2017, it illustrates an ongoing issue both in Ohio and nationally. As discussed in the introduction to this paper, diagnosing OUD in pregnancy or PEO in neonates continues to be a challenge. In spite of ongoing/updated recommendations from ACOG and other experts, there is no national standard for doing so, nor does such a standard exist in Ohio. A statewide and/or national standardized approach to screening and documentation would significantly enhance the quality of care given to these dyads. For instance, well-established OUD screening tests such as 4Ps, NIDA Quick Screen, and CRAFFT (for women 26 years of age or younger) integrated into the prenatal visits and ultimately accessible in a consistent location in the electronic medical record would provide a much-improved mechanism for early identification of PEO and standardization of care as recommended by ACOG 2021.[12] Such standardization would also make data gathering and research more straightforward, which would ultimately lead to further improvements in care for this population.

Another important finding of this paper is that of the 130 pregnant women with OUD, 91% were on Medicaid or Medicare. Thus, the government bears the *lion's share* of the cost for caring for women with OUD and their newborns. Cost-containment strategies (team-based care, standardization of nonmedication treatment, and standardization of medical treatment protocols) are all part of the opportunities that have been evaluated in our area and in Ohio at large. Another major cost-containment strategy that is being evaluated nationally is site of care for neonates with PEO. The noninferiority evaluation of rooming-in instead of NICU utilization, as well as offsite neonatal abstinence syndrome treatment facilities for the woman and infant after discharge, provide substantially improved cost without concerns for safety.[19, 20]

Local and regional interventional strategies, particularly those focused on identification and treatment of prenatal and postpartum OUD, create an opportunity to reevaluate the outcomes from this study. For example, since the collection of the data in this study, our local region has further developed 2 focused medical homes for pregnant patients with substance use disorders and their families.[21, 22] Additionally, the Ohio region has standardized the recommended medical home model for this population in the collaborative quality improvement work groups.[23] Lastly, the region has initiated and further developed a model of care treating neonatal abstinence syndrome in an outpatient setting supporting the postpartum parent and the infant together.[24]

PUBLIC HEALTH IMPLICATIONS

Whether due to the persistent stigmatization of those with SUD, the threat of engagement with social service agencies, injury to the physician-patient relationship, the relative infancy of addiction medicine, or perhaps the *disconnectedness* of the physician community from their colleagues and community agencies treating SUDs, the problem of maternal OUD/neonatal PEO and their consequences beg for a systematic, comprehensive, and multidisciplinary approach to screening, diagnosis, and treatment of pregnant women with OUD and PEO in their newborns. Consistent, standardized, respectful sharing of this diagnosis, as well as of treatment interventions, in the medical record would additionally greatly enhance care for these patients and would, hopefully, improve outcomes for all involved. In addition, this study highlights the need to reevaluate the diagnostic inclusion and accuracy, team-based care, length of stay and cost of care with this high-risk population as well as the updated modalities since this data collection.

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RESEARCH ARTICLE

Perspectives of Treatment Consumers, Treatment Providers, and Law Enforcement on Drug Treatment and Prevention

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ABSTRACT

Background: While much of the literature has focused on examining barriers to substance use disorders (SUD) treatment with individuals with SUD, there is a dearth of research from the perspective of treatment providers and law enforcement, 2 groups who witness the challenges for addressing SUD.

Methods: Using content analysis, this qualitative study explored the perspectives of individuals with SUD, treatment providers, and law enforcement on recommendations about SUD treatment and prevention. Data from 12 focus groups with individuals with SUD were analyzed and triangulated with interviews from treatment providers and law enforcement. Cross case analysis was utilized to identify common categories.

Results: The categories identified included education, judicial system, psychosocial barriers, resources, stigma, stages of change, and treatment. Results indicated all groups had similar ideas on how to address SUD. Participants provided recommendations in each category for addressing SUD.

Conclusion: Individuals with SUD, treatment providers, and law enforcement officers are affected by complex issues of SUD on micro, mezzo, and macro levels. Public health professionals can help to facilitate changes by advocating for prevention and intervention methods to be implemented to address SUD.

Keywords: Substance use disorders; Law enforcement; Treatment providers; Focus groups

INTRODUCTION

In 2017, an estimated 21.2 million Americans needed substance use disorders (SUD) treatment, yet only an estimated 3.7 million received treatment.[1] For individuals, families, and communities, SUD are associated with adverse outcomes such as medical and mental health conditions, lost wages, and criminal activity.[2] Community and governmental responses to SUDs have addressed them as public health and criminal justice matters.[3,4] While street-level enforcement strategies such as arrests have been the standard response toward illicit drug use,[5] public health responses addressing prevention, treatment, and harm reduction have been popular in recent decades. These include screening, brief intervention and referral to treatment,[6] medication treatment,[7] and harm reduction approaches such as support programs, resources on safer ways to use substances, take-home naloxone kits, supervised consumption services,[8,9] and syringe exchange programs.[10]

Ohio State and Regional Trends

From 2007 to 2018, drug overdose was the leading cause of death from planned and unplanned injuries in Ohio.[11] Ohio has the fifth-highest overdose death rate in the nation,[12] with an age-adjusted overdose death rate of 35.9, as compared to a national average of 20.7.[13] The Cincinnati region, as identified by the Ohio Substance Abuse Monitoring Network (OSAM), encompasses 13 counties in Southwest Ohio.[14] Death rates by unintentional drug overdoses range from 23.6 to 53.3 per 100 000 people in these counties.[15]

Study Background

Research on barriers to SUD treatment has predominantly been conducted with individuals with SUD. Limited research has been explored with the counselors and therapists providing SUD treatment or with the law enforcement officials enforcing substance use laws and policies.[3,16] Counselors provide an essential perspective to the discussion, as they are privy to the challenges of SUD treatment delivery and maintain connections to those receiving treatment.[16] Research with law enforcement populations can offer insights, as they have wide discretion in how they enforce the law.[17] Furthermore, the criminal justice system has served as a primary service delivery system for adults facing the challenges of SUD.[17] This study contributes to the underdeveloped literature investigating law enforcement officers' attitudes toward drug use and treatment.[4]

Study Purpose

Established in 1999, the OSAM Network is a prospective, longitudinal study of illicit and prescription drug abuse in Ohio.[18] Regional epidemiologists conduct focus groups with persons receiving SUD treatment (treatment consumers). These focus group findings are cross-referenced with findings from individual interviews and focus groups conducted with community professionals who provide SUD prevention/treatment services (ie, social workers and counselors/therapists), as well as with those whose work is directly impacted by substance use disorders (ie, law enforcement, probation officers, and coroners). Once integrated, these data provide Ohio's behavioral health authority, Ohio Mental Health and Addiction Services (OhioMHAS), real-time, epidemiologic descriptions that policymakers need to plan prevention and intervention strategies. This study was a smaller examination of a larger study that OSAM conducts twice a year to monitor drug trends in specific regions. Our study examined a focus group question that was not analyzed in the larger study.

The research question analyzed for this study was: "Imagine you could speak to the governor and other state officials right now. What recommendations regarding drug abuse prevention and treatment, specific to this region, would you make?"

METHODS

This expedited study was approved by the institutional review board. Participants included individuals who were using illicit drugs or had stopped using illicit drugs within 6 months prior to study enrollment, treatment providers who provided SUD treatment, and law enforcement officers. Focus groups and interviews occurred August 2018 through May 2019.

Setting and Design

Recruitment occurred by the first author calling SUD facilities and law enforcement in the region and requesting their participation. Agencies then received an email with a flyer to distribute with information about the study, location, date and time of group, and incentive payment.

Focus groups (n=12) were implemented at SUD residential, intensive outpatient, and outpatient treatment centers. Eligible participants were individuals receiving treatment for SUD aged 18 years or older who spoke English and had less than 6 months in recovery from SUD. Participants were provided a $20 gift card to a local store.

Providers and law enforcement were interviewed individually or in focus groups at their location or at a location such as a library. Treatment providers and law enforcement were eligible if they were working at a SUD treatment facility or in law enforcement and had knowledge on drug abuse in Ohio within the past 6 months. Due to ethical considerations, treatment providers and law enforcement did not receive monetary compensation. Three focus groups and 1 interview occurred with treatment providers. Three interviews and 1 focus group took place with law enforcement officers.

Participants

Eighty-nine treatment consumers, 18 treatment providers, and 8 individuals in law enforcement were interviewed regarding drug abuse prevention and treatment. The interviews and focus groups were conducted in 5 counties in Ohio: Butler, Clermont, Clinton, Hamilton and Warren. Focus groups ranged from 4 to 12 participants per group of treatment consumers. Table 1 describes the demographics of the treatment consumers. Missing data included 2 participants not answering questions on income and poverty status and 1 participant not answering questions on ethnicity and graduation rate. Demographic information of providers and law enforcement were unavailable.

Procedures

Focus groups for treatment consumers were conducted in a room at the SUD treatment center between or after SUD treatment groups. Before the start of the focus group, participants were screened for eligibility, informed the interview would be recorded, assured of anonymity, and assured treatment would not be impacted if they declined or decided to participate. Confidentiality among focus group participants was also stressed. Participation consent was then obtained. Participants completed a demographic survey prior to the start of the focus group. The focus groups were facilitated by the first author with a coauthor present to observe and take notes. A debriefing session was held by the researchers after each focus group to discuss observations and record field notes.

Interviews with treatment providers and law enforcement occurred with the first author. Similar to procedures with treatment consumer participants, screening for eligibility, consent, request to record the interview, and assurance of anonymity of responses occurred. The first author documented field notes after each interview.

Data Analysis

The audio recordings of the interviews and focus groups were transcribed verbatim by the second author. Participants were deidentified. The transcriptions were read by the first author to check for consistency. Qualitative content analysis process was used to analyze the data.[19] Through an iterative process, the research team constructed a qualitative coding scheme, which was applied to the interview transcripts.[20] As themes emerged from the data, they were added to the scheme, which allowed for inductive analysis.[21]

Transcripts from the treatment consumers were reviewed by the first 3 authors independently to identify common codes though an iterative process. Next, preliminary codes were identified. The first 3 authors then met and developed a codebook. These authors recoded the transcripts with the codebook and discussed any discrepancies. After reaching saturation with the treatment consumers disorders transcripts, the authors triangulated the data[22] by utilizing cross case analysis[23] with the treatment providers and law enforcement transcripts. Peer debriefing[24] also occurred.

Table 1. Demographics

Characteristic	N	%
Gender		
Male	50	56%
Female	39	
Race		
White	68	76%
African American	20	
Ethnicity		
Latinx	4	4%
Age in years		
< 20	1	1%
20–29	12	13%
30-39	36	40%
40-49	12	13%
50-59	23	26%
≥ 60	5	6%
Education		
Less than high school graduate	22	25%
High school graduate	32	36%
Some college or associate degree	29	33%
Bachelor’s degree or higher	5	6%
Household income		
< $12 000	37	42%
$12 000 to $20 999	17	19%
$21 000 to $28 999	12	13%
$29 000 to $37 999	8	9%
≥ $38 000	11	12%
Drug of choice		
Alcohol	31	35%
Cocaine, crack	17	19%
Cocaine, powdered	16	18%
Ecstacy/Molly	6	7%
Heroin/Fetanyl	31	35%
Marijuana	32	36%
Methamphetamine	23	26%
Prescription opioids	26	29%
Prescription stimulants	9	10%
Sedative-hypnotics	18	20%
Suboxone®/Subutex®	25	28%
Other drugs*	4	4%

Sample Description (n=89)
Not all participants filled out forms completely; therefore, numbers may not equal total participants.
Some respondents reported multiple drugs of use during the past 6 months.
*lysergic acid diethylamide (LSD) and dextromethorphan cough syrup (DXM)

RESULTS

Codes were identified in each focus group that overlapped with all groups conducted. Table 2 provides information on codes and categories, whereby the specific codes were identified by participant group and specific transcript (C=clients, P=providers, L=law enforcement). Overall, recommendations regarding drug abuse prevention and treatment in Ohio overlapped for treatment consumers, treatment providers, and law enforcement. Eight categories were identified.

Access to Care

Treatment consumers reported the biggest barrier to SUD treatment was access to care: *"More availability … there needs to be more bed space."* They discussed how they could not get the help they needed in a timely manner. Treatment providers also reported this issue and discussed how they had to provide a lower level of treatment until the treatment consumers could be admitted. "*We have patients that come into our program and we are just not providing them the services they need."* Law enforcement also saw a great need for treatment. *"We need easier access to providers."* Insurance, or lack thereof, was discussed. This included private and Medicaid, as Ohio has state-run Medicaid insurance. Many treatment consumers lose their jobs, rendering them without insurance. A treatment consumer summarized the problem succinctly: "*A lot of rehabs only accept private insurance, and a lot of the people that are doing drugs won't have insurance*." Treatment providers talked about the time it took to get a client to get Medicaid, their frustration with the system, as well as their concern that clients would not be able to stay alive long enough to get treatment: "*Our clients are struggling to stay alive [while] waiting for Medicaid to go through*." Even those who did have benefits did not always have access to care: "[*I'm*] *here [in treatment at a community agency] because the VA is too busy right now."* Recommendations focused on bringing more SUD treatment providers to rural areas, changing the process to more quickly get Medicaid coverage for individuals who need SUD treatment services, and providing more and longer-term treatment at different care levels so that treatment accessed is appropriate to the individual's severity of SUD regardless of their insurance provider or ability to pay.

Table 2. Categories and Codes

Categories	Definition	Codes collapsed into categories	Found in focus groups or interviews with		
			Treatment consumers	Treatment providers	Law enforcement
Access to care	Ability to get treatment that is needed	Access, Insurance	1C, 2C, 4C, 5C, 6C, 7C, 8C, 9C, 10C, 11C	1P, 2P, 3P	1L, 3L
Education	Lack of preparation and knowledge regarding SUD, drugs and alcohol, and addiction provided to individuals in the school system, family members/ friends of those with SUD	Prevention, Lack of education	1C, 2C, 5C, 6C, 7C, 8C, 9C, 10C, 11C, 12C	2P, 4P	1L, 2L, 3L, 4L
Judicial system	Refers to laws, jail, or anything related to legal system	Jails, Decriminalization	3C, 5C, 6C, 7C, 8C, 9C, 10C, 11C, 12C	3P	1L, 2L, 3L
Environmental barriers	Environmental factors that impede recovery	Unemployment, Housing, Homelessness, Transportation	2C, 4C, 5C, 6C, 7C, 9C, 11C	1P, 3P, 4P	2L, 3L
Resources	Providing outside support through services and material goods	Finances, Material goods, Allocation of money, Case management, Community engagement, Advocacy, Outreach, Insurance	2C, 3C, 4C, 5C, 6C, 7C, 8C, 9C, 10C, 11C, 12C	1P, 2P, 3P, 4P	1L, 2L, 3L, 4L
Stigma	Negative perception of those treatment consumers	Stigma, Isolation	1C, 2C, 6C, 8C, 10C, 9C, 12C	2P, 3P, 4P	1L, 2L, 3L
Stages of change	How ready is the individual to receive treatment	Readiness to change	1C, 2C, 3C, 4C, 5C, 6C, 7C, 8C, 10C, 9C, 11C, 12C	3P	2L, 3L
Treatment	The type of services a client receives to aid in addressing SUD	Medication-assisted treatment, Therapies, Integrated health, Sober living	1C, 2C, 3C, 4C, 5C, 6C, 7C, 8C, 9C, 10C, 11C, 12C	1P, 2P, 3P, 4P	1L, 2L, 3L, 4L

Note: Transcripts analyzed for categories and codes are indicated by number and group. C=clients, P=providers, L=law enforcement

Education

Treatment consumers, treatment providers, and law enforcement saw a need to educate the public. All groups agreed that: "*Prevention has to start at a young age"* (law enforcement). It was suggested that education take place in schools. Treatment consumers who were in recovery thought they should be a part of this process: *"Maybe start having some recovering addicts go and speak to kids."* Educating parents on how to talk about SUD with their children was recommended. Using media and venues such as community centers and churches were discussed. Furthermore, medical professionals need to provide education regarding the safe use of prescribed medications that are potentially addictive. For example, a treatment consumer reported: *"And I also think that when a doctor prescribes these opiates, that doctor also need to explain that they are very addicting. When they gave me all my prescriptions, not one doctor came up to me and said, 'Oh, this is very addictive.'"* Treatment consumers and treatment providers suggested education on medication treatment for those needing help. "*Educating people to what's available out there, as far as, like, medications and treatment*" (treatment consumer).

Judicial System

The challenges to recovery within the judicial system were discussed. For one, it was difficult for individuals to stay drug free while incarcerated. *"Jail's not going to do you any good, 'cause you can get high in jail… probably easier than you can on the street, at this point"* (treatment consumer). Therefore, controlling the influx of illegal substances in prison was recommended. All groups discussed the impact of having a drug charge for individuals trying to make a positive change in their life. *"And if you're giving them this drug record and they get out of jail and they can't get a job, so then what are they supposed to do?"* (law enforcement). Treatment consumers, treatment providers, and law enforcement discussed decriminalization as a possible way to help: *"So decriminalize … Emphasize that it's a medical issue"* (treatment providers). Concern about the overall cost for incarceration was discussed as well as the effectiveness of prison: *"How much is it to arrest them and take them to jail and leave them sit there?"* (law enforcement). All groups reported additional outside pressure, such as those from the judicial system, was sometimes necessary. A treatment consumer reported: *"…but though I think you need a little more encouragement, such as: you are, you must do this. You must go in treatment. You must, or you, you know, you're never going to get off probation or whatever. Just, something to kick your butt."*

Treatment consumers and providers discussed drug court and the treatment in jail that helped treatment consumers to become stable in recovery. *"I attribute my sobriety, majority of it, now to, the TC* [therapeutic community] *program that I went through that is now offered within the prison system"* (treatment consumer). Overall, all groups felt there needed to be programs in place for those who were in and/or interested in recovery and involved in the judicial system: *"… people need opportunities for second chances"* (treatment provider).

Environmental Barriers

Environmental barriers were discussed, including housing, employment, and transportation needs. Unfortunately, many of the treatment centers were not located along transportation routes that were accessible to treatment consumers, especially those in rural areas: *"I've been payin' Uber and Lyft rides every day to get here and back… seventy or eighty [dollars] for the ride every day and fifteen for the juice [Methadone] when I get here. That's for me to stay clean, and you know, I'm lucky that I can do that. A lot of people can't afford that kind of thing"* (treatment consumer).

In addition to the recommendations to bring more SUD treatment facilities to rural areas, which was mentioned by multiple participants, one treatment consumer had a recommendation to provide mobile treatment clinics similar to those provided for mammograms: *"… it's already bad enough you don't want to have to come here. Then it was like, having to come here three times a week, three hours at a time, gas back and forth. You know, how they got those … mobile breast cancer vans? Maybe do like one of them for the outlying communities. So people don't have to travel as far."*

As mentioned in the previous section, many participants discussed that felony drug convictions can severely limit employment and housing options, which led to recommendations of making it easier to have felony convictions expunged.

Resources

All groups had suggestions on resources that could help treatment consumers. These included case management, outreach, access to Narcan, advocacy, and funds. "*Case management is so important, because you need someone to help you and guide you, let you know where those resources are*" (treatment provider). Treatment consumers who experienced outreach talked about how it helped them to seek treatment, and more was needed. The need to access Narcan was important to all groups. All groups realized that funding for resources was needed, and thought that the public was onboard, but not necessarily the government. *"Honestly, I think that if it was put on the ballot for an increase in funding, I think that it would pass in this area, because of how bad things are"* (treatment provider). Treatment providers talked about advocating for the individuals they treated but saw little impact: *"But is limited to our population because of the resources, the lack of resources, we need to move forward and address those and everybody comes to those meetings* [meetings with legislators] *and shakes their heads and says, 'Oh I didn't understand' but then nothing gets changed"* (treatment provider). One law enforcement personnel suggested a way to access the money and resources needed: *"So, it'd be nice if the state of Ohio somehow could, whether it was OMAS, or whether it was the governor, state legislator, someone could declare a health emergency. And have the resources on the street, to not only save lives but shift addiction."*

Stigma

Health-related stigma is a social process whereby social groups are devalued, rejected, blamed, and excluded on the basis of a socially discredited health condition or health-related problem.[25] Treatment consumers reported the stigmatization they received as a group: *"We've got a bad stigma on us and I don't think that, you know, we get a fair fighting chance because we've got so many people against us."* Treatment providers and law enforcement agreed. A treatment provider summed up why treatment consumers face stigma: *"I think a big problem in our state is that it is still seen as a moral issue ... Rather than a medical issue."* Treatment consumers discussed how isolating it felt: *"That's just, like, me personally like, for a minute, I just felt like I was in a black hole. I couldn't talk to anybody about this so I didn't talk to anybody about it. But it just made my addiction worse."* Treatment providers and law enforcement saw this as impeding recovery, as they would go back to their previous lifestyle. *"So they go right back to the people that they know, who will actually spend time with them. What are they doing? Probably drugs. They feel hopeless, so what do they want to do? Probably more drugs. We set the system up to just completely not support you in recovery, if you do get stuck in it"* (law enforcement).

All groups discussed the need to support more drug-free activities to decrease the feelings of isolation. Additionally, recommendations were made to offer opportunities to prepare those in the community to support those with SUD: *"I think there should be, like, class or meetings for people who are dealing with people who have addictions, more like empathy, compassion. Because a lot of these people, they don't feel like they have anyone they can turn to or talk to"* (treatment consumer).

Stages of Change

The stages of change, applied to treatment consumers, is drawn from the transtheoretical model, conceptualizes behavior change as a process that unfolds over time, and involves a series of 5 stages: precontemplation, contemplation, preparation, action, and maintenance.[26,27] All groups discussed the realized importance of the individual with SUD wanting to change: *"He can throw me in jail a hundred times. If I'm not ready, I'm not gonna quit"* (treatment consumer). They also discussed the challenges of continuing to maintain that substance-free lifestyle: *"But it's, from what we see and it's almost... Like a revolving door"* (law enforcement). The solution often suggested was making treatment available for longer periods of time: *"But if I would have been at treatment for a full ninety days, I would have had more drive to continue my recovery"* (treatment consumer).

Treatment

All groups had suggestions about treatment. Sober living opportunities for individuals in recovery were discussed in all groups: *"Sober living that are MAT* (medication-assisted treatment)*-friendly"* (treatment provider). *"You had a transitional living type o' sober living facility where they go in there and they stay there for six months"* (law enforcement). Integrated care was discussed as a need: *"Part of treatment is getting physically healthy ... So, getting people back in and seeing a doctor regularly"* (treatment consumer). Treatment providers and consumers discussed how some programs only provided medication treatment but not counseling, so individuals do not get needed help. As a treatment consumer shared: *"'Cause the other place I was goin' in, you just pay 'em and got your medicine and then you left. I think there needs to be counseling, not just hand out the medication."* Providers talked about their concern that there was a growth in different types of medication treatment but not one that has a history of success: *"We, we got all these suboxone programs... Poppin' up everywhere for profit. But yet methadone is still the gold standard, for treating opioid addiction, but yet we still have the same regulations that have been in place for probably the last thirty years."* Treatment consumers also discussed this challenge with methadone, leading to less methadone clinics: *"Remove the tight, unyielding restrictions they've had on it since the sixties."* Overall, all groups agreed treatment was essential to addressing drug abuse: *"Treatment is the most powerful tool that can change lives"* (treatment provider).

DISCUSSION

Substance use disorder is a common and under-treated problem that has a major impact on individuals, their families, and the community. While most research has focused on understanding the barriers to SUD treatment, qualitative studies have sought out suggestions and recommendations about SUD treatment and prevention among treatment consumers, treatment providers, and law enforcement,[3,28-30] but none have explored the perspectives of all 3 of these groups simultaneously.

Participants interviewed from all 3 groups shared recommendations within the same categories (education, judicial system, psychosocial barriers, resources, stigma, stages of change, and treatment) when asked what they would propose to the governor and other state officials regarding drug abuse and prevention. Similar to a recent study by Bunting and colleagues,[29] the participants identified individual, interpersonal, institutional, organizational, and system-level barriers, yet were still able to provide system-level recommendations appropriate for public policy interventions.

Recommendations addressing access to care included helping individuals receive appropriate levels of treatment regardless of where they live, their insurance provider, or status. Suggestions regarding the judicial system included advocating for treatment over incarceration and using the judicial system for leverage when needed. Decriminalization and revoking drug felony convictions were frequent suggestions especially because of the limiting impacts felony convictions have for employment and housing. A possible solution to help treatment consumers in the judicial system is to connect them to a caseworker prior to being released. In Massachusetts, the Hampden County jail developed a program whereby health care teams worked within the correctional facility and the community to provide care for individuals during their release.[31] By providing individuals with support to access resources, they may be more likely to become connected to services.

Recommendations for overcoming psychosocial barriers included decreasing transportation challenges through mobile treatment vans and providing treatment in rural areas. Efforts to address stigma included recommendations to offer more drug-free activities and targeted education efforts for community members with stigmatizing beliefs.

The importance of recognizing the readiness for individuals to seek treatment was a frequently mentioned concept in all groups, with recommendations to ensure that treatment is available when people are ready. For many individuals, readiness fluctuates over time, rather than being a linear experience, which underlies the importance of having treatment available on demand, as readiness may wane if too much time is allowed to pass before access to treatment is available.[30]

Finally, recommendations for treatment were suggested by all groups. This included increasing all levels of treatment; ie, medication treatment, sober living, and integrated health care. This echoes sentiment found by Browne and colleagues, whose participants suggested partnerships between care providers to ensure the holistic needs of individuals who use substances are met while also providing flexible agency operating times as a way for treatment to be accessible beyond typical business hours.[28]

Limitations

There were some limitations in this study. Focus groups varied in the number of participants. Also, participants self-selected to participate in the study. Social desirability may have impacted data provided by participants. Furthermore, generalizability of findings is limited due to convenience sample within a specific geographical location as well as the nature of qualitative research exploring more in-depth topics. Finally, demographic information on treatment providers and law enforcement officers was not collected.

PUBLIC HEALTH IMPLICATIONS

Public health can address SUD on micro, mezzo, and macro levels. Counselors who provide treatment can link clients to case management services or provide outreach to individuals who are actively using substances or have recently overdosed. For example, in Cincinnati's Colerain Township, the community paramedicine model is utilized, whereby a team of police officers, firefighters/emergency medicine technicians (EMTs), and social workers make home visits within 1 week to an individual who overdosed and EMTs were called to the scene.[32] School personnel such as counselors and health educators could help to design programs on SUD for parents and pupils, such as working with individuals in recovery to share their stories and providing parents with talking points to discuss SUD with their children. These interviews show that in addressing SUD, law enforcement, treatment providers, and treatment consumers are often in agreement over the importance of treatment options. Public health professionals could build coalitions with community groups and representatives from treatment providers and law enforcement to agree on options when addressing SUD. Furthermore, public health professionals can lobby legislators for funding to support treatment options, advocate for laws to reduce sentencing for drug use, and replace prohibitive regulations associated with methadone treatment to increase accessibility. Future public health researchers can design studies on the effectiveness of prevention and treatment options to determine impact.

Conclusion

Treatment consumers, treatment providers, and law enforcement officers are affected by complex issues of SUD on micro, mezzo, and macro levels. Yet these 3 groups identified possible solutions to address SUD. Public health professionals can help facilitate changes by advocating for prevention and intervention methods to be implemented to address SUD.

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RESEARCH ARTICLE

Effects of Regional Income, Race, and Educational Level on Incidence of Diabetes and Heart Disease in Ohio

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ABSTRACT

Background: Socioeconomic factors such as income, education, race, age, and weight are thought to be contributing factors for the incidence of chronic diseases such as diabetes and cardiovascular disease. Diabetes and cardiovascular disease are not only serious health complications but also cause significant financial burden to the health care system, both in Ohio and the US. This study seeks to examine the relationship of these socioeconomic factors to the prevalence of these 2 diseases in Ohio using the data available from Behavioral Risk Factor Surveillance Systems (BRFSS).

Methods: Fourteen regions in Ohio were analyzed using logistic regression for socioeconomic impacts on diabetes and cardiovascular disease. Data for this study were obtained from the Behavioral Risk Factor Surveillance Systems (BRFSS) for the years 2011 through 2018.

Results: Our results indicate that a strong relationship exists between age and weight with both diabetes and cardiovascular disease in all 14 regions of Ohio, as expected. However, the contribution of the other socioeconomic factors, except income and education levels, is less certain.

Conclusion: This study suggests that besides promoting public health programs that focus on weight and age, effort should be made to evolve strategies promoting increased levels of income augmentation in the population.

Keywords: Diabetes; Cardiovascular disease; Socioeconomic factors; Ohio

INTRODUCTION

Diabetes is a group of metabolic disorders characterized by increased level of glucose in blood, either due to deficiency of the hormone insulin or the inability to utilize insulin adequately in the body of the affected.[1] Type 2 diabetes, the most common form of diabetes among adults, happens when either insulin is not made in adequate amounts, is not utilized appropriately even when present, or both the aforementioned conditions exist at the same time.[2] Uncontrolled diabetes may lead to serious health complications such as kidney disease, cardiovascular disease, increased risk of infection, neuropathy, and blindness.[3]

In addition to the morbidity and mortality associated with diabetes, treatment for diabetes is expensive and increases economic burden on the health care system both in Ohio and in the US.[4] According to the Ohio Diabetes Action Plan, 2018, Centers for Disease Control and Prevention (CDC) estimated that the expenditure incurred due to diabetes in Ohio is $15.8 billion per year. The estimated costs include direct health care costs, loss due to inability to work, and mortality.[4] Many studies have predicted behavioral risk factors that include but are not limited to sedentary lifestyle, smoking, advanced age, obesity, diet, or urbanization.[4-9] It would be reasonable to presume that in addition to making changes in lifestyle and behavior, as suggested by previous studies, identifying socioeconomic factors affecting prevalence of diabetes and making an effort to modify those can also help in decreasing the financial burden.[10,11]

Another group of diseases known as cardiovascular disease (CVD) is the leading cause of mortality in the Western world and the risk factors are similar to those in diabetes, which include smoking, lack of physical activity, poor nutrition, and obesity.[12,13] At one time CVD was thought to be the disease of affluence, prevalent in the Western world.[14] Evidence collected since then has indicated that socioeconomically disadvantaged population, that is, individuals belonging to moderate- or low-income groups are also at risk.[14] Among the factors deemed responsible for morbidity and mortality due to CVD, diet and diet-related conditions and behavior are of utmost importance.[15,16] Part of the cause of CVD in those belonging to the lower income groups may therefore be attributed to quality of nutrition which is dictated in part by economic affluence or lack thereof.

As mentioned, quality of nutrition affects both type 2 diabetes and CVD, the 2 diseases that are the focus of this study.[8,15,16] Severe discrepancies exist between the diets of those belonging to the different socioeconomic levels. The difference in diets is not only due to affordability but also due to availability of quality food items, awareness, cultural influence, and area of residence. Studies have suggested that people of low socioeconomic status tend to spend most of their resources on food items of low nutritional value such as packaged food, food with high sugar and saturated fat content, and less on more nutritious fresh produce, lean meats, and fish.[17-19] This is compounded by limited access to supermarkets where healthy food items are available and by lack of will or means to exercise.[19] Another factor that contributes to cardiovascular health is alcohol consumption. It has been shown that although moderate consumption of alcohol may be beneficial to cardiovascular health,[20,21] regular consumption of large quantities may have adverse effects.[22-24] Members of the population belonging to the socioeconomically disadvantaged group drink large quantities of beer and sweetened beverages as opposed to the socially advantaged who consume wine known to be beneficial to health.[25] Another factor that contributes to all causes of mortality is education. Galea et al[26] reported that in the year 2000, education could have significantly reduced all causes of mortality, a vast majority of which could be accounted for by cardiovascular diseases. It is well known and accepted that socioeconomic disparities can be correlated with inequalities in cardiovascular health.[27-29]

The role of socioeconomic factors causing increased risk for diabetes and CVD has been studied in other regions of the US and the world, however, relatively fewer studies have been conducted in Ohio. Schwartz et al examined the self-reported cases of diabetes in the 11 Appalachian counties of Ohio and found a disproportionate number of cases in this region compared to the state and national averages.[30] Individual counties sometimes issue reports concerning diseases such as diabetes, and the Ohio Department of Health issues an annual report based on the BRFSS survey, but comprehensive analyses of the socioeconomic aspects of the disease are lacking.[31,32] This study attempts to partially fill the gap in regional aspects of the incidence of diabetes and heart disease.

METHODS

Participants

Survey data originating from individual counties in Ohio are rare, therefore, data from the Ohio Behavioral Risk Factor Surveillance System (BRFSS) for the years 2011 through 2018 were used for this study. The BRFSS survey collects, “prevalence data among adult U.S. residents regarding their risk behaviors,” including those behaviors that can affect their health status including the causes of preventable deaths in the adult population in each state.[33] The Ohio BRFSS survey was conducted by a private contractor that used both landlines and cell phones to randomly (random-digit-dialing) interview 700 to 1 000 noninstitutionalized adults (18 years or older) per month.[34] The state-collected cross-sectional data are then sent to the CDC where they are aggregated, edited, and weighted.[33] Data are weighted using iterative proportional fitting to account for the increased use of cell phones and to include other characteristics such as education level, marital status, and home ownership.[35]

Setting and Design

The Ohio Department of Health (ODH) has created 14 regions within the state based on existing geographic and underlying demographic data (J. Sleesman, ODH, personal communication, June 29, 2021). These regions are listed in Table 1. These regional groupings were used in our model to coincide with the state information and for comparison purposes. Besides regions, other socioeconomic variables of interest were age, weight, years of education, level of income, and race. Age and weight are known to be positively related to the higher incidences of both diabetes and heart disease.[2] The other factors of income, education, and race are socioeconomic and are also thought to be factors in the incidence of both diseases.[36] Some studies show disparities between urban and rural areas regarding disease, but regions, on a statewide basis, have not been examined to any great extent.

The CDC changed the weighting methodology for BRFSS data in 2011, therefore Ohio BRFSS data for the years 2011 through 2018 were used to examine the relationships between reported diabetes and reported heart disease in each county in Ohio.

Procedures and Measures

Access to use the Ohio BRFSS survey data in this study was approved by the Ohio Department of Health and sent electronically to the authors in SAS format.[a]

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[a] “BRFSS **data** used in these analyses were obtained from the Ohio Department of Health (ODH), supported by the Centers for Disease Control and Prevention (CDC). Use of these data does not imply that ODH or CDC agrees or disagrees with the analyses, interpretation, or conclusion in this report.” Statement taken from the “2019 Data User Agreement for Access to Ohio Behavioral Risk Factor Surveillance System (BRFSS).”

Table 1. County Regional Groupings

Region 1	Defiance, Fulton, Henry, Lucas, Paulding, Williams, Wood
Region 2	Allen, Auglaize, Hancock, Hardin, Mercer, Putnam, Van Wert
Region 3	Crawford, Erie, Huron, Ottawa, Richland, Sandusky, Seneca, Wyandot
Region 4	Cuyahoga, Geauga, Lake, Lorain
Region 5	Ashland, Holmes, Medina, Stark, Summit, Wayne
Region 6	Ashtabula, Columbiana, Mahoning, Portage, Trumbull
Region 7	Delaware, Knox, Marion, Morrow, Union
Region 8	Fairfield, Franklin, Licking, Madison, Pickaway
Region 9	Champaign, Clark, Darke, Greene, Logan, Miami, Montgomery, Preble, Shelby
Region 10	Butler, Clermont, Clinton, Hamilton, Warren
Region 11	Adams, Brown, Fayette, Highland, Pike, Ross, Scioto
Region 12	Coshocton, Guernsey, Morgan, Muskingum, Noble, Perry, Tuscarawas
Region 13	Belmont, Carroll, Harrison, Jefferson, Monroe, Washington
Region 14	Athens, Gallia, Hocking, Jackson, Lawrence, Meigs, Vinton

Outcome Variable-Diabetes

In the BRFSS surveys, the incidence of type 2 diabetes was established by asking each participant, "(Ever told) you have diabetes? Response: 1 = Yes; 2 = Yes, but female told only during pregnancy; 3 = No; 4 = No, prediabetes or borderline diabetes; 7 = Don't know/ Not sure; 9 = Refused."[37]

Outcome Variable-Heart Disease

Similarly, to determine incidence of heart disease, the survey question was, "(Ever told) you had angina or coronary heart disease? Response: 1 = Yes, 2 = No, 7 = Don't know/Not sure, 9 = Refused."[37] The predictor variables of age, weight, level of education, and level of income were also determined from the BRFSS surveys for each year.

Predictors-Age and Weight

These 2 continuous variables were answered in the BRFSS survey simply by asking the questions, "What is your age?" and, "About how much do you weigh without shoes?"[37] The expected answer for weight was to be in pounds. If the answers were given in metric form, the data were recoded to obtain answers in pounds. Age was recoded to count only those individuals 18 years and older while weight was recoded to calculate weight in pounds.

Predictor-Income

The BRFSS survey asked respondents, "Is your annual household income from all sources: 1) Less than $10 000, 2) Less than $15 000, 3) Less than $20 000, 4) Less than $25 000, 5) Less than $35,000, 6) Less than $50 000, 7) Less than $75 000, 8) $75 000 or more?"[37] The individuals were classified into 1 of the 8 levels. Those responses were recoded into 5 levels for our model for ease of calculation.

1. Less than $25 000
2. Greater than or equal to $25 000 and less than $35 000
3. Greater than or equal to $35 000 and less than $50 000
4. Greater than or equal to $50 000 and less than $75 000
5. Greater than or equal to $75 000

Predictor-Level of Education

The initial survey question was, "What is the highest grade or year of school you completed?" 1) Never attended school or only kindergarten, 2) Grades 1 through 8, 3) Grades 9 through 11, 4) Grade 12 or GED, 5) College 1 to 3 years, 6) College 4 years or more."[37] For this study, the 6 levels were pared down to the following 4 levels.

1. Less than high school
2. Grade 12 or GED
3. College 1 to 3 years
4. College 4 years or more

Predictor-Race

Respondents were asked to identify their race or ethnicity. Five categories of race were included in the study as a calculated value to adhere to standardized reporting for race and ethnicity. The categories of race are: 1) White only, non-Hispanic, 2) Black only, non-Hispanic, 3) Other race only, non-Hispanic, 4) Multiracial, non-Hispanic, 5) Hispanic.[37]

Predictor-Region

Since the study was concerned with regional effects, the 14 regions (Region 1 through 14) were also included as predictors. The BRFSS survey included county of residence information. The SAS model was coded to group residents into 1 of the 14 regions based on their county of residence.

Statistical Analysis

A logistic regression model was used to analyze the relationship because of the dichotomous outcome variables and both continuous and categorical predictor variables. The SAS PROC SURVEYLOGISTIC procedure was used to provide the statistical analysis.[b] The SAS program was especially compatible with the datasets provided because of its ability to account for survey weighting.

Logistic methods of analysis first estimate coefficients for the independent variables, which are then used to determine odds ratios. The odds ratios are determined by comparing the categorical interval under consideration to a reference interval. The references were selected based on the worst possible outcome within their respective categorical range except for race. For example, for the income variable, the income reference was "Income < $25 000." Income less than $25 000 was selected as the reference group because household income for a family of 4 below $25 000 suggests the household is living in poverty. For educational level, "Less than high school" was selected as the reference group because those individuals who fall within this category have decreased chances for good paying jobs and the associated benefits. Of the 14 regions included in the study, "Region 14" was selected as the reference because it was the poorest region in the state in terms of income. For the 8 years of the study, Region 14 ranked last in average median income[c] in 7 of those 8 years.[38] In addition, the Appalachian Regional Commission considers Athens and Meigs counties in Region 14 as "distressed." The distressed rating is based not solely on income but other factors such as poverty and unemployment as well.[39] In determining the reference for race, non-Hispanic Whites was used as the reference group because this group has relatively lower rates of heart disease and diabetes.[40,41]

Logistic regression models should meet the assumptions associated with their use. Basically, 5 assumptions were examined regarding the model and data: 1) the dependent variable must be binary, 2) observations should be independent of each other, 3) the absence of multicollinearity, 4) linearity between continuous independent variables and the log odds of the dependent variable, and 5) the use of a large sample size.[42-44] The use of the dichotomous variable, having diabetes or heart disease, as dependent variables satisfy the first assumption. The second assumption was satisfied because the survey was conducted with independent random phone calls. To check for multicollinearity, a correlation matrix was obtained from the model and examined for highly correlated relationships. No significant correlations among independent variables were observed. Also, as part of the model, scatterplots were examined for each model comparing the log odds of the dependent variable to the continuous variables of age and weight. Visual examination of these plots showed an excellent linear pattern for log odds of both diabetes and heart disease versus age, while the plot for weight was not as clear. This could be because both diabetes and heart disease are related to an individual being obese and obesity is related to one's body mass index (BMI). Since BMI is a function of both weight and height, some people could be obese at 180 pounds, while others would not. This could account for the unusual plots for weight (K. Yeager, Kent State University-Statistical Consultant, personal communication, February 8, 2021). For assumption 5, a minimum sample size of a least 500 is recommended for logistic regression.[44] Sample sizes for all 16 models in our study approached 10 000 observations, which is quite sufficient to meet the assumption.

In addition to meeting the assumptions, the models underwent global null hypothesis tests to discern whether they fit the data better than an empty model. The likelihood ratio test, the efficient score test, and the Wald test were used to make this determination. Essentially, these tests are examining whether the model has at least 1 predictor that is relevant in explaining whether an individual has diabetes or heart disease.[45] For this study, all 16 models met all 3 global tests.

RESULTS

Table 2 displays the results of the analysis of effects or whether each of the predicator variables as a group affects the outcome variables. The age and weight predictors were significant for the entire time of the study for both diabetes and heart disease. Income was significant for all 8 years for diabetes and for 6 of the 8 years for heart disease. Race was a significant effect for 5 years for diabetes, but only 3 years for heart disease. Education and region were considerably less influential for both diseases.

To examine the effects in more detail the results of the maximum likelihood estimated logistic regression coefficients are displayed in Tables 3 and 4 along with their respective significance. The coefficients represent the change in log odds of the outcome for a 1 unit increase in the predictor variable. For example, in determining the incidence of diabetes, the coefficient on the predicator variable, "Income ≥ $75 000" in 2018 was -0.3859. For a 1 unit change in the income predictor, the log odds of getting diabetes decrease by -0.3859 compared to those with an income below $25 000.[46]

As expected, age and weight were significant positive factors contributing to the incidence of both diabetes and heart disease for all 8 years of the study. In 7 of the 8 years, households with income levels below $35 000 had a positive relationship to the incidence of diabetes as indicated by the positive coefficient as compared to those with incomes less than $25 000. Households having income levels greater than $50 000 and less than $75 000 had negative relationships to incidence of diabetes in 6 of the 8 years compared to those with incomes less than $25 000. Households with income levels greater than $75 000 had statistically significant negative relationship to the incidence of diabetes all 8 years compared to

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[b] The analysis for this paper was generated using SAS 9.4 software. Copyright © 2002-2012 SAS Institute Inc. SAS and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc., Cary, NC, USA.

[c] Using Table 1 as a reference, each region's average median income was calculated by adding the yearly median income for all the counties that were included in the region and then dividing by the number of counties. Data were obtained from the US Census yearly median income per county tables. Calculations available upon request from authors.

Table 2. Type 3 Analysis of Effects—F Values

Diabetes								
	2011	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Effect								
Weight	204.52**	256.83**	220.27**	238.32**	183.29**	96.71**	197.43**	209.59**
Education	1.26	2.29	2.41	1.56	2.66*	0.67	0.74	1.91
Income	2.88*	7.71**	3.29*	11.03**	2.82*	4.33**	11.86**	9.50**
Age	233.22**	319.56**	361.97**	318.21**	334.37**	317.25**	305.85**	304.19**
Race	5.00**	3.01*	3.61**	3.56**	2.54*	1.51	2.07	0.68
Region	1.24	1.06	1.84*	1.21	1.14	1.49	2.32**	1.48
Heart Disease								
	2011	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Effect								
Weight	67.98**	55.75**	35.14**	42.05**	24.32**	51.99**	26.70**	49.56**
Education	1.98	3.13*	1.11	0.50	0.87	6.42**	0.01	1.97
Income	4.45**	3.89**	4.48**	4.82**	4.43**	2.23	5.45**	1.40
Age	261.90**	213.31**	366.24**	276.29**	216.15**	179.57**	377.28**	274.68**
Race	3.03**	1.63	5.62**	1.48	1.21	1.60	2.07	3.01*
Region	0.64	1.41	0.58	1.31	2.77**	0.99	2.21**	0.63

*Denotes $p < 0.05$
**Denotes $p < 0.01$

those with incomes less than $25 000. The Analysis of Effects table indicated that for the 5 years from 2011 through 2015, race was a significant factor, however, the analysis of the coefficients only showed significance for non-Hispanic Blacks for 2011 and 2012 and for other races (besides non-Hispanic Black, Hispanics, and Multiracials) for 2012 and 2013 compared to non-Hispanic Whites.

For the incidence of heart disease, Table 4, income level had similar effects, albeit not as strong. At income levels above $75 000, negative relationships existed compared to those with incomes less than $25 000 but were only statistically significant 4 years out of the 8. Once again incomes below $35 000 seem to establish a positive association for heart disease, while income levels greater than $35 000 and less than $50 000 indicated negative relationships in 5 of the 8 years compared to those with incomes less than $25 000. Income levels greater than $50 000 and less than $75 000 had negative coefficients 6 of 8 years and at the greater than $75 000 level all 8 years were negative compared to those with incomes less than $25 000.

The coefficient values of the logistic regression are used to calculate an odds ratio, which is the multiplicative change in the odds for a 1 unit change in a predicator variable. For example, in Table 5, the odds ratio point estimates for diabetes for those with "Income > $75 000 vs < $25 000" in 2018 is 0.446. Since 0.446 is less than 1, the interpretation is the odds a person whose income was greater than or equal to $75 000 would be less likely to have diabetes than a person whose income was less than the $25 000.[47] In this case, the odds of a person with an income greater than $75 000 acquiring diabetes would decrease by 55.4% (1 – 0.446 = 0.554) compared to a person with an income of less than $25 000. If the odds ratio point estimate was greater than 1, then the person whose income was greater than $75 000 would have higher odds of developing diabetes compared to the person whose income was less than $25 000. The results for all odds ratios are found in Tables 5 and 6.

DISCUSSION

Perhaps the most interesting finding for incidence of diabetes was at a certain level of income, the sign on the logistic regression coefficient changes from positive to negative. For each year of this study, income levels within the range of $35 000 to $50 000 and $50 000 to $75 000 have negative coefficients in 6 of the 8 years. When the range of income is greater than $75 000, all 8 years show a negative coefficient. The implications of the negative coefficients are that not only are individuals at an advantage with higher incomes in terms of the incidence of diabetes, but also the turning point in terms of better diabetes outcomes seems to be when income increases to at least $35 000. One Canadian study[48] has indicated that income below $29 000 is significantly related to a higher incidence of diabetes and another study indicated that the gap is widening.[49]

The income effect on incidence of heart disease was similar but not quite as strong. At the $35 000 to $50 000 level, negative coef-

Table 3. Logistic Regression Estimates for Incidence of Diabetes per year

Parameter	2011	2012	2013	2014	2015	2016	2017	2018
Intercept	-8.0769**	-7.5892**	-8.0353**	-7.9558**	-8.2259**	-7.0276**	-7.3268**	-7.6728**
Weight	0.0159**	0.0143**	0.0148**	0.0149**	0.0138**	0.0116**	0.0127**	0.0135**
College 1 - 3 years	-0.0567	0.1114	0.0952	0.1624	0.2005*	-0.0270	0.0597	0.1394
College > 4 years	-0.1588	0.1771*	-0.2509*	-0.0723	-0.1501	-0.1156	-0.0684	-0.0776
Grade 12 or GED	0.0952	-0.0592	0.0629	0.0746	0.1244	-0.0184	0.0901	-0.0902
Income ≥ $25k < $35k	0.2064	0.0858	0.1588	0.1566	0.2270*	-0.1256	0.3053*	0.1026
Income ≥ $35k < $50k	-0.0493	0.1509	-0.0804	-0.2528*	-0.0828	0.0632	-0.1590	0.1108
Income ≥ $50k < $75k	0.0108	-0.2434*	-0.0500	-0.0512	-0.1319	0.0075	-0.1288	-0.2493**
Income ≥ $75k	-0.3348**	-0.3140**	-0.3010*	-0.3773**	-0.2263*	-0.2424*	-0.4182**	-0.3859**
Age	0.0552**	0.0513**	0.0608**	0.0581**	0.0616**	0.0560**	0.0551**	0.0529**
Hispanic	-0.2351	0.2200	-0.1583	0.1229	0.6049	0.1883	0.3268	0.2952
Multi-Racial	-0.5258	0.1056	0.0099	-0.2159	-0.6614	0.2913	-0.3193	-0.0688
Non-Hispanic Black	0.4948*	0.3897*	-0.1033	0.2118	0.2931	-0.1749	-0.0559	0.1351
Other Race	0.5212	-0.6708*	0.6838*	0.2204	-0.1561	0.0479	0.3679	-0.4439
Region 1	0.0668	0.0782	-0.0106	0.0497	0.0642	-0.0256	-0.0335	-0.0122
Region 2	-0.0955	-0.4388*	-0.3229	-0.1181	-0.4181**	-0.0134	-0.2575	-0.0763
Region 3	-0.0593	0.0812	0.0572	-0.3248*	-0.0918	0.1522	-0.1848	-0.1061
Region 4	-0.2914	-0.0359	0.1376	-0.0588	-0.0911	-0.3483*	-0.1621	-0.0251
Region 5	-0.1155	0.0192	-0.2514	-0.1133	-0.1564	-0.0589	-0.2359	-0.1289
Region 6	-0.2206	-0.1605	-0.1333	-0.2350	-0.1352	0.0452	-0.0396	0.0242
Region 7	0.0846	-0.0291	-0.1059	-0.0774	0.0053	-0.2396	-0.0219	-0.2232
Region 8	0.1023	-0.1090	0.1717	0.0720	-0.0331	-0.0734	-0.1385	0.1721
Region 9	-0.0576	0.0471	-0.1297	0.1307	0.1201	-0.0297	0.0474	-0.0824
Region 10	0.1417	0.1333	-0.0801	-0.1320	0.1959	0.1603	-0.1919	0.2465
Region 11	0.1370	0.4795*	-0.0284	0.1566	0.2132	-0.0940	0.2638	0.2366
Region 12	-0.1742	0.0236	-0.1731	0.2156	0.1535	-0.1116	0.2721*	-0.3278*
Region 13	0.6063**	-0.0306	0.4493**	0.1679	0.0183	0.1488	0.2482	0.1339

*Denotes p < 0.05
**Denotes p < 0.01

Table 4. Logistic Regression Estimates for Incidence of Heart Disease per year

Parameter	2011	2012	2013 Est.	2014	2015	2016	2017	2018
Intercept	-9.3572**	-7.8188**	-8.6138**	-8.7519**	-8.3388**	-8.3009**	-8.0869**	-8.2390**
Weight	0.0115**	0.0079	0.0075**	0.0068**	0.0071**	0.0076**	0.0071**	0.0071**
College 1 - 3 years	-0.0178	0.1159**	-0.1308	0.1345	0.1852	-0.1343	0.0100	0.0552
College > 4 years	-0.2661*	-0.3394	-0.1605	-0.0232	-0.0165	-0.3602**	-0.0215	-0.2848*
Grade 12 or GED	-0.0467	0.0424	0.1022	-0.0544	0.0307	-0.1827	0.0109	-0.0046
Income ≥ $25k < $35k	0.4251**	-0.0422	0.1846	-0.0922	0.2558	-0.1009	0.0551	0.0039
Income ≥ $35k < $50k	0.0133	-0.2520	-0.1286	0.1920	-0.1379	0.0290	-0.1853	-0.0346
Income ≥ $50k < $75k	-0.2415	0.1887	-0.2294	-0.1615	-0.2025	-0.1448	-0.1065	0.0526
Income ≥ $75k	-0.4688**	-0.2113**	-0.2664	-0.3425**	-0.3457*	-0.1204	-0.2186	-0.2199
Age	0.0639**	0.0615	0.0732**	0.0728**	0.0674**	0.0641**	0.0709**	0.0730**
Hispanic	-1.2435*	0.1574*	-0.6280	-0.6512	-0.6057	-0.5606	0.4363	0.1432
Multi-Racial	0.4508	0.6291	1.4432**	-0.0560	0.7752*	-0.3353	0.0499	-0.4467
Non-Hispanic Black	0.2863	-0.2172	-0.8444**	0.3185	0.0530	-0.0095	-0.6670**	-0.5844*
Other Race	-0.2128	-0.5476	0.0640	-0.0033	-0.1943	0.5119	0.5685	1.1396**
Region 1	-0.1438	0.0783	0.1119	0.1680	0.1634	0.1844	0.2514	-0.0863
Region 2	-0.0560	0.0392	-0.2650	0.3167	0.0723	0.3711	0.0163	0.0241
Region 3	-0.1344	0.0967	-0.0706	-0.0813	-0.2186	0.1189	-0.0061	-0.1075
Region 4	0.0083	-0.4175*	0.0260	-0.4097*	-0.4303	0.0743	-0.3140	-0.0276
Region 5	0.0564	0.1275	-0.0541	-0.2122	-0.4567*	0.0116	-0.2154	0.0530
Region 6	0.4027	-0.0060	-0.3186	-0.3354	-0.0761	0.2096	-0.2531	0.0199
Region 7	-0.1488	-0.4444	-0.0749	-0.0920	-0.4162	-0.1632	-0.2277	0.1940
Region 8	0.1338	0.1671	0.1595	-0.2963	-0.4273*	-0.5307*	-0.5845**	-0.3791*
Region 9	-0.2162	-0.1675	-0.0192	0.0044	0.3945	-0.0946	0.1043	-0.0215
Region 10	-0.1860	-0.0782	0.0047	0.0210	-0.0294	-0.1670	0.0749	-0.0444
Region 11	0.0190	0.0888	0.0610	0.2320	0.1516	0.0963	0.3370	-0.0062
Region 12	0.2352	0.5193**	-0.0399	0.1829	0.4261	-0.0079	0.1493	-0.1257
Region 13	0.2338	-0.1173	0.3365	0.3426	0.1653	0.1341	0.1939	0.2951

*Denotes p < 0.05
**Denotes p < 0.01

Table 5. Odds Ratio Estimates and Significance for Incidence of Diabetes per year

Parameter	2011	2012	2013	2014	2015	2016	2017	2018
Weight	1.016*	1.014*	1.015*	1.015*	1.014*	1.012*	1.013*	1.014*
College 1 - 3 years vs < high school	0.838	0.987	1.002	1.387	1.455	0.829	1.151	1.117
College > 4 years vs < high school	0.756	0.739	0.709	1.097	1.025	0.758	1.013	0.899
Grade 12 or GED vs < high school	0.975	0.832	0.970	1.270	1.349	0.836	1.187	0.888
Income ≥ $25k< $35k vs < $25k	1.040	0.791	0.893	0.692*	1.013	0.655*	0.909	0.727*
Income ≥ $35k< $50k vs < $25k	0.806	0.844	0.703*	0.460*	0.743*	0.791	0.571*	0.733*
Income ≥ $50k< $75k vs < $25k	0.856	0.569*	0.724*	0.562*	0.708*	0.748	0.589*	0.511*
Income ≥ $75k vs < $25k	0.606*	0.530*	0.564*	0.406*	0.644*	0.583*	0.441*	0.446*
Age	1.057*	1.053*	1.063*	1.060*	1.064*	1.058*	1.057*	1.054*
Hispanic vs White[#]	1.020	1.303	1.289	1.587	1.984	1.718	1.908	1.237
Multi-Racial vs White[#]	0.763	1.162	1.495	1.131	0.559	1.904	1.000	0.860
Non-Hispanic Black vs White[#]	2.117*	1.544*	1.362*	1.735*	1.453*	1.194	1.301	1.054
Other vs White[#]	2.173	0.535	2.993*	1.750	0.927	1.493	1.988	0.591
Region 1 vs 14	1.211	1.146	0.650*	0.805	0.904	0.598*	0.626*	0.835
Region 2 vs 14	1.030	0.683	0.476*	0.680	0.558*	0.606*	0.501*	0.783
Region 3 vs 14	1.068	1.150	0.696	0.553*	0.773	0.715	0.538*	0.760
Region 4 vs 14	0.846	1.022	0.754	0.722	0.774	0.433*	0.551*	0.824
Region 5 vs 14	1.009	1.080	0.511*	0.684	0.725	0.579*	0.512*	0.743
Region 6 vs 14	0.909	0.903	0.575	0.605*	0.740	0.642	0.623*	0.866
Region 7 vs 14	1.233	1.030	0.591	0.709	0.843	0.483*	0.634*	0.676
Region 8 vs 14	1.255	0.950	0.781	0.823	0.820	0.570*	0.564*	1.004
Region 9 vs 14	1.069	1.111	0.577*	0.873	0.956	0.596*	0.679*	0.778
Region 10 vs 14	1.305	1.211	0.607*	0.671	1.031	0.721	0.535*	1.081
Region 11 vs 14	1.299	1.712	0.639	0.895	1.049	0.559*	0.843	1.070
Region 12 vs 14	0.952	1.085	0.553*	0.950	0.988	0.549*	0.850	0.609*
Region 13 vs 14	2.077	1.028	1.030	0.906	0.863	0.712	0.830	0.966

[#] Denotes non-Hispanic White
*Denotes the odds ratio falls within the 95% confidence interval

Table 6. Odds Ratio Estimates and Significance for Incidence of Heart Disease per year

Parameter	2011	2012	2013	2014	2015	2016	2017	2018
Weight	1.012*	1.008*	1.007*	1.007*	1.007*	1.008*	1.007*	1.007*
College 1 - 3 years vs < high school	0.706	0.937	0.726	1.211	1.469	0.444*	1.010	0.836
College > 4 years vs < high school	0.551*	0.594*	0.705	1.034	1.201	0.354*	0.978	0.595
Grade 12 or GED vs < high school	0.686	0.871	0.917	1.002	1.259	0.423*	1.010	0.788
Income ≥ $25k< $35k vs < $25k	1.165	0.698	0.775	0.609*	0.840	0.645*	0.670*	0.824
Income ≥ $35k< $50k vs < $25k	0.772	0.566	0.566*	0.809	0.567*	0.735	0.527*	0.793
Income ≥ $50k< $75k vs < $25k	0.598*	0.880	0.512*	0.568*	0.531*	0.618*	0.570*	0.865
Income ≥ $75k vs < $25k	0.477*	0.590*	0.494*	0.474*	0.460*	0.633*	0.510*	0.658*
Age	1.066*	1.063*	1.076*	1.075*	1.070*	1.066*	1.074*	1.076*
Hispanic vs White[#]	0.140*	1.196	0.553	0.352*	0.561	0.385	2.279	1.484
Multi-Racial vs White[#]	0.765	1.917	4.384*	0.639	2.233*	0.482	1.549	0.823
Non-Hispanic Black vs White[#]	0.649	0.823	0.445*	0.929	1.085	0.668	0.756	0.717
Hispanic vs White[#]	0.394	0.591	1.104	0.673	0.847	1.126	2.602	4.020*
Region 1 vs 14	1.062	0.965	0.970	1.009	0.596	1.524	0.801	0.742
Region 2 vs 14	1.160	0.928	0.665	1.171	0.544*	1.837	0.633	0.829
Region 3 vs 14	1.072	0.983	0.808	0.786	0.407*	1.428	0.619	0.726
Region 4 vs 14	1.237	0.588*	0.890	0.566	0.329*	1.365	0.455*	0.787
Region 5 vs 14	1.298	1.014	0.821	0.690	0.320*	1.282	0.502*	0.853
Region 6 vs 14	1.835	0.887	0.630	0.610	0.469*	1.563	0.483*	0.825
Region 7 vs 14	1.057	0.572	0.804	0.778	0.334*	1.077	0.496	0.982
Region 8 vs 14	1.402	1.055	1.017	0.634	0.330*	0.746	0.347*	0.554*
Region 9 vs 14	0.988	0.755	0.851	0.857	0.751	1.153	0.691	0.792
Region 10 vs 14	1.018	0.825	0.871	0.871	0.491*	1.073	0.671	0.774
Region 11 vs 14	1.250	0.975	0.921	1.076	0.589	1.396	0.872	0.804
Region 12 vs 14	1.552	1.500	0.833	1.024	0.775	1.257	0.723	0.713
Region 13 vs 14	1.549	0.794	1.214	1.201	0.597	1.449	0.756	1.086

[#] Denotes non-Hispanic White
*Denotes the odds ratio falls within the 95% confidence interval

ficients were recorded in 5 of the 8 years and 6 of the 8 years for the $50 000 to $75 000 level. When income was over $75 000, all 8 years had negative coefficients. Evidence from other studies have verified this finding and point out the gap between the higher income groups and lower groups is getting wider.[50,51]

Table 7 displays, for both incidences of diabetes and heart disease, the decreasing average magnitudes of the odds ratio estimates per income level for the length of the study.

The decreasing averages suggest that at income levels above $25 000, the odds of a person developing diabetes compared to a person with income lower than $25 000 will decrease—in some cases more than 10%. In comparing the average decline, income had a larger effect on incidence of diabetes than on the incidence of heart disease.

One of the purposes of this study was to examine if living within a certain region contributed to diabetes or heart disease. However, logistic regression estimates did not reveal sufficient evidence to verify this finding. The logistic regression did indicate that certain income levels have a strong influence on diabetes regardless of region. The same result occurred with the analysis of heart disease.

One interesting observation is that, in terms of regional effects, the year of study made a difference. For example, in the diabetes analysis, the odds ratios point estimates were significant in several regions for the years 2013, 2016, and 2017. For heart disease, the years 2015 and 2017 indicated evidence of regional effects. This could be because those regions had a significant change in income during the study time frame.

Furthermore, the study indicated that some regions, compared to Region 14, had higher odds of having both diabetes and heart disease. For example, Table 5 shows that for 2011, the odds ratio point estimates of having diabetes were greater than 1 in 10 of the 13 regions compared to Region 14, which is the poorest in the state. With income having such a strong influence on both diseases, one would think the other regions compared to the poorest region would all have point estimates less than 1. An odds ratio point estimate less than 1, is interpreted to mean, in this study, an individual living in that region is less likely to have diabetes. This surprising result may be indicative that diabetes may not be a regional phenomenon in Ohio. The same pattern was observed for heart disease. However, looking across the years of the study, the overall odds ratio estimates seem to decrease indicating changes in the incidences of the diseases. This is especially true for the later years of the study. In 2017, for diabetes, the odds ratios for all 13 regions were less than 1, and 10 of the 13 regions were less than 1 in 2018. For heart disease, the results were similar for 2017 and in 2018. Only 1 region was greater than 1. Regional effects may be more dependent on national economic events rather than regional characteristics. Or it could mean state efforts to control these diseases are effective across regions. More study needs to be undertaken to understand this trend.

Age and weight across the whole extent of the study were significant and positively related to having diabetes and heart disease. This result is not a surprise and reinforces the need for a healthy lifestyle.

Those individuals who had at least a high school education and above, generally had lower incidence of both diseases. In some years, there were slight increases in the odds ratio, but overall the more educated individuals had lower incidences of both diseases.

The study also indicated that non-Hispanic Blacks were more likely to have diabetes compared to non-Hispanic Whites (Table 5), but not as likely to have heart disease (Table 6). This is another rather surprising finding and needs to be evaluated separately. A study that looks at income, access to healthy food, and exercise patterns is needed to further analyze this aspect in more detail.

PUBLIC HEALTH IMPLICATIONS

The level of income is, perhaps, the most meaningful finding of this study and plays a significant role in the incidence of both diabetes and heart disease. The logistic regression estimates start to become negative in the $35 000 to $50 000 range of income indicating that an individual with income in this range will see better health outcomes than those with incomes below $35 000. Health care policy directed toward aiding those with low incomes could offer potential positive health care benefits regarding diabetes and heart disease.

Income Enhancement Programs

Since an increase in income is associated with decreasing incidence of both diabetes and CVD, any programs designed to embellish income would be helpful.[48,52] Although there are a variety of income-related tools available to state lawmakers the Earned In-

Table 7. Eight Year Average Odds Ratio (OR) per Income Level—Diabetes and Heart Disease

Income Level	Average Odds Ratio Diabetes	Average Odds Ratio Heart Disease
Greater than or equal to $25 000 but less than $35 000 vs Less than $25 000	0.840	0.778
Greater than or equal to $35 000 but less than $50 000 vs Less than $25 000	0.707	0.667
Greater than or equal to $50 000 but less than $75 000 vs Less than $25 000	0.658	0.643
Greater than or equal to $75 000 vs Less than $25 000	0.528	0.537

come Tax Credit (EITC), a program already in place in Ohio, would be ideal. The EITC is currently included as a part of the federal tax code and has also been implemented by 28 states to reduce poverty. Twenty-two of those states utilize a refundable tax credit that pays the amount of the credit to taxpayers who are eligible for a refund. However, 6 states, including Ohio, only offer a nonrefundable tax credit. Nonrefundable tax credits offer relief up to the amount of taxes owed. For example, if an individual is eligible for a $1 500 tax credit, but owes $1 000 in taxes, that individual would only be given $1 000—not the full amount of the credit. This does little to increase income and improve health outcomes for those living near or below the poverty line, and according to Policy Matters Ohio, an Ohio think tank, the EITC program in Ohio only affects about 5% of the neediest families.[53]

Other innovative programs are being attempted in other locales. Some of these programs include financial counseling, financial coaching, rules-of-thumb aids to income enhancement, financial education, individualized development accounts, children's savings accounts, incentivized tax-time savings accounts, prize-linked savings, credit building, reduced savings penalties, state intra-agency collaboration to enhance overall state health, increased access to early childhood care and education programs, increases to the state minimum wage, low barriers to food assistance programs such as the Supplemental Nutrition Assistance Program (SNAP), and ease of access to public benefit programs such as rent, utility, and food assistance.[53,54]

Food Taxes and Subsidies

A recent meta-analysis has shown that "food pricing changes through taxation, subsidies, and other factors" can have positive effects on health. The study indicated that when prices were decreased on healthful foods the percentage change in consumption was greater than the percentage decrease in price. It was also found that when prices of unhealthful foods and beverages increased through taxation, the percentage change in consumption decreased, but by a lower percentage than the percentage change in price.[55] This would suggest that the health of Ohioans might benefit by some type of food subsidy program.

Some cities, such as Boulder, Colorado; the District of Columbia; Philadelphia, Pennsylvania; Seattle, Washington; and 4 California cities (Albany, Berkeley, Oakland, and San Francisco), have enacted soda taxes.[56] There is evidence that an additional tax on sugar-laden soft drinks decreases consumption of these beverages.[57] Less sugar usually means increasing levels of health. However, at this point in the US no statewide tax on the sugar in soda has been enacted.

Existing programs such as SNAP offer some assistance to those individuals and households in poverty. Although eligibility requirements are primarily set by the federal government, they can be modified by the individual states who administer the SNAP programs. In 2020, an individual eligible for SNAP benefits averaged about $125 per month while households received an average of $246 per month. Although this may seem like a reasonable amount of money, it works out to about $1.39 per person per meal, hardly an amount for a feast.[58] As such, Policy Matters Ohio suggests the state change its work requirements regarding SNAP benefits. Eligibility for SNAP benefits in Ohio is dependent on a set of work requirements. The mandate to "exempt all areas that meet exemption guidelines" applies until the federal requirements on work are eliminated.[53] Ohio currently exempts a few mostly rural areas from the work requirement while ignoring urban area exemptions. Policy Matters Ohio suggests making all areas exempt, which would increase the number of persons eligible for SNAP benefits.[53]

A few in-kind programs are available in Ohio such as The Emergency Food Assistance Program (TEFAP) and the Commodity Supplemental Food Program (CSFP), and these could be expanded. The less income spent on food leaves more to spend on health care.

As mentioned previously, diet plays a crucial role in prevention of both diabetes and CVD. It is known that increased consumption of fresh fruits and vegetables can reduce the risk for both diabetes and heart disease.[59,60] Improving nutrition in poor communities may therefore help in preventing and controlling the incidence of both diabetes and CVD. Quality of nutrition is determined not only by affordability but also by availability of healthy food which is dependent on area of residence and ultimately on socioeconomic status. In this regard, opening subsidized grocery stores in low-income areas that are readily accessible and affordable will prove beneficial.

Regional Differences

Regional differences were not significant in this study apart from years 2013, 2016, and 2017 for diabetes and 2015 and 2017 for heart disease. In these years, the estimated odds ratios were significant for several regions. This incompatibility could be attributed to some type of sampling bias or some negative event in the local economy such as a plant closing. With this finding in mind, policy efforts should probably target the entire state rather than specific regions. Although some pockets of regional and local poverty and health problems persist, local governments and other interested parties are better prepared to identify those areas and address remediation through existing channels.

Collaboration

To improve the state's response to diabetes and heart disease, a collaborative and unified effort among the various departments would be appropriate. For example, Ohio's Creating Healthy Communities (CHC) program receives funding from the Centers for Disease Control and Prevention's (CDC) Preventive Health and Health Services Block Grant Program.[61] As of 2019, these funds support community health programs in 23 counties in Ohio.[62] Collaboration starts at the local level with various concerned parties meeting, identifying problems, and then submitting a competitive application for a grant from the Ohio Department of Health. At the state level, each application is viewed and evaluated by a committee consisting of various health care officials and professionals representing different areas of expertise.

Another program that encourages collaboration among the various stakeholders is the State Health Improvement Plan (SHIP). The goal of the SHIP program is "to improve health, well-being and economic vitality in Ohio" by leveraging the resources of 13 state agencies. Advisory committees and input from subject matter experts from around the state are used to formulate the plan.[63] At the local level, public and private partnerships focus on the 3 priority factors of improving community conditions, addressing health behaviors, and increasing access to care along with improving the 3 priority health outcomes of mental health and addiction, chronic disease, and maternal and infant health.[63]

Leveraging the use of federal monies and increasing the collaboration among state agencies is an efficient way to deliver services without duplication of effort at both the state and local levels. The Ohio Department of Health should continue to pursue such activities as a cost-effective solution to chronic diseases such as diabetes and heart disease.

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RESEARCH ARTICLE

The Relationship Between Medical Diagnoses, Risk Perceptions, and Social Distancing Compliance: An Analysis of Data from the Toledo Adolescent Relationships Study

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ABSTRACT

Background: The health belief model suggests that individuals' beliefs affect behaviors associated with health. This study examined whether Ohioans' pre-existing medical health diagnoses affected their belief about personal health risk and their compliance with social distancing during the coronavirus disease 2019 (COVID-19) pandemic. Prior research examining physical and mental diagnoses and social distancing compliance is nearly nonexistent. We examined whether physical and mental health diagnoses influenced individuals' beliefs that their health is at risk and their adherence with social distancing guidelines.

Methods: The study used longitudinal cohort data from the Toledo Adolescent Relationships Study (TARS) (n = 790), which surveyed Ohioans prior to and during the COVID-19 pandemic. Dependent variables included belief that an individual's own health was at risk and social distancing compliance. Independent variables included physical and mental health diagnoses, pandemic-related factors (fear of COVID-19, political beliefs about the pandemic, friends social distance, family social distance, COVID-19 exposure), and sociodemographic variables (age, gender, race/ethnicity, educational level).

Results: Individuals who had a pre-existing physical health diagnosis were more likely to believe that their personal health was at risk during the pandemic but were not more likely to comply with social distancing guidelines. In contrast, individuals who had a pre-existing mental health diagnosis were more compliant with social distancing guidelines but were not more likely to believe their personal health was at risk. Individuals who expressed greater fear of COVID-19 believed their health is more at risk than those who expressed lower levels of fear.

Conclusion: Health considerations are important to account for in assessments of responses to the pandemic, beliefs about personal health risk, and social distancing behavior. Additional research is needed to understand the divergence in the findings regarding physical health, beliefs about personal health risk, and social distancing compliance. Further, research is needed to understand how mental health issues impact decision-making related to social distancing compliance.

Keywords: Physical health; Mental health; Compliance; Risk; COVID-19

INTRODUCTION

In 2019, the coronavirus disease 2019 (COVID-19) was identified in the Wuhan province in China.[1] As of October 2021, there have been 44 857 861 COVID-19 cases and 723 205 deaths in the United States due to this contagious disease.[2] In Ohio alone, there have been 1 499 485 cases of COVID-19 as of October 2021 and 23 327 deaths.[3] During the COVID-19 pandemic, various guidelines and mandates were put in place to ensure public health safety. In Ohio, examples included maintaining a 6-foot distance from others, known as social distancing, and wearing a mask when out in public. Even with the availability of COVID-19 vaccines, these public health measures continued to be recommended in Ohio. Moreover, it seems that following these guidelines would be especially important for those individuals most at risk for severe symptoms, such as individuals with prior health diagnoses, if they contract the virus.

According to the Centers for Disease Control and Prevention (CDC), risk for severe illness due to COVID-19 increases with the following pre-existing health diagnoses: cancer, chronic kidney disease, chronic lung disease, dementia, diabetes, down syndrome, heart conditions, AIDS/HIV, immunocompromised state, liver disease, obesity, sickle cell disease, solid organ or blood stem cell transplant, stroke, and substance use disorders.[4] Because these health conditions put Ohioans most at risk for complications if they contract COVID-19, it is important to identify factors that affect compliance with public health recommendations and mandates among individuals with and without health diagnoses.

Further, although younger adults, compared with older adults, tend to have fewer physical health conditions, a significant proportion of young adults live with 1 or more physical health diagnoses. For example, among young adults in their 20s to early 40s, 2.9% have diabetes and 10.6% have high blood pressure,[5] 8.5% have high cholesterol, and 4.7% have heart disease.[6] According to the CDC, 2.3% of adults in their mid-20s to early 30s, suffer from hepatitis B, and .029% have AIDS/HIV.[7] Among young adults, 8.0% live with asthma,[8] and .9% have had a cancer diagnosis.[9] Mental health concerns are also prevalent in this age group. Prior to the pandemic, 11.6% of individuals aged 25 to 35 years reported being diagnosed with anxiety, 15.2% reported diagnosed depression[10], and 4.76% reported diagnosed ADD/ADHD.[11] To date, however, there is little, if any, research regarding whether these pre-existing medical diagnoses contribute to individuals' beliefs that their health is at risk due to COVID-19, and whether pre-existing medical diagnoses affect social distancing compliance. Studying this age group is of critical importance because in the United States individuals aged 20 to 49 years have accounted for much of the spread of the COVID-19 virus.[12]

There are varied reasons that individuals have provided for not following social distancing guidelines. In Italy, for example, individuals were less likely to comply if the duration of the stay-at-home order was longer than expected.[13] Additionally, individuals who perceived the disease to be more deadly as evidenced by the number of people they know who have had COVID-19 reported a lower likelihood of social distancing compliance in what has been dubbed the "fatalism effect."[14] Thus, it appears that beliefs and expectations affect compliance.

Research on sociodemographic correlates of beliefs and behaviors during the pandemic has included gender, race/ethnicity, age, and economic background. More women than men have reported taking precautions to protect themselves from COVID-19.[15] Possessing knowledge of COVID-19 has led to increased levels of social distancing for women, but not men.[16] Women, compared with men, reported a greater sense of danger due to the pandemic.[17] Socioeconomic background also has played a role in compliance in that those with higher socioeconomic status reported more instances of taking precautions against COVID-19.[15] Yet, lower income prior to the pandemic was associated with a greater sense of danger due to the pandemic.[17] Individuals with a high school education or lower have reported higher numbers of close contact (ie, less compliance with social distancing).[18] Race/ethnicity was associated significantly with social distancing behaviors with Black respondents reporting higher compliance with social distancing.[6] Some research has found that younger individuals, compared to older individuals, reported that they were less likely to go out in general; yet, individuals who were older than 70 years were less likely to have gone out the previous day compared with younger individuals.[18] Older age also was associated with greater feelings of pandemic-related danger.[17]

Previous research has found that in the United States political party affiliation and political ideology have played a role in the degree to which individuals have complied with social distancing regulations. For example, individuals who resided in Republican counties were less compliant with stay-at-home orders than individuals who resided in Democratic counties.[19] Additionally, individuals affiliated with the Democratic Party reported lower likelihoods of compliance when the stay-at-home order was issued by a Republican governor.[19] Viewers of conservative media outlets, such as Fox News, tended to be less compliant with stay-at-home orders.[20] Regarding beliefs about personal health risk, individuals who identify as Democrats reported higher levels of pessimism regarding health relative to individuals who identify as Republicans.[15] Moreover, those who endorsed Donald Trump for US President were less likely to believe that they were at risk for COVID-19.[21] In sum, in the United States, politics have influenced whether individuals believe they are at risk for COVID-19 and whether they followed social distancing guidelines.

Despite the serious health implications of COVID-19, there is a paucity of research on health diagnoses and compliance with social distancing guidelines[6] or whether individuals believe that their health is at risk if they contract COVID-19. An important conceptual model for understanding health behaviors is the health belief model. This model posits that individuals will engage in health behaviors if they believe they are (1) more at risk for contracting a disease, (2) likely to experience more serious consequences for that disease, (3) able to access potential protection that could reduce susceptibility and/or severity of the disease, (4) able to benefit from potential protection efforts, and (5) certain that the benefits outweigh any barriers that could prevent the disease.[22] As mentioned previously, several medical conditions can lead to serious health consequences from COVID-19.[4] Following the health belief model, individuals with diagnosed medical conditions prior to the pandemic may be more likely to believe that they are at risk for serious consequences of COVID-19 and may be more compliant with social distancing guidelines. However, this may not be the case. As mentioned previously, politics can drive social distancing compliance[15,19,21] and socioeconomic status can as well.[15] Thus, it is imperative to examine beliefs about personal health risk and social distancing compliance separately because believing that one is at high risk may not necessarily influence greater compliance with social distancing recommendations and regulations.

The purpose of this study is to examine how physical and mental health diagnoses influence beliefs about personal health risk and social distancing compliance in Ohio utilizing a longitudinal cohort data set. Examining physical and mental health diagnoses from previous waves of data can work to prevent recall bias associated with cross-sectional studies.[6] Longitudinal data allow more assurance of time order of the variables so we can be sure that the physical and mental health diagnoses occurred before the COVID-19 pandemic. We argued that beliefs about personal health risk may not influence social distancing compliance as the health belief model would suggest, as the COVID-19 pandemic has been increasingly politicized.[15,19,21] The research questions assessed whether physical or mental health diagnoses affect: (1) belief about personal health risk, and (2) social distancing compliance. We expect that political beliefs[15,19,21] and socioeconomic status[15] would guide social distancing behaviors. Our first hypothesis states the following: Individuals with a physical or mental health diagnosis will be more likely to believe their personal health is at risk relative to individuals without a medical diagnosis. Our second hypothesis states the following: Individuals with a physical or mental health diagnosis will be more likely to follow the social distancing guidelines relative to individuals without a medical diagnosis.

Although the fatalism effect posits that respondents who know more people with COVID-19 will comply less with social distancing recommendations, this may not apply to individuals' beliefs about their own risk.[14] Based on prior work, COVID-19 fears, political beliefs about the severity of the pandemic, whether significant others follow social distancing guidelines, and likelihood of COVID-19 exposure will influence belief about personal health risk as well as adherence with social distancing.

The current study used longitudinal cohort data from the Toledo Adolescent Relationship Study (TARS) (n = 790), which surveyed Ohioans prior to and during the COVID-19 pandemic. Dependent variables included personal health risk belief and social distancing compliance. Independent variables included physical and mental health diagnoses, pandemic-related indicators (ie, fear of COVID-19, political beliefs about the pandemic, friends social distance, family social distance, COVID-19 exposure), and sociodemographic variables (age, gender, race/ethnicity, educational level).

METHODS

Setting and Design

This study used data from the Toledo Adolescent Relationship Study (TARS). The initial TARS sample was interviewed in 2000 and 2001 and consisted of a stratified random sample of 7th, 9th, and 11th graders from Lucas County, Ohio. According to US Census Bureau data, Lucas County is similar to national demographics regarding education, income, and race.[23] The TARS data contains 7 waves of data with Wave 1 (2000-2001), Wave 6 (2019), and Wave 7 (2020) being utilized for this study. As such, the data were collected prior to and during the pandemic. Internal review board approval was received for each wave of data collection.

Participants

The baseline sample included 1321 respondents aged 12 to 18 years. The most recent interview, Wave 7, included 822 respondents aged 31 to 38 years. The sampling frame was based on school rosters in Lucas County, Ohio, with an oversample of Black and Hispanic respondents. Rosters were available through Ohio's Freedom of Information Act, and respondents did not have to attend school to participate in the study. Due to small sample sizes, we excluded respondents who reported their race as "other" (n = 18), or who were missing data on the dependent variables (n = 7). The final analytical sample is 790 respondents with 73.46% of the sample currently living in Ohio.

Measures

Dependent Variables

Beliefs about personal health risk were collected at Wave 7 (during the pandemic). We asked how strongly respondents agreed or disagreed with the following: "I am at a high risk of becoming infected." The scale ranged from (1) strongly disagree to (5) strongly agree.

Social distancing compliance was collected at Wave 7 and is a self-developed 6-item summed scale. Respondents were asked how often they did the following when the social distancing guidelines were suggested: (1) "increase physical space between you and others (six feet is recommended) to avoid spreading illness," (2) "stay home to avoid spreading illness," (3) "go to grocery store or pharmacy," (reversed) (4) "go to a workplace that requires contact with others," (reversed) (5) "hang out or spend time with friends (not living with you)," (reversed) and (6) "hang out or spend time with family (not living with you)" (reversed). The scale ranged from (1) never to (5) as much as possible ($\alpha = .70$).

Independent Variables

Physical health diagnoses were collected at Wave 6, prior to the pandemic, and were measured by asking whether respondents were told by a doctor, nurse, or other health care provider that they have "cancer, lymphoma, or leukemia," "high cholesterol, triglycerides, or lipids," "high blood pressure or hypertension," "high blood sugar or diabetes," "heart disease or heart failure," "asthma," "chronic bronchitis or emphysema," "epilepsy or another seizure disorder," "hepatitis B or C," "sleep apnea," "chronic kidney disease or kidney failure," "blood clot, stroke, or mini stroke," "HIV/AIDS," or "a sexually transmitted disease such as genital herpes, warts, chlamydia, HPV, gonorrhea, or syphilis."[24] Responses were (0) no and (1) yes.

Mental health diagnoses were collected at Wave 6 and were measured by asking whether respondents were told by a doctor, nurse, or other health care provider that they have "depression," "post-traumatic stress disorder or PTSD," "anxiety or panic disorder," or "attention problems or ADD or ADHD."[24] Responses were (0) no and (1) yes.

COVID-19 Indicators

Fear of COVID-19 was a self-developed 3-item summed scale collected at Wave 7. We asked how often during the pandemic did respondents experience the following: (1) "Worried you might have contracted the virus," (2) "Worried one or more of family might contact COVID-19," and (3) "Listened to news or read social media about COVID-19 developments." Responses included (1) never to (5) very often ($\alpha = .71$).

Political beliefs were a self-developed 2-item summed scale collected at Wave 7, which asked how strongly respondents agreed or disagreed with the following: (1) "Politicians, the news, and social media have exaggerated the risk," and (2) "Government should not tell me what to do." Responses included (1) strongly disagree to (5) strongly agree ($\alpha = .71$).

Friends social distance compliance was measured at Wave 7 with the following: "How many of your friends and acquaintances practice social distancing?" Responses included (1) none to (5) all.

Family social distance compliance was measured at Wave 7 with the following: "How many of your family members practice social distancing?" Responses included (1) none to (5) all.

Exposure to COVID-19 was a self-developed 2-item summated scale. We asked the following: (1) "Do you personally know someone who has/had the virus," and (2) "Do you know someone who is in a job that puts them at higher risk for exposure to COVID-19?" The scale responses were (0) no and (1) yes ($\alpha = .46$).

Sociodemographic Indicators

Age is measured at the Wave 7 interview. Respondents were, on average, age 34, with a range of 31 to 38 years of age. Gender is measured at Wave 1, with male as the comparison. Race/ethnicity is measured at Wave 1, and included non-Hispanic White (reference), non-Hispanic Black, and Hispanic. Educational attainment, measured at Wave 6, included high school or less (reference), some college, and college graduate. Month of interview indicated when respondents completed the interview ranging from 6 (June) to 10 (October/November).

Statistical Analyses

We examined descriptive statistics for all variables (Table 1). Next, we estimated belief about personal health risk with Ordinary Least Squares (OLS) regression models (Table 2). Model 1 regressed personal health risk onto physical health diagnosis and mental health diagnosis. Model 2 regressed belief about personal health risk onto physical health diagnosis, mental health diagnosis, and the COVID-19 variables. Model 3 regressed health belief onto physical health diagnosis, mental health diagnosis, and the sociodemographic variables. Model 4 regressed belief about personal health risk onto physical health diagnosis, mental health diagnosis, the COVID-19 variables, and the sociodemographic variables. Finally, we examined social distancing compliance in terms of physical and mental health diagnoses with a series of OLS regression models (Table 3). Model 1 regressed compliance on physical health diagnosis and mental health diagnosis. Model 2 regressed compliance on physical health diagnosis, mental health diagnosis, and the COVID-19 variables. Model 3 regressed compliance on physical health diagnosis, mental health diagnosis, and the sociodemographic variables. Model 4 regressed compliance on physical health diagnosis, mental health diagnosis, the COVID-19 variables, and the sociodemographic variables. Interview month is included but not presented in the tables.

RESULTS

The mean value of belief about personal health risk is 2.69, which represents a midpoint on a scale ranging from 1 to 5 (Table 1). The average social distancing score was 19.65, indicating that most respondents responded to values above the midpoint. Regarding the key independent variables, over half (50.82%) reported a physical health diagnosis, and 43.65% reported a mental health diagnosis. The mean score for fear of COVID-19 was 9.62 indicating that most respondents responded to values above the midpoint. The mean score on conservative political beliefs was 5.93 indicating values just below the midpoint of the scale, which ranged between 2 and 10. Friends who social distance and family who social distance averaged above the midpoint, 3.64 and 3.72, respectively, indicating values just above the midpoint of the scale between 1 and 5. Exposure to COVID-19 was low with a mean score of 1.43 indicating values just above the midpoint of the scale between 0 and 2.

Respondents' mean age was 34.10. Nearly 60% of the sample was female. One-fifth (20.00%) of the sample was Black, 11.07% Hispanic and two-thirds (68.93%) White. About 18.49% of respondents have a high school degree or less, 42.14% reported some college, and 39.37% reported a college degree.

In Model 1 (Table 2), physical health was associated positively with belief about personal health risk. Physical health diagnosis is positively related to both personal health belief risk and the health belief risks of others. Mental health was not significantly related to belief about personal health risk in Model 1, and this was true

Table 1. Means/Percentages and Standard Deviations of Dependent Variable, Independent Variables, and Control Variables (n=790)

	%/Mean (SD)	Min	Max
Dependent variables			
Belief about health risk	2.69	1	5
Social distancing compliance	19.65	5	25
Health diagnosis			
Physical health diagnosis	50.82%	0	1
Mental health diagnosis	43.65%	0	1
COVID-19 variables			
Fear of COVID-19	9.62	3	15
Political beliefs	5.93	2	10
Friends social distance	3.64	1	5
Family social distance	3.72	1	5
Exposure to COVID-19	1.43	0	2
Sociodemographic variables			
Age	34.10	31	38
Gender			
Male	40.35%	0	1
Female	59.65%	0	1
Race/Ethnicity			
White	68.93%	0	1
Black	20.00%	0	1
Hispanic	11.07%	0	1
Educational attainment			
High school or less	18.49%	0	1
Some college	42.14%	0	1
College degree or more	39.37%	0	1
Month of interview completion			
June	36.23%	0	1
July	24.91%	0	1
August	18.24%	0	1
September	12.70%	0	1
October/November	7.92%	0	1

Source: Toledo Adolescent Relationship Study (TARS) 2001-2020
Dependent variables collected in seventh interview (2020)
Independent Variables collected at first, sixth, and seventh interviews (2001-2020)

even when physical health was not included in the model (not shown). In Model 2, the relationship between physical health and belief about health risk remained significant with the inclusion of the COVID-19 variables. Individuals who expressed greater fear of COVID-19 believed their personal health is more at risk than those who expressed lower levels of fear. Model 3 examined how physical health diagnosis, mental health diagnosis, and the sociodemographic variables influenced belief about personal health risk. The significant relationship between physical health diagnosis remained the same as in Models 1 and 2. Women, compared with men, were more likely to believe their health was at risk. Black, compared with White, respondents were more likely to believe their health was at risk. Individuals with a college degree, compared to those without a degree, were less likely to believe their health was at risk. Model 4 included the full set of covariates and showed how physical health diagnosis, mental health diagnosis, the COVID-19 variables, and the sociodemographic variables influenced health beliefs. The significant relationship between physical health diagnosis and belief about personal health risk remained the same in all models. Fear of COVID-19, family social distance, exposure to COVID-19, gender, and possessing a college degree remained significant. Those with a college degree or more were significantly less likely to believe that their health is at risk.

In Model 1 (Table 3), mental health diagnosis was found to be positively associated with social distancing compliance. Those with a mental health diagnosis were more likely to adhere to social distance guidelines compared to those without a mental health diagnosis. Physical health diagnosis was not associated with social distancing compliance and was not associated with compliance in a model without the mental health indicator (not shown). In Model 2, the relationship between mental health and social distancing compliance remained significant with the inclusion of the COVID-19 variables. Those who expressed greater fear of COVID-19 were more likely to social distance than those who expressed lower levels of fear. Individuals who expressed conservative political beliefs were less likely to social distance than individuals who expressed liberal political beliefs. Individuals who have friends and family who social distance were more likely to

Table 2. OLS Regression Models Estimating Personal Health Risk (n=793)

	Model 1			Model 2			Model 3			Model 4		
	b	se		b	se		b	se		b	se	
Intercept	2.49	.09	***	1.06	.35	**	1.62	.87		-.11	.85	
Health diagnosis												
Physical health diagnosis	.24	.09	**	.24	.08	**	.23	.09	*	.22	.08	**
Mental health diagnosis	.09	.09		-.02	.09		.04	.09		-.05	.09	
COVID-19 variables												
Fear of COVID-19	---	---		.15	.02	***	---	---		.16	.02	***
Political beliefs	---	---		.01	.02		---	---		-.01	.02	
Friends social distance	---	---		.04	.07		---	---		.06	.06	
Family social distance	---	---		-.12	.06	*	---	---		-.14	.06	*
Exposure to COVID-19	---	---		.15	.07	*	---	---		.17	.07	**
Sociodemographic variables												
Age	---	---		---	---		.03	.03		.05	.02	
Gender												
(Male)												
Female	---	---		---	---		.11	.09	***	.05	.09	
Race/Ethnicity												
(White)												
Black	---	---		---	---		.01	.12	**	-.06	.11	
Hispanic	---	---		---	---		-.09	.14		-.21	.13	
Educational attainment												
(High school or less)												
Some college	---	---		---	---		-.10	.12		-.15	.12	
College degree or more	---	---		---	---		-.30	.18	*	-.52	.12	***

Source: Toledo Adolescent Relationship Study (TARS) 2001-2020
Notes: * p ≤ .05 ** p ≤.01 *** p ≤ .001. Reference category in parentheses. Month included but not shown.

social distance than individuals whose friends and family did not. Model 3 examined how physical health diagnosis, mental health diagnosis, and the sociodemographic variables influenced social distancing compliance. The significant relationship between mental health diagnosis and social distancing compliance was similar as reported in Models 1 and 2. Further, older individuals, compared to younger individuals, were less likely to social distance. Women, compared with men, were more likely to social distance. Individuals with a college degree or more were more likely to social distance than those without a college degree. Model 4 examined how physical health diagnosis, mental health diagnosis, the COVID-19 variables, and the sociodemographic variables affected social distancing compliance. The significant relationship between mental health diagnosis and social distancing compliance remained across all models. Fear of COVID-19, conservative political beliefs, friends and family social distancing, age, and gender all remained statistically significant. Educational attainment was not associated with social distancing once the full set of covariates were included in the model.

DISCUSSION

Using longitudinal cohort data collected in Ohio the current study examined whether physical health and mental health diagnoses were associated with beliefs about personal health risk and social distancing compliance. We found that individuals who were diagnosed with a physical health problem prior to the pandemic were more likely to believe that their health was at risk during the pandemic. Despite this finding, Ohioans with a physical health diagnosis were not more likely to comply with social distancing guidelines. Individuals who had received a mental health diagnosis from a doctor or other professional prior to the pandemic were more likely to comply with social distancing recommendations than individuals who did not have a mental health diagnosis. Individuals with a prior mental health diagnosis, however, were not more likely to believe their health was at risk.

The current study adds to a limited body of research on physical and mental health issues and social distancing behaviors. Consistent with a recent study by Papageorge and colleagues,[6] results do not indicate a significant relationship between physical health and social distancing, yet the findings indicate that individuals who have a physical health diagnosis believe they are more at risk for COVID-19 even as they do not report greater compliance with social distancing.

Thus, complicating the basic tenets of the health belief model, these individuals recognize that they are at risk but are not more likely to take the actions needed to protect themselves from the virus. This could reflect structural or social impediments to effec-

Table 3. OLS Regression Models Estimating Social Distancing Compliance (n=790)

	Model 1			**Model 2**			**Model 3**			**Model 4**		
	b	se		b	se		b	se		b	se	
Intercept	19.88	.23	***	16.98	.82	***	23.12	2.14	***	21.28	2.00	***
Health diagnosis												
Physical health diagnosis	-15	.22		-.20	.20		-.09	.22		-.16	.20	
Mental health diagnosis	.67	.23	**	.64	.20	***	.50	.23	*	.52	.20	*
COVID-19 variables												
Fear of COVID-19	---	---		.19	.04	***	---	---		.18	.04	***
Political beliefs	---	---		-.42	.05	***	---	---		-.38	.05	***
Friends social distance	---	---		.61	.15	***	---	---		.57	.15	***
Family social distance	---	---		.36	.14	*	---	---		.39	.14	**
Exposure to COVID-19	---	---		.01	.16		---	---		.00	.16	
Sociodemographic variables												
Age	---	---		---	---		-.13	.06	*	-.14	.06	**
Gender												
(Male)												
Female	---	---		---	---		1.16	.22	***	.67	.20	***
Race/Ethnicity												
(White)												
Black	---	---		---	---		.40	.29		.02	.26	
Hispanic	---	---		---	---		.39	.35		.21	.32	
Educational attainment												
(High school or less)												
Some college	---	---		---	---		-.07	.30		-.12	.27	
College degree or more	---	---		---	---		.93	.31	**	.15	.29	

Source: Toledo Adolescent Relationship Study (TARS) 2001-2020
Notes: * p ≤ .05 ** p ≤.01 *** p ≤ .001. Reference category in parentheses. Month included but not shown.

tive social distancing, or attitudes, such as fatalism[5] or political beliefs[15,19,21] that may play a role. If the fatalism effect is at play here, these results suggest that it is not just the risk of others that influences social distancing compliance, but their own risk may cause less social distancing compliance. Future research should examine how health belief risk affects social distancing compliance. Conversely, individuals who had a previous mental health diagnosis are more likely to social distance, even as they indicate that they are not at greater risk for COVID-19. This is consistent with recent CDC findings underscoring that none of the mental health indicators contribute to having a higher risk of contracting COVID-19.[4] Some mental health conditions may be associated with a more general decrease in the desire to socialize, and conditions such as agoraphobia, in particular,[25,26] relate to a fear of leaving home. Both anxiety and depression may be linked to an increase in other types of 'fears' resulting in a heightened sensitivity to the issue of COVID-19 and resulting desire to comply fully with the social distancing recommendations.

The results of this study point to the need to examine the divergence in findings; those with physical health diagnoses recognized their risks but were not more likely to comply. Although we find that the associations between health and pandemic-related beliefs and behaviors are not explained by COVID-19 indicators or sociodemographic measures, future research needs to consider the type of health condition or severity of the health condition.

This study, however, is not without limitations. First, the TARS sample is concentrated around Lucas County, Ohio. Due to the local nature of the data, it is not possible to generalize to the entire population of either Ohio or the United States. Nevertheless, the characteristics of Toledo, Ohio, and the surrounding area are similar to those of other Ohio regions in terms of racial diversity and age[27] and to national demographics in terms of education, income, and racial diversity.[23] In addition, this study does not account for degree of severity for individual diagnoses as the health diagnoses measures are dichotomous variables. It may be that individuals suffer from varying degrees of their diagnosis. It is also possible that although individuals may have physical health diagnoses, their relatively young ages may play a role. Finally, this study does not examine underlying motivations for social distancing or beliefs about personal health risk. Further research determining how the pandemic has shaped beliefs and behaviors is warranted. Despite these limitations, this study makes contributions to the literature on social distancing compliance and beliefs about health risk.

This study contributes to the literature on social distancing compliance and beliefs about personal health risk in 2 key ways. Although previous research has focused mostly on gender,[15] the length of the pandemic,[13] and politics,[6,15,19] this study focused on the physical and mental health circumstances of a large, heterogeneous sample. Receiving a diagnosis from a doctor or health care provider may be a more accurate indicator of current health of the respondent than self-reported physical health or mental health. Additionally, TARS is a longitudinal study, whereas many recent studies on COVID-19 are cross-sectional so causality cannot be established. Other recent studies have relied on convenience samples, so generalizability is questionable, or are based on retrospective questions that are subject to recall bias.[6] With longitudinal data, we were able to examine how earlier medical diagnoses impacted current social distancing compliance and beliefs about personal health risk.

PUBLIC HEALTH IMPLICATIONS

Although health beliefs are important for understanding compliance with various public health recommendations, the current study describes a disjuncture between beliefs and action that warrants greater attention by researchers and practitioners. Those adults in their mid-30s who had received a physical health diagnosis well understood that they were at increased risk but did not take the efficacious actions that corresponded to those beliefs. Conversely, the respondents who had received mental health diagnoses did not believe they were at heightened risk (consistent with CDC findings indicating no increased risk[4]), but nevertheless were more likely to comply than those without such diagnoses. This suggests the need for researchers to continue to investigate mechanisms underlying not only the association between beliefs and action but differences between general viewpoints and the process of making changes in basic patterns of social behavior. Recognizing the way individuals are positioned economically, politically, and socially may affect the nature of beliefs, compliance itself, and these disjunctures. Public health messages should be sensitive to these complex influences, and to variability in life circumstances as reflected in physical and mental health problems.

There have been 1 089 357 cases of COVID-19 in Ohio as of May 2021 and there have been 19 528 deaths due to COVID-19 as of May 2021.[3] The daily COVID-19 cases in Ohio have been between 1000 and 5000 from January until April of 2021, with numbers decreasing in May.[3] Although signs of improvement are encouraging, understanding the dynamics involved in social distancing is important as this can be an effective strategy in the event of future outbreaks. It is well-documented that young adults are not the most vulnerable age group in terms of general risk, but those with health problems constitute an important exception to this general finding.

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RESEARCH ARTICLE

A Comparison of Nonprofit Hospital Charity Care Policies and Community Benefit in Central Ohio to Peer Cities

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ABSTRACT

Background: Nonprofit hospitals in the United States are required to provide community benefits, including charity care, to receive tax exemption from the federal government. Central Ohio's nonprofit hospitals have agreed to the same charity care policies, which may be unique compared to other communities across the county. The aim of this research is to compare the charity care policies of hospitals in Columbus, Ohio, to their peer cities, investigating if hospitals in similar cities have common shared charity care thresholds and to determine if hospitals in peer cities provided similar levels of community benefit.

Methods: Tax data from nonprofit hospitals in 21 cities were collected and analyzed using Microsoft Excel (Microsoft Corporation). City community benefit data was summed and averaged using Excel to create a graphical representation of the data.

Results: Only Columbus, Ohio, and Providence, Rhode Island, reported the same charity care thresholds across hospitals. Data demonstrate that Columbus provides less community benefit in dollars to total expenses compared to peer cities; however, this appears to be only true regarding other community benefit excluding charity care. Columbus was near the median among cities examined in regard to percentage of charity care to total community benefit.

Conclusion: Results suggest variability in the amount and type of community benefit nonprofit hospitals provide. Central Ohio hospitals have the same charity care thresholds and spent approximately the same in total community benefit however it is not transparent how these funds are utilized. Current federal regulations do not assess whether the community benefits reported are affecting community health outcomes.

Keywords: Community benefit; Charity care; Tax exemption; Nonprofit hospital

INTRODUCTION

The purpose of this descriptive research is to investigate Central Ohio hospitals' community benefit compared to their peer cities and to determine if these hospitals are unique in their collaborative efforts to provide charity care. This information is crucial in understanding current community benefit policies and guidelines on how to improve community benefit services to the areas hospitals serve. In the 19th century, United States hospitals were established to treat the impoverished, providing shelter while treating their illnesses.[1,2] Government played a role in health care delivery not only by operating hospitals but also by creating regulatory and funding mechanisms to provide healthcare access for the elderly and disabled. Medicare and Medicaid were developed in the 1960s as basic insurance programs for Americans who did not have health insurance. These government programs have changed over the past 60 years by providing more Americans with affordable health care options.[3]

Currently, the United States government provides incentives to nonprofit hospitals that provide community benefits and charity care with a tax-exemption status making it more desirable for hospitals to provide community and charity care benefits. In 2019, there were approximately 5200 nonfederal general hospitals in the country, according to the American Hospital Association, with nearly 3000 nonprofit and almost 1000 state and local government operated hospitals.[4] Today, nearly 60% of hospitals in the United States are nonprofit in which most are tax-exempt because of their status as charitable entities.[5] A study by John Hopkins found that on average, nonprofit hospitals saved approximately 6% of total expenses, or about $11.3 million per hospital, due to tax exemptions.[6]

In 1956, the United States formalized the tax-exempt status for nonprofit hospitals if they provided charity care within their ability to do so.[7] Community benefit was first articulated to the American Hospital Association in 1969 by the Internal Revenue Service (IRS), not in an official document but in a letter of opinion.[8] Initially, most community benefit services were directed at increasing scope of care to seniors and those with complex chronic problems attempting to prevent hospital readmissions. Through the 1980s and 1990s several organizations, like the American College of Healthcare Executives, and various states attempted to create policies including the requirement of community benefit documentation; however, there was no federal enforcement, leaving hospital community benefit vague and undefined. In 2007, the Schedule H section of the Tax Form 990 was added by the IRS and was required for all nonprofit hospitals to maintain their tax-exempt status. In 2010, following passage of the Patient Protection and Affordable Care Act, the IRS instituted the requirement that all tax-exempt hospitals conduct community health needs assessments every 3 years and report it annually on Form 990. The community health needs assessment identifies health needs, targets programs to address these needs, and measures the impact of community benefit activities. Despite efforts from the IRS, state, and other hospital organizations, there are still no quantifiable measures or goals required of nonprofit hospitals in reporting or exhibiting community benefit delivery for federal or most state purposes. There is no requirement for hospitals to demonstrate a direct relationship between the hospital's community benefit activity and the health status of the community in which they serve.[8]

There is a lack in guidance on how to assess the outcomes of the activities being funded as a result of the more recent IRS specifications following The Patient Protection and Affordable Care Act. There have been no proposed logic models for the delivery of community benefit by the IRS and community benefit funds are typically devoted primarily to charity care. This approach spreads community benefits across various minimally regulated programs therefore making it unlikely to promote a change in a community's health status. Results of 1 research report suggested that evidence-based programs and specific measurable outcomes are crucial in maximizing community benefit as well as modifications to the IRS Tax Form 990, Schedule H to assess benefits to the community in which the nonprofit hospital serves.[8] This would include assessments of community health status and better specifications regarding the allocations of funds outside of charity care.[8] The same report found that hospital funding of community health activities often leads to increased hospital community collaboration.[8] Hospital collaboration is crucial because no institution can single-handedly change the health status of a community due to the complexities of community health needs.[8]

The majority of hospital community benefit funds, nearly 85%, are spent on charity care and uncompensated clinical care, leaving minimal funds for community health activities.[8] In 2009, a study showed 1800 nonprofit hospitals spent an average of 7.5% of their reporting expenses on community benefit with a range of spending from 1.1% to 20.1%.[7] Other types of community benefit are not well defined on the IRS Tax Form 990, Schedule H; however, other types of community benefit could include community building and health improvement services, cash/in-kind contributions, health professions education, subsidized health services, community research, and Medicaid shortfall.[5,6,9]

Regarding community benefit, results of a review of literature indicated that implementation of charity care policies nationally is inconsistent, and there is no mandate on who should be eligible for charity care.[10,11] Thus, there is no set minimum eligibility criteria for charity care, and the law does not address which specific services should be covered and included in community benefit.[10] One of the challenges of evaluating community benefit and charity care is that the IRS has not established desired outcomes or regulations, therefore, it is up to the hospital or health system to determine the levels of charity care and community benefit provided.[8] In addition, few states dictate community benefit requirements other than reporting, with no responsibility to report community health needs assessments, minimum levels of community benefit, and minimum income eligibility standards for charity care.[5] This makes the evaluation of community benefit and validation of charity care program establishment difficult to assess, especially when comparing hospital systems.

Much prior research regarding community benefit proposes implementing federal and state policy to determine set outcomes or goals for community benefit for hospitals,[8,12] and in the same articles authors describe the lack of implementation of community benefit and charity care without benefits related to health behaviors, measurable goals, and outcomes. Consequently, without these guidelines it can be inferred that community benefit may not be making a community impact and cannot be evaluated in its effectiveness.

The Central Ohio Hospital Council (COHC) serves as a forum for Central Ohio's community hospitals to collaborate and address issues that impact the delivery of health care to central Ohioans. Per the COHC, Central Ohio hospitals are part of the nonprofit hospital community that provide health care for all residents regardless of their ability to pay, and residents can receive the same quality of care from all of Central Ohio's hospitals. The COHC believes that the total expense of charity care in central Ohio is equally distributed across all hospital systems. This research was designed to articulate the levels of community benefit and charity care in Central Ohio and provide fundamental reasoning for a change in community benefit policy based on current guidelines. The aim of this research is to compare the charity care policies of hospitals in Columbus, Ohio, to their peer cities to investigate if hospitals in similar cities have shared charity care thresholds. An additional purpose of this research is to determine if hospitals in peer cities to Columbus, Ohio, provide similar amounts of community benefit.

METHODS

The COHC collaboration in Columbus, Ohio, includes Mount Carmel Health System, Nationwide Children's Hospital, OhioHealth, and The Ohio State University Wexner Medical Center. These health systems collaborate with each other and other community stakeholders to improve the value, quality, and accessibility of health care in central Ohio.[10] Central Ohio's nonprofit hospitals have agreed on the same charity care policies, which may be unique compared to other communities across the county. In 2013, the COHC board of directors adopted a uniform charity care standard for all central Ohio hospitals in which was determined that patients earning less than 200% of the federal poverty level (FPL) are not billed for services, and those under 400% of the FPL receive a substantial discount for medical services. These hospitals also assist patients in applying for Medicaid, which covers adults earning up to 138% of the FPL in Ohio.[13]

Since 2007, United States nonprofit hospitals have been required by the IRS to report information regarding their community benefit activities, mostly regarding dollars spent toward community benefit. These hospitals must report their community benefit as part of their annual tax return.[14] Columbus, Ohio, hospital tax data were compared to its peer cities which peer cities were determined by The Columbus Foundation's *Benchmarking Central Ohio* report.[15] See Table 1.

Peer cities' nonprofit hospitals were identified by utilizing the American Hospital Association's 2020 Hospital Guide.[4] The data from each city's hospitals were collected via the IRS Tax Form 990,

Table 1. Nonprofit Hospital Systems in Columbus, Ohio, and Peer Cities

City and State	Nonprofit Hospital Systems
Columbus, Ohio	Mount Carmel, Nationwide Children's Hospital, OhioHealth,*The Ohio State University Wexner Medical Center
Charlotte, North Carolina	Novant Health Inc.
Chicago, Illinois	Advocate North Side Health Network, Ann & Robert H. Lurie Children's Hospital of Chicago, Bathany Homes and Methodist Hospital, Holy Cross Hospital, La Rabida Children's Hospital, Loretto Hospital, Mercy Hospital and Medical Center, Mount Sinai Hospital Medical Center, Norwegian American Hospital Inc., Palos Community Hospital, Roseland Community Hospital Association, Saint Anthony Hospital, South Shore Hospital Corporation, St. Bernard Hospital, Swedish Covenant Health, Thorek Memorial Hospital, University of Chicago Medical Center
Cincinnati, Ohio	Bethesda Hospital Inc., Christ Hospital, Cincinnati Children's Hospital Medical Center, Mercy Health, The Good Samaritan Hospital of Cincinnati, Ohio
Cleveland, Ohio	The Cleveland Clinic Foundation, St. Vincent Charity Medical Center
Indianapolis, Indiana	Community Health Network Inc., Indiana University Health Ball Memorial Hospital Inc., Indiana University Health Blackford Hospital Inc., Indiana University Health Inc., St. Vincent Hospital and Health Care Center Inc.
Jacksonville, Florida	Baptist Medical Center of the Beaches Inc., St. Vincent's Medical Center Inc.
Kansas City, Missouri	Children's Mercy Hospital, St. Luke's Hospital of Kansas City
Louisville, Kentucky	Baptist Health, Jewish Hospital and St Mary's HealthCare, Norton Hospitals, University Medical Center
Milwaukee, Wisconsin	Ascension SE, Children's Hospital of Wisconsin Inc.
Minneapolis, Minnesota	Allina Health System, Children's Health Care, Fairview Health Services, Hennepin Healthcare System Inc.
Nashville, Tennessee	Saint Thomas Midtown Hospital, Saint Thomas West Hospital, Vanderbilt University Medical Center
Orlando, Florida	The Nemours Foundation, Orlando Health
Pittsburgh, Pennsylvania	Highmark Health Group, St. Clair Health Corporation, The Children's Home of Pittsburgh, UPMC Pinnacle Hospitals
Portland, Oregon	Legacy Emanuel Hospital and Health Center, Legacy Good Samaritan Hospital and Medical Center, Portland Adventist Medical Center, Providence Health and Services- Oregon
Providence, Rhode Island	Rhode Island Hospital, The Miriam Hospital
Raleigh, North Carolina	Duke University Health System Inc., Rex Hospital Inc., WakeMed
San Antonio, Texas	Christus Santa Rosa Health System
San Diego, California	Rady Children's Hospital-San Diego, Scripps Health, Sharp Memorial Hospital
San Jose, California	O'Connor Hospital

*The Ohio State University Wexner Medical Center is a government operated hospital; no other government operated hospitals were included in this research

Schedule H via GuideStar, which is a nonprofit database run by Candid.[12] GuideStar was used to extract data from the most current tax year, 2018, including Columbus and each peer city hospital's total expenses, the percentage of FPL in factoring eligibility for free and/or discounted care, total charity care benefit, total other community benefit, and the total community benefit provided per hospital. We standardized charity care and total community benefit by dividing the reported expenditure of each hospital by its own operating expenses as reported on Form 990 for the purpose of comparability. Using Microsoft Excel, each city's hospital data was summed and averaged to create a graphical representation of the data. Government hospital systems are not required to report nonprofit data on the Form 990, therefore this information was unable to be obtained from GuideStar. The COHC collects community benefit data from their partner hospitals, so The Ohio State University Wexner Medical Center data were also included to compare Central Ohio's hospital systems' data. In addition, for-profit hospitals are not required to report this information.

RESULTS

The number of nonprofit hospitals varied between cities from 1 to 17, which largely correlated to the size of the city. Chicago, Illinois, the largest peer city, has 17 nonprofit hospitals. Columbus, Ohio, has 3 nonprofit hospital systems not including The Ohio State University Wexner Medical Center. Charlotte, North Carolina, San Jose, California, and San Antonio, Texas were the 3 peer cities with only 1 nonprofit hospital. The median number of nonprofit nongovernment hospitals per the 20 cities researched was 3.

There were varying levels of charity care thresholds throughout the peer cities and hospital systems with the lowest level for free care being 100% FPL to 300% FPL at the highest. Subsequently, the lowest percentage of FPL for discounted care was 250% and the highest was 600%. Columbus, Ohio, and Providence, Rhode Island, were the only cities, of those researched, with the same charity care thresholds across hospitals. Both of the nonprofit hospitals in Providence reported a 200% FPL for free care and a 300% level for discounted care.

Columbus, Ohio, falls near the median in percentage of charity care to total hospitals expenses at 6.27%, with San Diego, California, at the lowest, 1.96%, and Charlotte, North Carolina, at the highest, 12.96%. Columbus falls directly between its fellow Ohio cities with Cleveland below it, at 6.03%, and Cincinnati above it, at 7.29%. With The Ohio State University Wexner Medical Center factored in, Columbus is in the bottom third due to the high total expenses incurred at the James Cancer Hospital and Solove Research Institute.[1] See Figure 1.

Columbus, Ohio, falls in the lowest quartile when comparing the total community benefit to total hospital expenses, at 7.57%. Columbus moves ahead of 1 city with the addition of The Ohio State University Wexner Medical Center at 9.31%. The city with the lowest level of charity care to total hospital expense was Milwaukee, Wisconsin, at 4.02% and the highest was Cleveland, Ohio, at 17.3%. See Figure 2.

The last comparison was the percentage of charity care to total community benefit. Again Columbus, Ohio, was in the median of this data range at 66.7%. The lowest was Louisville, Kentucky, at 25%, and the highest was Charlotte, North Carolina, at 98.6%. When The Ohio State University Wexner Medical Center was factored in the percentage in Columbus decreased to 50.4%. Looking at the data, Columbus provides similar levels of charity care to other peer cities like Minneapolis, Nashville, Cleveland, Raleigh, Kansas City, and Cincinnati. However, Columbus provides a lower percentage of community benefit to total expenses than only Milwaukee, Orlando, and Charlotte. Columbus is similar to other cities in comparison to percentage of charity care of total community

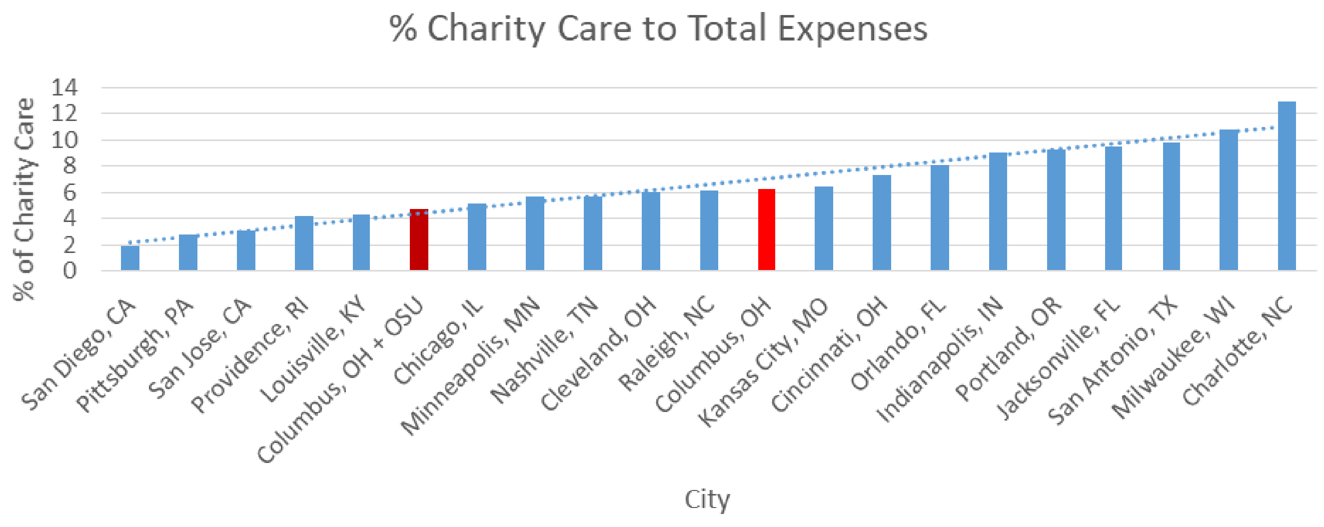

Figure 1. Percentage of Averaged City's Nonprofit Hospital(s) Charity Care to Averaged Total Expenses

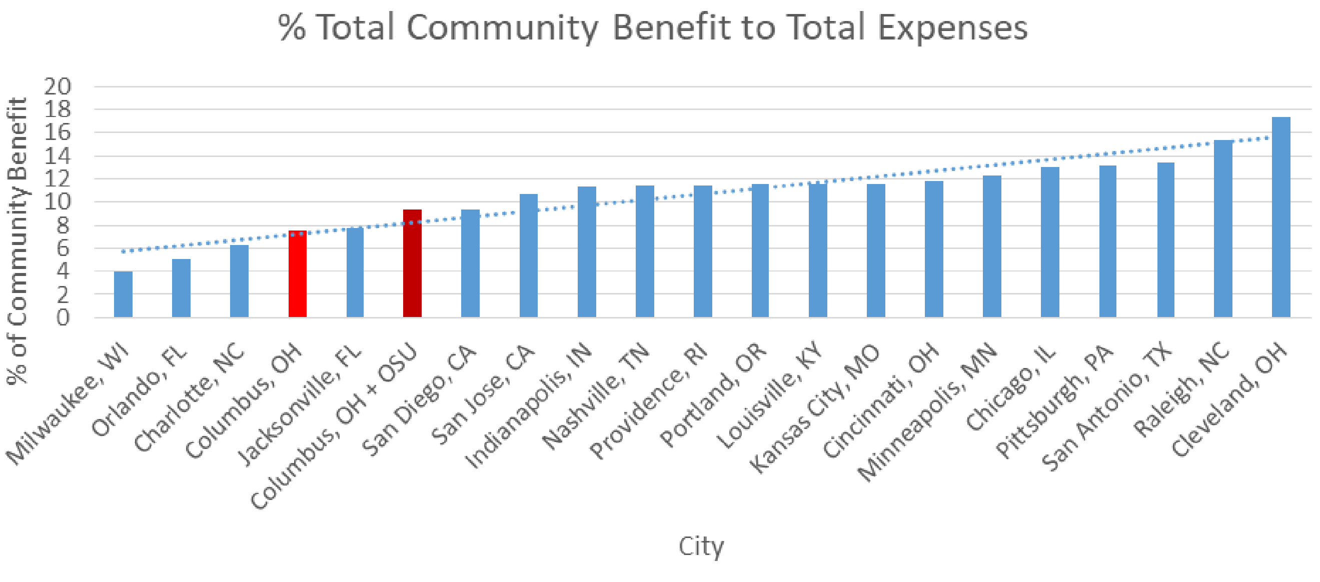

Figure 2. Percentage of Averaged City's Nonprofit Hospital(s) Total Community Benefit to Averaged Total Expenses

benefit with 10 cities between approximately 50% to 70%. See Figure 3.

It is believed by the COHC that the total expense of charity care in central Ohio is equally distributed across all hospitals systems due to its shared charity care thresholds. Charity care dollars to total expenses at each institution is 1.36% The Ohio State University Wexner Medical Center, 4.50% Nationwide Children's Hospital, 6% Mount Carmel, and 7% OhioHealth. Despite The Ohio State University Wexner Medical Center reporting a lower percentage of charity care to total expenses, they do provide similar levels of total community benefit to total expenses with each institution reporting 9.12% The Ohio State University Wexner Medical Center, 11.32% Nationwide Children's Hospital, 7% Mount Carmel, and 9% OhioHealth. See Figure 4.

DISCUSSION

The purpose of this research was to determine if hospitals in peer cities to Columbus, Ohio, provided similar levels of community benefit. From the data used for this analysis, only Columbus, Ohio and Providence, Rhode Island, have a common income threshold

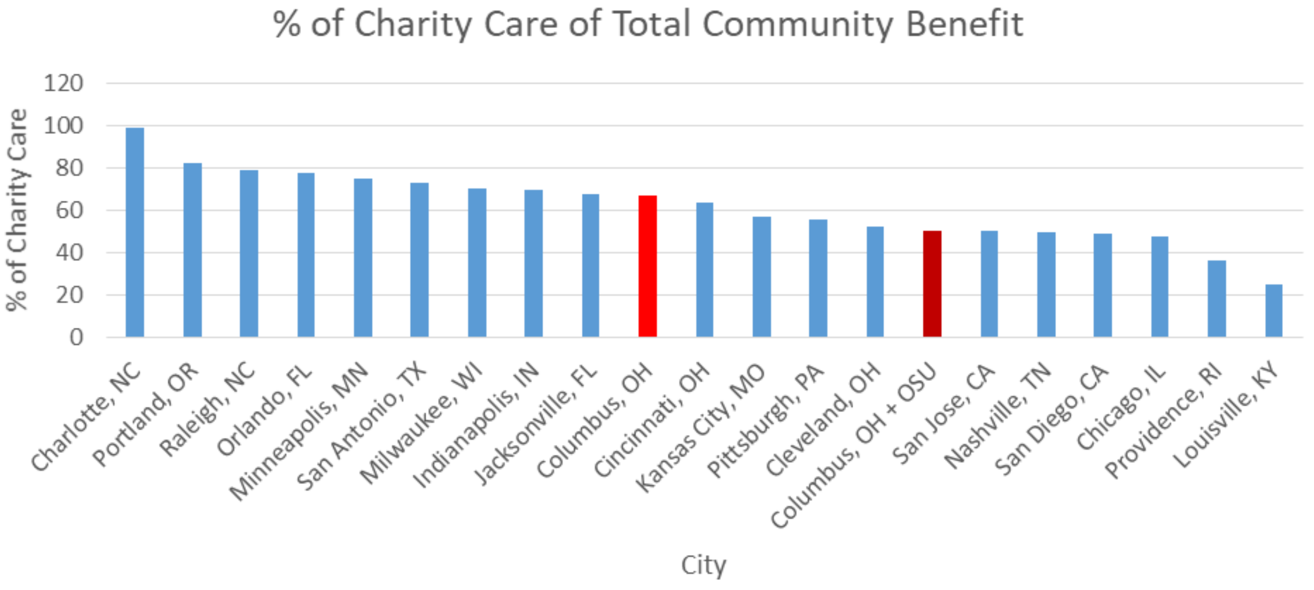

Figure 3. Percentage of Averaged City's Nonprofit Hospital(s) Charity Care of Averaged Total Community Benefit

(percentage of federal poverty guidelines) for free and discounted care across all hospital systems in their metro area. There is a collaboration between Central Ohio hospitals to have the same income thresholds to determine charity care, however, it is unknown if a similar collaboration exists in Providence. Common charity care thresholds ensure that one hospital system is not being utilized more than another due to its charity care policies. The amount of charity care provided by a hospital will also depend largely on the location of the hospital and ease of access to those that would qualify for charity care. There did appear to be a trend or grouping of common policies between hospital systems, for example in Cincinnati and Chicago, but not for all hospitals across the board. The data demonstrate that Columbus does provide less overall community benefit in regard to total expenses compared to peer cities; however, this appears to be only true regarding other community benefits apart from charity care. Columbus was near the median in regard to percentage of charity care to total community benefit. Despite Columbus being on the lower end of the percentage of community benefit provided compared to other peer cities, Columbus, at 7.57%, is near the average of a study of 1800 United States nonprofit hospitals who reported an average of community benefit of 7.5%.[7] When The Ohio State University Wexner Medical Center was factored into the Columbus analysis, they provided a slightly higher percentage of total community benefit to total expenses.

This work may be lacking a complete data set in capturing the entire story of community benefit due to government run hospitals not included in the data analysis, except for The Ohio State University Wexner Medical Center. Subsequently, the average community benefit and charity care values reported in this research might not capture the entire community benefit of a city. However, this information is thought to be the first research regarding hospital's specific community benefit. This information is helpful to not only the hospitals and the communities they serve, but also helpful to federal and state government to monitor if nonprofit hospitals are performing the way they should to deserve tax-exempt status.

Results of 1 study indicated hospitals that reported community benefit allocated less than 8% of all community benefit expenditures to community health improvement with most of the funds utilized for charity care, health professional training, Medicaid costs, and research.[9] This is a concern given the financial benefit hospitals are accruing from their tax-exempt status, which across all states was estimated at $12.6 billion in 2002 and $24.6 billion in 2011.[9] A recent study reported that there is high variability across nonprofit hospitals regarding community benefit. This study found that 62% of nonprofits provided community benefits greater than the tax benefits they received; however, if only charity care is factored in then only 20% of the nonprofit hospitals in the study exceed the value of their tax exemption.[6] These studies

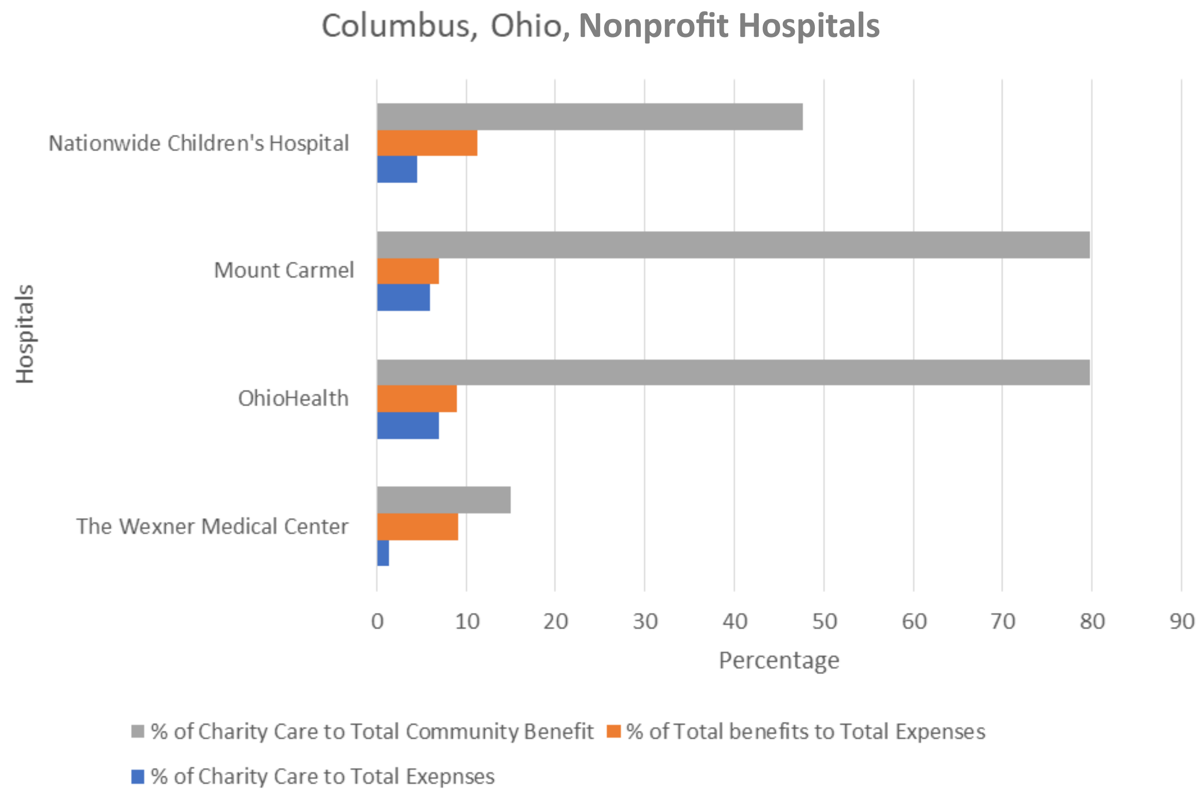

Figure 4. Community Benefit Data for the Central Ohio Hospitals

suggest that many nonprofit hospitals benefit greatly from their tax-exempt status yet provide minimal community benefits.[6,9,16] This demonstrates a lack in regulation regarding nonprofit hospitals use of community benefit. By researching community benefit and how Central Ohio hospitals stack up to their peer cities, it is evident there is a lack in government regulation of community benefit nationally. Of those states who have adopted some type of community benefit regulation, they were consistently associated with higher levels of hospital-provided community benefits. A 2018 article suggests that state regulatory intensity conveys a strong signal to community hospitals that more spending is expected.[5] This proposes that federal regulation would most likely have the same effect.

Since 1969, hospitals have been required to provide services to the communities they serve in exchange for tax exemption and over time this has become known as community benefit, which includes charity care through financial assistance programs.[17] Nonprofit hospitals also supplement shortfalls for coverage in Medicaid patients.[11] Compared to the national average, Ohio has a similar uninsured population at approximately 8.5% in 2018.[18] This factor would impact the amount of charity care Central Ohio's hospitals provide to total expenses as well as the amount of charity care provided for the peer cities uninsured population. Another factor that would determine the amount of charity care provided is whether hospitals are located in a state with Medicaid expansion, like Ohio, due to The Patient Protection and Affordable Care Act. Therefore, Central Ohio hospitals may not provide as much charity care as other cities whose states did not expand Medicaid. Central Ohio's nonprofit hospitals have agreed on the same charity care policies, which is unique compared to other communities across the county. The amount of charity care provided in the Columbus area may have an effect on the total resources available for other community benefits. Historically research shows that the 85% of community benefit funds is spent on charity care and uncompensated clinical care, consequently leaving minimal funds for community health activities.[8] This leaves a major problem for funding for other community benefits which have been shown to make an impact on the communities in which they serve.

A review of nonprofit hospital community benefit in the United States from 2010 to 2019 found a limited role of hospital leadership related to community benefit. This lack of leadership could cause disorganization and misuse of community benefit funds. Results of a survey conducted in 2011 found that hospital governing boards did not engage in community benefit planning and only 36% of the systems surveyed had assigned responsibility to manage and execute community benefit.[7] This same survey also reviewed community needs assessments which are now required of hospitals by the IRS every 3 years to maintain their tax-exempt status. In 2013, few hospitals studied had a broad spectrum of community members in the community needs assessment process. Ironically, the hospitals in communities with the lowest needs based on county health rankings were more likely to complete community health needs assessment activities versus those with the greatest health need. There was also found to be poor collaboration between nonprofit hospitals and public health departments with approximately 50% of collaboration demonstrated between entities.[7]

Efforts to improve hospital community benefit and health have been shown to include high quality collaboration between all stakeholders, including consultants. Prior research has shown hospitals reporting high levels of community health needs assessment implementation, including the creation of community health programming, spent more on community improvement versus those who did not implement changes following a community needs assessment.[7] This demonstrates the need for IRS policy change to enforce and monitor hospital community health needs assessment implementation, the development of strategies for improvement, and provide incentives for change. While community benefit has been researched there is minimal examination of the current data including specific values or what type of community benefit is actually being provided to the community other than charity care. One possible solution would be increased transparency of data with the development of an online database to access hospital's community benefit activities. Another solution would be the development of clear expectations and enforcing accountability, which could be set at a federal or state level. There have been reports of a *race to the bottom* effect with setting specific hospital spending guidelines, but this could be offset by not providing specific standards in regard to financial costs but in terms of expected community health outcomes as a result of hospital community benefit spending.[13] From this research it is evident there is a significant need for policy change and data transparency for community benefit to truly have an impact on population and community health.

Limitations

There are some limitations to this study. The latest tax year that could be obtained for all hospitals was from 2018; therefore, there is most likely variation in data as this is only capturing 1 year of tax reporting. In addition, government hospitals are not required to submit an IRS Tax Form 990, Schedule H; therefore, all government hospitals, including Veterans Health Administrations, were excluded from this research, except The Ohio State University Wexner Medical Center whose data was supplied by the COHC. Not reflected in this article are inherent state differences in health policy. Varying levels of community benefit policy per state could contribute to overall differences across health care systems when comparing Columbus to its peer cities. Lastly, 12 of the 20 hospitals did not report a percentage for the federal poverty guideline in factoring eligibility for free and/or discounted care, but reported a number in the tens of thousands. No reference value or definition could be located from the IRS or a literature review, however it is suspected that number is reported as income level versus percentage of the federal poverty guideline. For data analysis, hospitals and hospital systems that reported a dollar amount for federal poverty level, the number was converted to a percentage of the federal poverty guideline by the 2021 poverty guidelines for the 48 contiguous states and the District of Columbia published via the United States Department of Health and Human Services.[19]

PUBLIC HEALTH IMPLICATIONS

Using Columbus, Ohio, as a focal point for data collection it is clear that there is variability in the amount and type of community benefit nonprofit hospitals provide. Central Ohio hospitals provide the same charity care thresholds and appear to provide similar total community benefit dollars across hospital systems; however, the hospitals do not directly report how funds are being used and have no legal obligation to do so. Current federal regulations and standards do not assess whether the community benefits reported are affecting community health outcomes. A higher standard of community benefit reporting and implementation needs to be enforced including the use of outcome measures and specific population health information, like improved community access to health services, overall enhanced health of the community, and increased community medical knowledge, to have an effect on community health outcomes. These standards should include desired community health outcomes, like those mentioned above, rather than specific community benefit financial spending requirements and guidelines to avoid a *race to the bottom* effect on community benefit. Hospital community benefit should target the greatest need in a community, directly linking public health issues of a community such as health disparities and serving underserved populations.

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RESEARCH ARTICLE

Increasing Capacity for Evaluation of Community-Based Organizations: Lessons from the Ohio Equity Institute

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ABSTRACT

Background: Community-based organizations (CBOs) play an important role delivering disease prevention and health promotion activities to address community health needs and improve the health of individuals living in their communities. While CBOs play this important role, evaluation of the services they deliver is hampered by limited infrastructure to systematically collect data from these organizations. To address this gap, we report on a case study of the development of the Ohio Equity Institute (OEI) Data Portal. The OEI is a statewide initiative that supports 65 CBOs across Ohio to deliver 3 evidence-based interventions (ie, CenteringPregnancy, Community Health Workers, and Home Visiting) to address infant mortality in underserved populations.

Methods: Employing principles of community-engaged stakeholder research and user-centered design, we conducted Plan-Do-Study-Act cycles, including semistructured interviews with 43 key informants, to improve the development, implementation, and use of the OEI Data Portal.

Results: This process identified both technical and implementation challenges, and offered opportunities to make improvements to the data collection system itself as well as to the integration of this system with CBO workflows. These improvements yielded significant gains in terms of the quantity and quality of data submission, ultimately contributing to ongoing outcome evaluation efforts.

Conclusion: Our findings provide important insight into the challenges experienced by CBOs when participating in a statewide CBO data evaluation infrastructure development and implementation. As Ohio and other states push to expand collaborations between CBOs and health care organizations, leaders should leverage existing data collection to facilitate a more comprehensive and effective process.

Keywords: Community-based organizations; Infant mortality; Disparities; Evaluation

INTRODUCTION

Community-based organizations (CBOs) play an important role delivering disease prevention and health promotion activities to address community health needs.[1-3] Community-based organizations, which are defined as public or nonprofit organizations that represent their communities and provide health and educational services,[3] facilitate state and national population health initiatives.[4-6] Moreover, as of 2017, several state Medicaid programs incentivize health care systems to work with CBOs to address social determinants of health.[7] The relationship between CBOs and health care providers is further encouraged by funding programs, such as the Robert Wood Johnson Foundation's Culture of Health.[8]

To participate in these efforts and support partnerships with health care organizations, it is important for CBOs to build evaluation capabilities both to guide their own efforts as well as to demonstrate to funders and other stakeholders that they are effectively implementing evidence-based interventions.[9] Research suggests that building evaluation capacity, or the ability to perform evaluations, requires CBOs and their staff to buy into the importance of evaluation, commit sufficient resources to collect data, and collaborate with external researchers to develop sustainable evaluation methods.[10-13]

Previous efforts to strengthen internal evaluation capacity have centered on providing CBOs with onsite technical assistance, developing evaluation skills through training programs, and offering interactive web-based systems to guide evaluation design.[14-16] These efforts emphasize building capacity at the organization level so that CBO managers and staff can take the necessary steps to evaluate the implementation efficacy of interventions,[16,17] which has been shown to positively affect implementation success.

Although previous research has highlighted the process of building internal evaluation capacity in CBOs, evidence is limited for building evaluation capacity across CBOs. This gap is particularly important because it is not uncommon for multiple CBOs to programmatically deliver similar components of evidence-based interventions as part of state or regional initiatives.[18,19] Within the similar interventions, CBOs may seek opportunities to coordinate their efforts to identify overlap of program activities, collect data, and conduct process and outcome evaluations.[13,17] More broadly, cross-CBO evaluation efforts can provide evidence of the effectiveness of state-level strategic efforts to use CBOs to support population and public health.

The economic investments being made by private and public funders warrant a deeper understanding of how CBOs participating in the same intervention can develop the capacity to evaluate intervention implementation efficacy and programmatic outcomes. To better understand the process of building evaluation capacity across multiple CBOs, we use a case study research design to explore and describe the challenges experienced by stakeholders participating in the Ohio Equity Institute's (OEI) building of a statewide CBO evaluation infrastructure. In subsequent sections, we describe the OEI initiative and the process of building the evaluation infrastructure. The lessons learned from the experience of building the OEI data infrastructure will be helpful for other efforts in Ohio, as well as in those for other states aiming to build robust data collection systems to support CBOs delivering evidence-based interventions.

Background: The Ohio Equity Institute Initiative

In 2017, Ohio ranked 42nd in the nation for infant mortality, with an infant mortality rate of 7.3 infant deaths per 1000 births.[20] Moreover, the infant mortality rate in Ohio is almost 3 times as high among Black infants (ie, 14.3 per 1000 births for Black infants compared to 5.1 per 1000 births for White infants in 2019).[21] Ohio Equity Institute was created to help address these racial disparities in birth outcomes.[22]

Ohio Equity Institute is a collaboration between state agencies, including the Ohio Department of Health (ODH), the Ohio Department of Medicaid (ODM), and the Ohio Department of Higher Education (ODHE), working with local CBOs in the 9 Ohio counties with the largest disparities in infant mortality rates between Black and White infants. In 2018, OEI began to provide funding to 65 CBOs to deliver 3 evidence-based interventions focused on reducing the disparity in infant mortality: CenteringPregnancy group prenatal classes; Home Visiting; or Community Health Workers (CHWs).[23-32] The OEI also funded some additional evidence-based interventions including fatherhood programs, community events, a doula program, and a program connecting women to care that did not use CHWs. Services began being provided in August 2018, and by May 31, 2019, CBOs had reached 10 074 program participants. Taken together, these interventions were focused on improving the health of pregnant women, infants, and their families within the Ohio counties disproportionately impacted by the disparity in infant mortality.

As a component of OEI, ODM and ODHE cosponsored an evaluation grounded in the collection of participant-level data with the goal of determining the extent to which the selected interventions serve high-risk Medicaid enrolled pregnant women and assessing the effect of these interventions on health care utilization and birth outcomes. This evaluation was proposed in order to build the evidence for the specific impact of the 3 OEI interventions in Ohio, and to allow for the transition from a county-based approach to a participant-based approach to measuring impact.

METHODS

Building the OEI Data Portal

To support the OEI evaluation, a team of researchers and technical experts developed and deployed the OEI Data Portal, a data collection system that could be used across all CBOs and was coordinated by a central evaluation team. The OEI Data Portal was built on the Qualtrics web-based software platform[33] that was extended through the development of a custom code base to expand the usability of the system in relation to the tracking and management of participant data by CBOs. The development of the OEI Data Portal proceeded using a 5-step approach: (1) development of a list of appropriate metrics to be collected by the OEI Data Portal based on a literature review and consultation with the OEI stakeholders (ie, ODM, ODH, ODHE); (2) hold initial interviews with CBOs to understand their existing data collection process and technical capacity; (3) draft specifications of the OEI Data Portal based on initial interviews with CBOs; (4) build the OEI Data Portal based on the draft specifications; and (5) provide training sessions to the CBOs on use of the OEI Data Portal.

The initial interviews with the CBOs (ie, Step 2) revealed a range of technological capabilities and resources that the CBOs use to collect data. For instance, some CBOs were collecting data using paper forms, some were using electronic spreadsheets, and others were using more advanced online data entry systems (ie, electronic health records) with data reporting capabilities. Given this variability, the development of the OEI Data Portal involved considering 3 collection modes as a way to provide each CBO the ability to select the data submission format most appropriate for their existing workflow: (1) an online data submission portal that facilitated electronic data submission directly from the CBOs to the OEI Data Portal; (2) paper forms along with mail, fax, scanning, and email options for use by the CBOs; and (3) data submission using common spreadsheet programs (ie, Microsoft Excel).

Five data collection forms were designed to collect data about program participants at 4 time points: Enrollment, Encounter, Group encounter (ie, for CenteringPregnancy programs), Birth, and Exit (see Appendix). The Enrollment form is intended to be administered at the first contact between the CBO and the program participant and collects contact information, social security and Medicaid identification number (ID), demographics, gestation at enrollment, prenatal care, housing, transportation, enrollment in social/government programs, and risk factors (ie, low food access, depression, stress, social support, smoking, alcohol use, and drug use). The Encounter forms are designed to be used at all subsequent interactions between the CBO and the participant (or group) and collect the date of the encounter, updates on contact information, and any referrals to additional services. The Birth form is fielded following delivery and reports the infant's name, gender, race, feeding method, and safe sleep practices. The Exit form is completed at the final interaction between the CBO and the program participant, and collects infant well-child care, immunizations, postpartum visits, emergency department visits, father involvement, child care, and updates on housing, employment status, and program enrollment. The OEI Data Portal went live in October 2018 and was designed for CBOs to report data monthly for program participants. As of March 2021, the OEI Data Portal has data on over 120 000 participant contacts with the CBOs.

Plan-Do-Study-Act Cycles

Following the roll out of the OEI Data Portal, the OEI evaluation team engaged in a series of 3 Plan-Do-Study-Act (PDSA) cycles in October 2018 (PDSA Cycle 1), April 2019 (PDSA Cycle 2), and June 2019 (PDSA Cycle 3).[34] The goal of the PDSA cycles was to identify opportunities to continuously improve the efficiency and quality of data collection and reporting. This process embraces aspects of user-centered design in a codevelopment model where real-time feedback is solicited from end users and communicated to developers of a system.[35] Below we detail the steps of this evaluation process and then present the key findings.

Data Collection

All CBOs funded as part of OEI were included in our study sample. After the roll out of the OEI Data Portal, each CBO was invited to a series of 3 key informant semistructured one-on-one and group interviews across the 3-cycle PDSA process to provide information on system optimization. Under the conditions of their funding arrangements, each CBO supplied an administrative contact to the OEI evaluation team. We worked with this administrative contact to identify key informants. Key informants included project managers, program directors, and data administrators.

The goal of PDSA Cycle 1 was to conduct interviews with programs near the beginning of the data collection effort with particular attention to both how they were collecting data and how they were submitting data. This approach served as a quality check for the initial implementation of the system and strengthened engagement between the evaluation team and CBOs. The goal of PDSA Cycles 2 and 3 was to conduct phone interviews with CBO project and data managers to understand the remaining technical issues and identify best practices related to data collection and submission and to interview individuals from programs that were not yet collecting and reporting data at the time PDSA Cycle 1 took place. In PDSA Cycle 3, programs could opt out of participating if they had completed past PDSA calls and did not have any additional input.

All interviews used a semistructured approach that consisted of a series of open-ended questions. Questions were asked about how the organization collects data (eg, "How do you currently collect data about participants in your program?"; "ODM will require agencies receiving funding to collect and report evaluation data about participants to our evaluation team. What would your preferred mode be for sending participant data?"), challenges with data collection (eg, "What are the biggest barriers you face in data collection?"), recommendations to improve the data collection process (eg, "What areas/outcomes do you wish you knew more about or could measure?"), and expectations about program evaluation (eg, "What are you currently doing to evaluate the impact of your program?; What areas/outcomes do you wish you knew more about or could measure?"). Interviews lasted 15 to 45 minutes. This study was approved by The Ohio State University institutional review board, and informed consent was obtained for all individuals included in the study.

Data Analysis

All interviews were recorded but not transcribed, and detailed notes were taken of each interviewee's responses using a memoing approach.[36] The research team then met weekly to share notes and discuss common themes that emerged in the interviews throughout each PDSA cycle. After development of an initial codebook, the matrix method was applied to categorize the memos and validate our thematic analysis:[37-39] the interviewers independently organized notes for each theme for each interviewee allowing for data condensation and synthesis across cases. This process is commonly used for rapid-cycle identification of actionable insight, rather than exploration of theoretically deep concepts.[40,41] This approach was appropriate in this instance to identify common challenges that could be communicated to the developers of the OEI Data Portal to improve the quality of data collection and reporting in a timely manner. Thus, our findings below report on the common or recurring themes from the interviews that were identified in each PDSA cycle, including how the developers resolved each issue.

RESULTS

A summary of the number of interviews conducted during each PDSA cycle and the number of CBOs represented is provided in Table 1. Some interviewees represented data coordination and submission for multiple CBOs. Of the 65 CBOs, those that did not participate in interviews fell into 3 categories: CBOs using a separate system, the Ohio Comprehensive Home Visiting Integrated Data System (OCHIDS), not the OEI Data Portal, for reporting (n=12); CBOs with business associate agreement/contractual issues preventing data submission (n=13); and CBOs not collecting or submitting data (n=3).

Challenges in Data Collection

Across PDSA cycles, we identified common challenges across the CBOs using the OEI Data Portal and documented the response by the OEI evaluation team to address each specific issue. Challenges were broadly categorized into technical issues (Table 2) and implementation issues (Table 3). We distinguished between these 2 types of issues: those that required changes to the OEI Data Portal itself; and those that required changes to the data submission process, the data collection forms, or the reporting requirements.

Technical Challenges

The technical challenges often pertained to issues related to the usability of the OEI Data Portal system's data entry component. For instance, CBOs noted that they lacked the ability to update patient contact information, or that they were unable to track their own data entry. These types of issues were addressed by the OEI evaluation team by adding functionality to the OEI Data Portal, as well as making metadata (ie, the date forms were submitted) more accessible to users. Other issues related to the individual's experience of using the OEI Data Portal, such as the speed at which the system operates. These types of issues were resolved by providing the CBOs with additional instruction on use of the OEI Data Portal, such as the internet setting specifications (i.e., preferred browser) that optimize the use of the system.

Implementation Challenges

Implementation challenges were more prevalent in PDSA Cycle 1 than in PDSA Cycles 2 and 3. Broadly, implementation issues pertained to submitting data in formats different from those specified in the OEI data collection forms, not understanding how to answer certain questions, and CBOs not collecting specific variables. Most issues were resolved by changes to the OEI data collection forms or by clarifying reporting needs.

However, a subset of implementation issues was not related to the data portal itself but stemmed from the workflow of the CBOs. For instance, CBOs noted that health literacy issues may be limiting participant responses to questions. Some CBOs described being able to walk through forms with program participants, but not all CBOs had the resources to provide this targeted attention.

Another major issue pertained to the sensitivity of questions. For example, 1 question on the Enrollment form requested the demographic information for the biological father and some participants chose not to provide this information. Similarly, some questions, such as drug use, were viewed as potentially too sensitive. This issue was particularly relevant for the CenteringPregnancy programs where participants might be filling out forms in the presence of individuals seen as authority figures (ie, group facilitators and a doctor) as well as other group members. One approach to addressing these issues was to ask for this information at the second or third encounter with a client, as this would allow an opportunity to develop trust and comfort with the CBO staff.

Participants were similarly concerned about the privacy of the identifiable information that they report (i.e., Medicaid IDs, social security numbers, birthdates, addresses). This issue was particularly prominent for CBOs that served predominantly immigrant populations who may have concerns related to citizenship. The CBOs perceived that these participants had a general distrust for the government and may not necessarily distinguish between ODM and other federal agencies. To address this issue, one CBO requested that a disclaimer be added to the data collection form stating that the information would only be used for quality improvement purposes.

Quality of OEI Data Portal

By PDSA Cycle 3, most interviewees remarked on their satisfaction with the usability and experience of the OEI Data Portal. We conducted data quality checks throughout the PDSA process to identify the percent of missing or erroneous data from each CBO and to track the number of CBOs reporting data. Initially, 52% of data

Table 1. Categories Summary of Plan-Do-Study-Act (PDSA) Interviews and Representation of Community-Based Organizations (CBOs)

PDSA Cycle	Number of interviews	Number of CBOs represented
PDSA Cycle 1	12	20
PDSA Cycle 2	18	38
PDSA Cycle 3	13	31

Table 2. Technical Challenges and Solutions with Developing the OEI Data Portal

Challenge	Description	Resolution
PDSA Cycle 1 Challenges		
Inability to change participant contact information	CBOs were unable to make changes to contact information for participants once they were added to the portal.	A link was added to each participant's name that allows updates to contact information.
Inability to upload multiple data forms	The ability to place multiple data forms in the submission field, instead of placing them 1 at a time, was requested.	Three fields that can each accept 1 file were added, as Qualtrics does not allow fields that accept multiple simultaneous uploads.
Lag time in the data portal	Forms that were added or completed would not update immediately in the OEI Data Portal.	CBOs were provided instructions about the ideal internet settings to use Qualtrics effectively. The programs notified us that speed improved.
Inconsistent question order in different submission formats	The Excel spreadsheet questions did not follow the same order as the surveys on Qualtrics.	The Excel spreadsheet was modified so questions were in a consistent order with the Qualtrics survey.
Usability of encounter data collection form	The Encounter form was perceived as too intimidating and was not optimized for use by participants themselves.	A new Encounter form template was created with the same questions but a new format, designed to look like a sign-in sheet, and with questions worded to request information directly from the participant rather than from CBO staff.
PDSA Cycle 2 Challenges		
Unable to track data entry	CBOs could not see when they last entered data.	The date a form was submitted to the OEI Data Portal was added in place of the word "Complete" for the Enrollment, Birth, and Encounter forms.
Deletion of historical records from view	The OEI Data Portal deletes a participant's name when they exit the program. The CBOs did not like the inability to access forms for people who have exited, foreseeing a potential need to update information for participants.	Participants that have exited the program now appear in a separate table, and their data can be edited.
PDSA Cycle 3 Challenges		
Unable to correct data entry errors	Cannot unselect answer response if wrong choice is chosen	Surveys were altered to allow response changes throughout.
Confusing visual display	Text boxes do not align with data entry boxes.	Visual alterations were completed to better align data entry boxes on forms.
No process for exiting some patients	No way to complete exit form for patients that do not have postpartum visit	Enter known data and we can match outcome data using other data sources
Missing answer choices for gender	No nonbinary options (eg, trans) on forms, nor a 'Not Applicable' option for male participants	When gender is unknown, the question can be skipped. CBO staff encouraged to ask the question to the participant and write down the gender the participant calls themselves.
Data entry limitations	Limit on amount of group encounters that can be submitted requires using multiple sheets	More data entry lines for participants were added to Group encounter form in portal.

Notes: OEI = Ohio Equity Institute; PDSA = Plan-Do-Study-Act; CBO = community-based organization; CHW = community health worker.

Table 3. Implementation Challenges and Solutions with Developing the OEI Data Portal

Challenge	Description	Resolution
PDSA Cycle 1 Challenges		
Non-applicable questions	Concerns were raised about the fact that certain questions, such as home safety issues, do not always apply, so the question is left incomplete.	Added "none of the above apply" response option.
Missing data	In some cases, participants were not enrolled in Medicaid and therefore did not have a Medicaid identification number.	Instruction was included to leave the Medicaid identification field blank, rather than entering insurance identifiers for other insurance types.
Structural issues	A few programs – specifically, those that have CHWs completing care coordination and service connection tasks – provide services to people who are not either pregnant or recent parents.	A question was added to an updated Encounter form assessing whether the participant was pregnant or was a parent of an infant.
Incomplete legacy data collection systems	Many CBOs use the Care Coordination System (CCS)[a] to collect data, export this data to a spreadsheet, and submit it.	The CBOs were asked to export all CCS variables instead of only a subset so the maximum amount of data can be used for the OEI evaluation.
PDSA Cycle 2 Challenges		
Data collection inconsistent with workflow	Some programs, especially CHW programs, only see clients once and do not collect detailed demographic data, as their encounters are designed to quickly connect people to community resources.	A modified Encounter form with more data fields was provided to collect limited demographic information (eg, race, employment, and marital status) better suited to brief interactions.
Health literacy	Participant health literacy may limit ability to understand and answer questions on intake forms.	The CBOs were asked to assist participants in answering questions on forms and explain questions that may not be understood.
PDSA Cycle 3 Challenges		
Reluctance to provide answer to sensitive question	Participant hesitant to answer questions due to concerns about loss of benefits and services.	The CBOs were asked to collect this information on second or third visit to allow for greater trust, comfort and familiarity with CBO.
Concerns about use of the data	The CBOs expressed concern that some population subgroups may be concerned that the data will be reported to the federal government and therefore may be unwilling to give information.	Added disclaimer to data collection forms that the data is only for quality improvement purposes and will not be reported to the federal government.
Misalignment of data collection mode with workflow	CHWs and home visitors that are in the community cannot submit data during patient interactions given current technological approaches to data submission.	The OEI evaluation team has begun developing a mobile application to submit data.

Notes:[a]The Care Coordination System (CCS) is a legacy data collection system used for reporting data from CHW programs to Ohio Department of Medicaid.
OEI = Ohio Equity Institute; PDSA = Plan-Do-Study-Act; CBO = community-based organization; CHW = community health worker.

fields were complete and 33 CBOs reported data, but by the end of PDSA Cycle 3 this metric had improved to 55% of data fields complete for 58 CBOs. Thus, while the percent of complete data increased only slightly, the number of CBOs capable of reporting data increased substantially.

DISCUSSION

Community-based organizations are increasingly important providers of health education and can expand the capacity of health care organizations and government agencies to address social determinants of health. These agencies provide a wealth of services to communities, yet, given their funding structures, they frequently lack the resources to develop robust data collection and evaluation infrastructures. To this end, we developed the OEI Data Portal to evaluate 3 evidence-based interventions aimed at reducing disparities in infant mortality across the state of Ohio. Our PDSA process was able to identify, document, and redress several technical and implementation challenges in order to support data reporting. This case study provides insight for other efforts that seek to capture data across CBOs providing similar interventions for evaluation purposes.

Importance of Building Relationships

Our PDSA cycles highlight the need for ongoing relationships with CBOs in order to understand both their technical capacities and workflows in order to ensure high-quality data collection. For instance, many of the initial technical challenges that were identified related to a lack of familiarity of the OEI evaluation team with the specific needs and experiences of the CBOs, and they were resolved through engagement between the CBOs and the evaluation team. Similarly, the implementation challenges often resulted from a mismatch between the data collection forms and data entry process with the actual workflows of the CBOs. The ongoing communication and relationship between the OEI evaluation team and the CBOs facilitated by the PDSA process helped to identify and resolve these issues.

Engaging with the CBOs further required responding to their data submission preferences. A strength of the OEI Data Portal is its flexibility in this regard, as we offered a number of technologies to collect data: direct data entry, paper forms and fax, and data uploads of extracted files from other systems. While the preference for the majority of CBOs was direct data entry via the OEI Data Portal, CBOs affiliated with health care organizations preferred to deliver data via the upload of a data file.

These engagement efforts resolved immediate challenges CBOs reported with providing data to a common system, but also resulted in more complete and accurate data collection. The experience of having their data collection and entry needs met, and seeing more complete and accurate data through the development of the data collection system, can increase CBOs' trust in the evaluation team and process, which is critical in successful community-based efforts.[42,43]

Augmenting CBO-Provided Data

While CBO-provided data allowed us to understand participation in the 3 evidence-based interventions examined, both ODM and the CBOs seek to evaluate the impact of participation in the OEI interventions on infant mortality and low birth weight. This analysis requires matching information about patient use of the OEI interventions from the OEI Data Portal to information about birth outcomes and deaths from the state vital statistics records. Adding complexity to this issue is that some CBOs, such as the home visiting programs, submit data to OCHIDS, a separate and distinct system from the OEI Data Portal created by ODH to collect data from selected home visiting programs. The need to match data from the OEI Data Portal with other sources underscores the necessity of building a reliable data collection system. As programs such as Partnership for Healthy Outcomes[7] and the Robert Wood Johnson Foundation's Culture of Health[8] expand collaborations between CBOs and health care organizations, leveraging existing data collection and stakeholder-informed data collection such as our OEI Data Portal can facilitate a more comprehensive evaluation process.

Moving forward, state sponsors of CBOs may consider efforts to integrate data collection systems across multiple projects. Many existing state-based efforts to coordinate the exchange of health information across the state rely on community health information exchanges (HIEs) or regional health information organizations. However, HIEs are typically designed to facilitate exchange of health information between health care providers and are not optimized to the needs of CBOs. Further, HIEs are rarely oriented toward evaluation.[44] Nonetheless, leveraging the existing HIE infrastructure may offer states a potential shortcut to creating repositories of CBO data. The lessons we report in this case study of the OEI Data Portal could help in any efforts to adapt HIE platforms to the needs of CBOs.

Limitations

This study is subject to some important limitations. First, all the CBOs funded by OEI were selected in part due to their willingness to submit required data, potentially resulting in a sample of CBOs more prone toward accommodating reporting and evaluation requests. Second, the OEI experience may be specific to the state of Ohio, and, as a result, our findings may not be generalizable in different states with different regulatory and funding structures. Building a robust evaluation infrastructure and capturing high-quality data is a necessary first step prior to conducting any outcome evaluation. Future work will focus on evaluating the impact of the interventions on the specific outcomes of interest—infant mortality and low birth weight.

PUBLIC HEALTH IMPLICATIONS

Infant mortality is a complex problem impacting communities in Ohio, and multiple programs have been developed to reduce the risk of poor infant and maternal outcomes. Due to varying program designs, levels of data collection, and small program sizes, it is hard to assess the impact of individual programs on outcomes. The OEI can serve as a model for data collection from many similar CBO delivered programs across the state to enable evaluation of these efforts. Individual CBOs experienced technical and implementation challenges when starting to use the new data collection system. However, building relationships between CBOs and the evaluation team and providing training resulted in improved data quality and increased the number of organizations reporting data over the first year of data collection system implementation.

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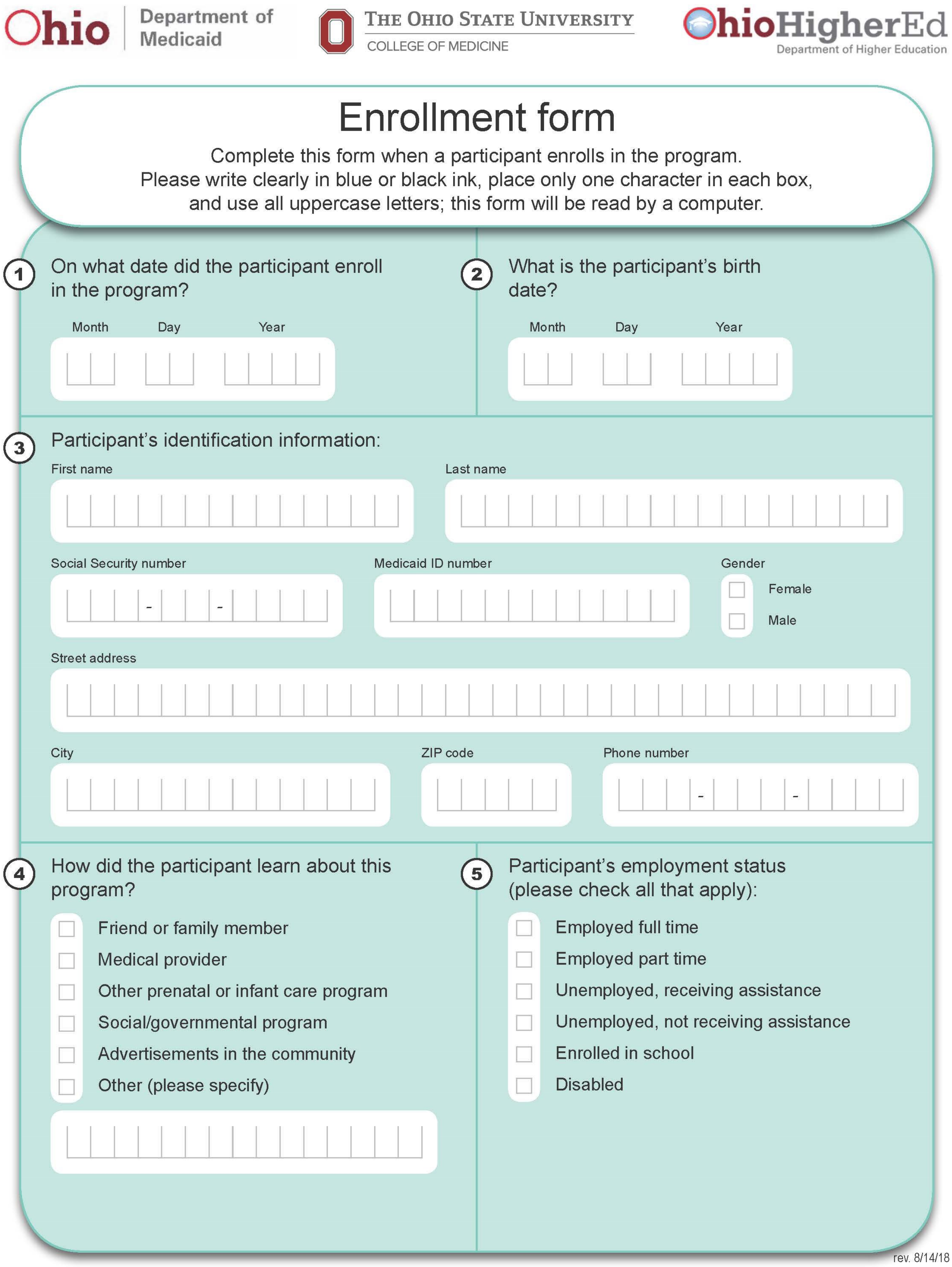
APPENDIX. Data Collection Forms



Ohio Department of Medicaid
The Ohio State University College of Medicine
OhioHigherEd Department of Higher Education

Enrollment form

Complete this form when a participant enrolls in the program.
Please write clearly in blue or black ink, place only one character in each box,
and use all uppercase letters; this form will be read by a computer.

① On what date did the participant enroll in the program?

Month Day Year

② What is the participant's birth date?

Month Day Year

③ Participant's identification information:

First name

Last name

Social Security number - -

Medicaid ID number

Gender
☐ Female
☐ Male

Street address

City

ZIP code

Phone number - -

④ How did the participant learn about this program?

☐ Friend or family member
☐ Medical provider
☐ Other prenatal or infant care program
☐ Social/governmental program
☐ Advertisements in the community
☐ Other (please specify)

⑤ Participant's employment status (please check all that apply):

☐ Employed full time
☐ Employed part time
☐ Unemployed, receiving assistance
☐ Unemployed, not receiving assistance
☐ Enrolled in school
☐ Disabled

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Enrollment

Page 2 of 4

Participant's last name and birth date

Month Day Year

⑥ Participant's marital status:

☐ Married
☐ Widowed
☐ Divorced
☐ Separated
☐ Single/never married
☐ Not married but living with partner

⑦ Current relationship between participant and other biological parent:

☐ Married
☐ Widowed
☐ Divorced
☐ Separated
☐ Never married

⑧ Living status between participant and other biological parent:

☐ Living together ☐ Not living together

If you marked living together, you may skip the address fields in the section at the bottom of this page. If not, complete these fields.

⑨ Other biological parent's birth date:

Month Day Year

⑩ Participant's race/ethnicity (please check all that apply):

☐ White
☐ Black or African American
☐ Hispanic or Latino
☐ Asian
☐ Native Hawaiian or Pacific Islander
☐ American Indian or Alaska Native
☐ Other (please specify)

⑪ Other biological parent's race/ethnicity (please check all that apply):

☐ White
☐ Black or African American
☐ Hispanic or Latino
☐ Asian
☐ Native Hawaiian or Pacific Islander
☐ American Indian or Alaska Native
☐ Other (please specify)

⑫ Other biological parent's identification information:

First name

Last name

Street address

City

ZIP code

Phone number - -

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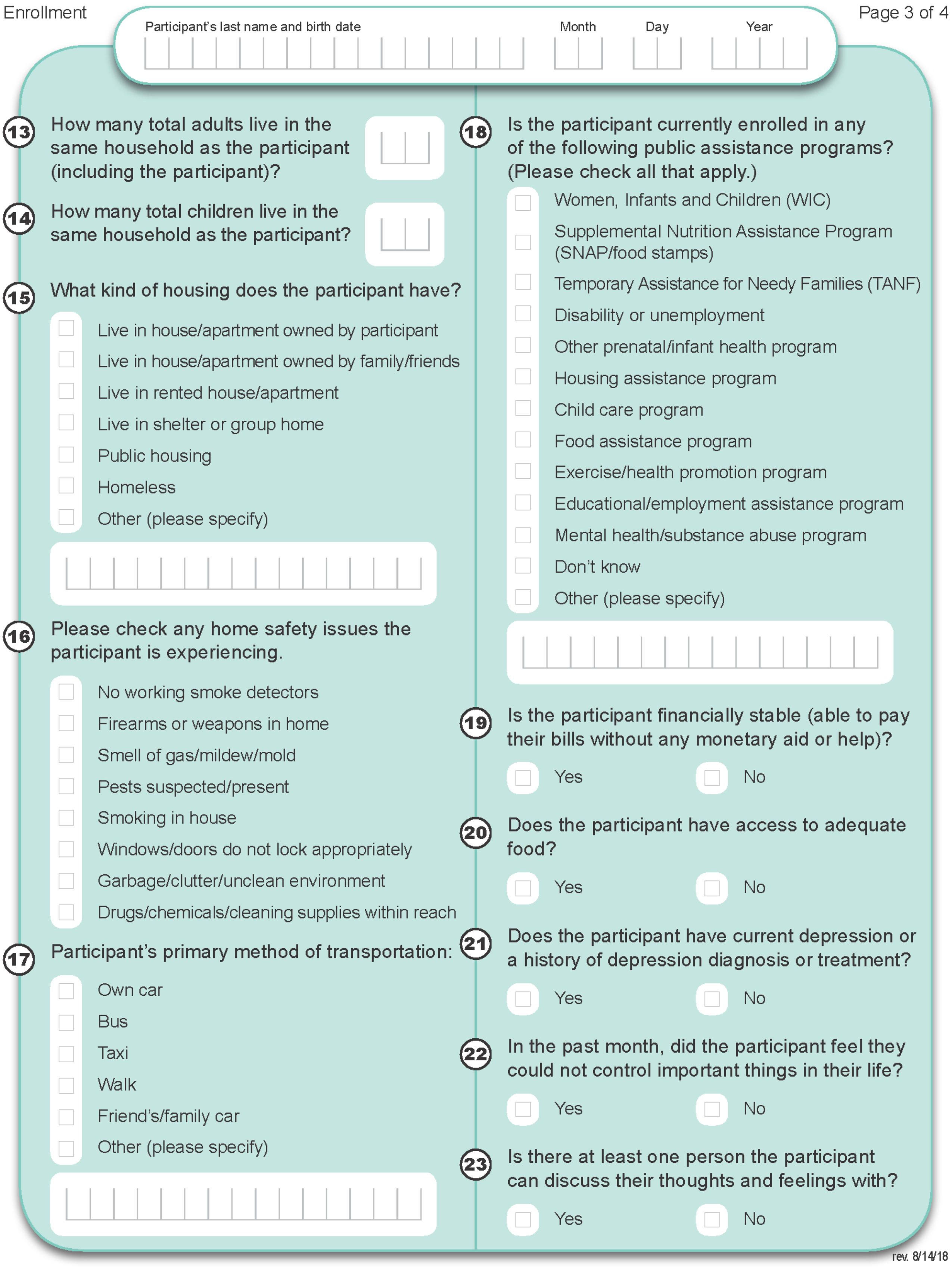

Enrollment

Participant's last name and birth date | Month | Day | Year

Page 3 of 4

⑬ How many total adults live in the same household as the participant (including the participant)? ☐☐

⑭ How many total children live in the same household as the participant? ☐☐

⑮ What kind of housing does the participant have?

- ☐ Live in house/apartment owned by participant
- ☐ Live in house/apartment owned by family/friends
- ☐ Live in rented house/apartment
- ☐ Live in shelter or group home
- ☐ Public housing
- ☐ Homeless
- ☐ Other (please specify)

⑯ Please check any home safety issues the participant is experiencing.

- ☐ No working smoke detectors
- ☐ Firearms or weapons in home
- ☐ Smell of gas/mildew/mold
- ☐ Pests suspected/present
- ☐ Smoking in house
- ☐ Windows/doors do not lock appropriately
- ☐ Garbage/clutter/unclean environment
- ☐ Drugs/chemicals/cleaning supplies within reach

⑰ Participant's primary method of transportation:

- ☐ Own car
- ☐ Bus
- ☐ Taxi
- ☐ Walk
- ☐ Friend's/family car
- ☐ Other (please specify)

⑱ Is the participant currently enrolled in any of the following public assistance programs? (Please check all that apply.)

- ☐ Women, Infants and Children (WIC)
- ☐ Supplemental Nutrition Assistance Program (SNAP/food stamps)
- ☐ Temporary Assistance for Needy Families (TANF)
- ☐ Disability or unemployment
- ☐ Other prenatal/infant health program
- ☐ Housing assistance program
- ☐ Child care program
- ☐ Food assistance program
- ☐ Exercise/health promotion program
- ☐ Educational/employment assistance program
- ☐ Mental health/substance abuse program
- ☐ Don't know
- ☐ Other (please specify)

⑲ Is the participant financially stable (able to pay their bills without any monetary aid or help)?

☐ Yes ☐ No

⑳ Does the participant have access to adequate food?

☐ Yes ☐ No

㉑ Does the participant have current depression or a history of depression diagnosis or treatment?

☐ Yes ☐ No

㉒ In the past month, did the participant feel they could not control important things in their life?

☐ Yes ☐ No

㉓ Is there at least one person the participant can discuss their thoughts and feelings with?

☐ Yes ☐ No

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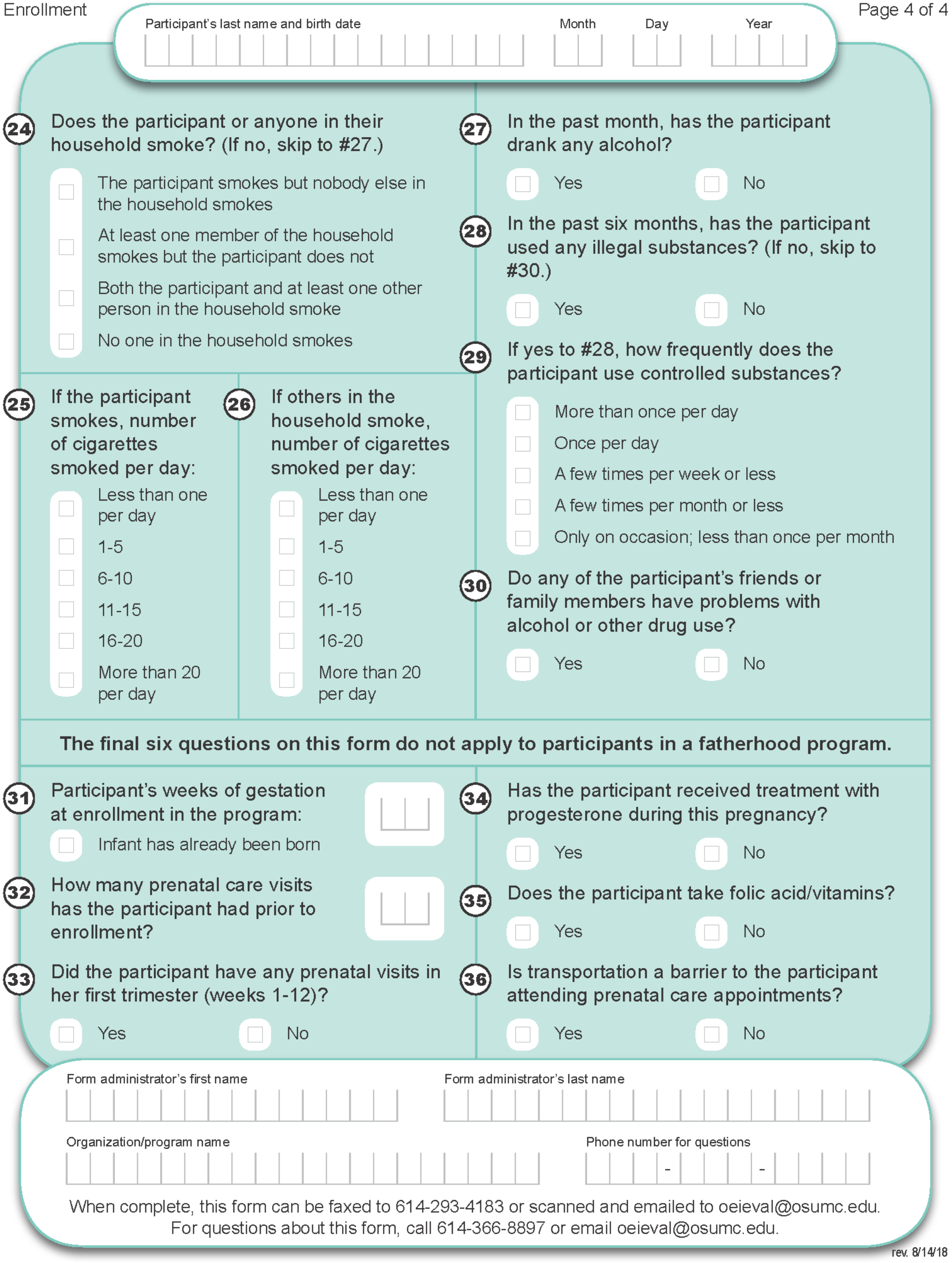

Enrollment

Participant's last name and birth date Month Day Year

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㉔ Does the participant or anyone in their household smoke? (If no, skip to #27.)

☐ The participant smokes but nobody else in the household smokes
☐ At least one member of the household smokes but the participant does not
☐ Both the participant and at least one other person in the household smoke
☐ No one in the household smokes

㉕ If the participant smokes, number of cigarettes smoked per day:

☐ Less than one per day
☐ 1-5
☐ 6-10
☐ 11-15
☐ 16-20
☐ More than 20 per day

㉖ If others in the household smoke, number of cigarettes smoked per day:

☐ Less than one per day
☐ 1-5
☐ 6-10
☐ 11-15
☐ 16-20
☐ More than 20 per day

㉗ In the past month, has the participant drank any alcohol?

☐ Yes ☐ No

㉘ In the past six months, has the participant used any illegal substances? (If no, skip to #30.)

☐ Yes ☐ No

㉙ If yes to #28, how frequently does the participant use controlled substances?

☐ More than once per day
☐ Once per day
☐ A few times per week or less
☐ A few times per month or less
☐ Only on occasion; less than once per month

㉚ Do any of the participant's friends or family members have problems with alcohol or other drug use?

☐ Yes ☐ No

The final six questions on this form do not apply to participants in a fatherhood program.

㉛ Participant's weeks of gestation at enrollment in the program:

☐ Infant has already been born

㉜ How many prenatal care visits has the participant had prior to enrollment?

㉝ Did the participant have any prenatal visits in her first trimester (weeks 1-12)?

☐ Yes ☐ No

㉞ Has the participant received treatment with progesterone during this pregnancy?

☐ Yes ☐ No

㉟ Does the participant take folic acid/vitamins?

☐ Yes ☐ No

(36) Is transportation a barrier to the participant attending prenatal care appointments?

☐ Yes ☐ No

Form administrator's first name

Form administrator's last name

Organization/program name

Phone number for questions - -

When complete, this form can be faxed to 614-293-4183 or scanned and emailed to oeieval@osumc.edu.
For questions about this form, call 614-366-8897 or email oeieval@osumc.edu.

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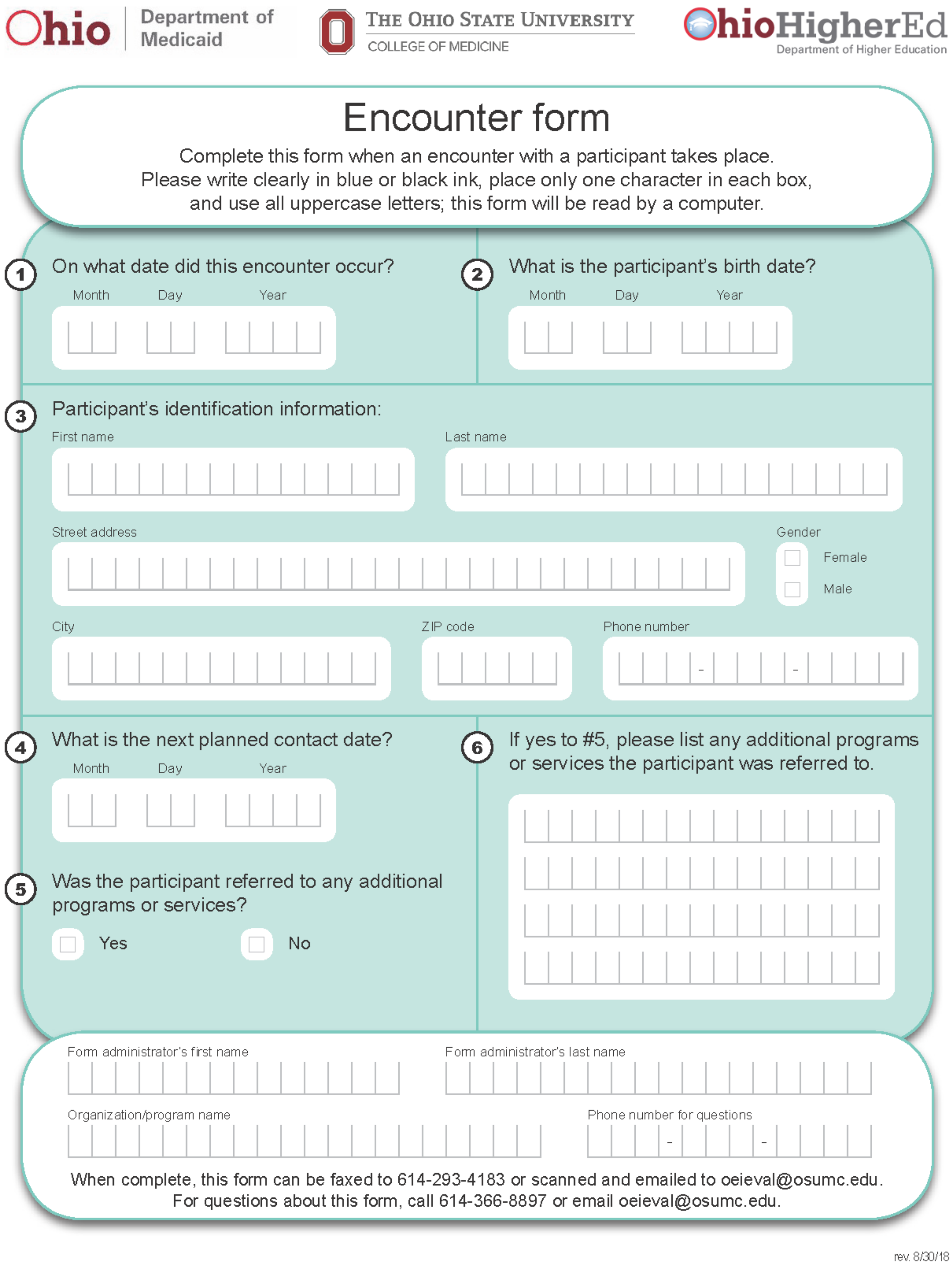

Ohio Department of Medicaid

The Ohio State University College of Medicine

Ohio Higher Ed Department of Higher Education

Encounter form

Complete this form when an encounter with a participant takes place.
Please write clearly in blue or black ink, place only one character in each box,
and use all uppercase letters; this form will be read by a computer.

① On what date did this encounter occur?

Month Day Year

② What is the participant's birth date?

Month Day Year

③ Participant's identification information:

First name

Last name

Street address

Gender

☐ Female

☐ Male

City

ZIP code

Phone number

④ What is the next planned contact date?

Month Day Year

⑤ Was the participant referred to any additional programs or services?

☐ Yes ☐ No

⑥ If yes to #5, please list any additional programs or services the participant was referred to.

Form administrator's first name

Form administrator's last name

Organization/program name

Phone number for questions

When complete, this form can be faxed to 614-293-4183 or scanned and emailed to oeieval@osumc.edu.
For questions about this form, call 614-366-8897 or email oeieval@osumc.edu.

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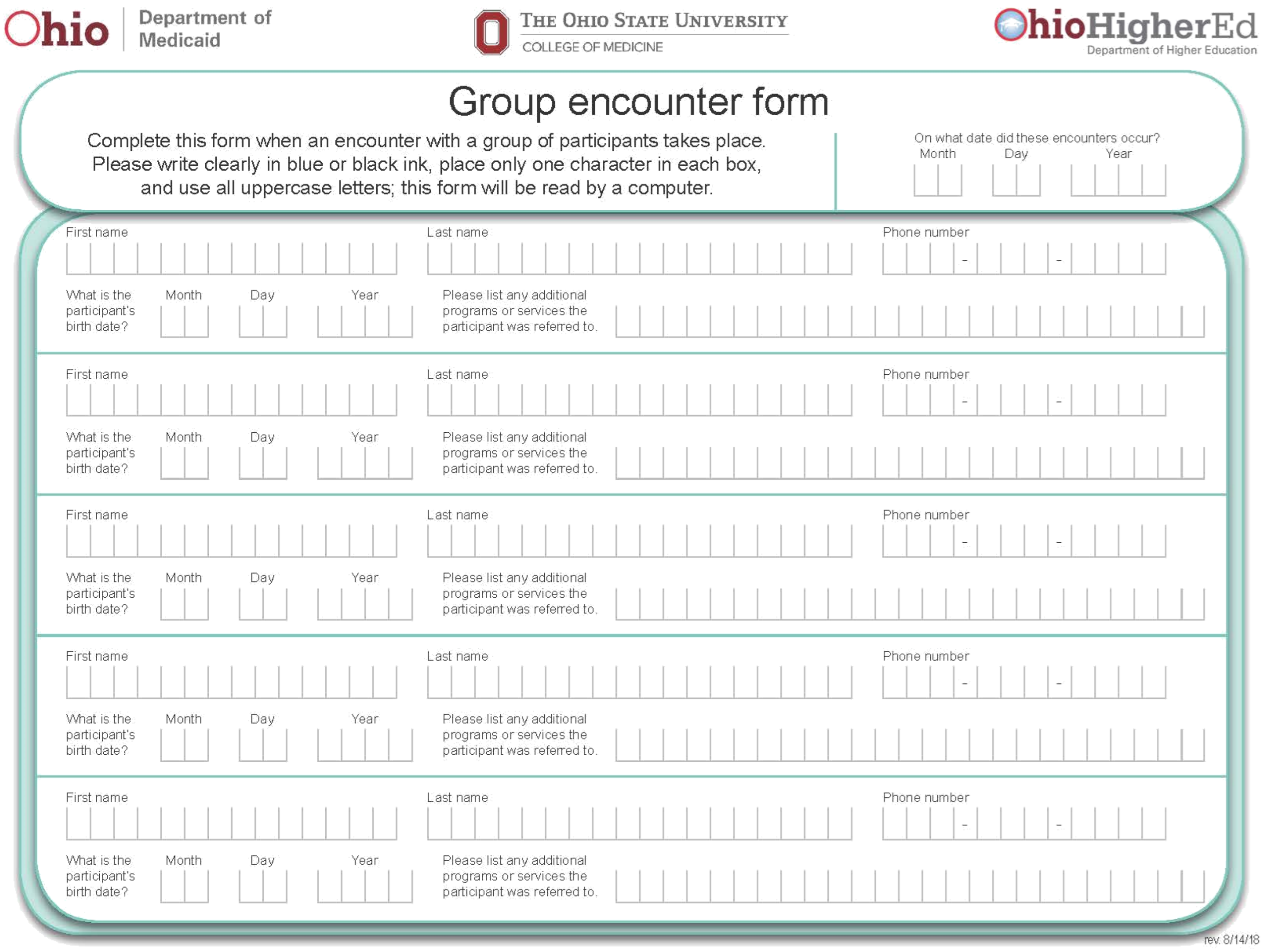


Ohio | Department of Medicaid

THE OHIO STATE UNIVERSITY
COLLEGE OF MEDICINE

OhioHigherEd
Department of Higher Education

Group encounter form

Complete this form when an encounter with a group of participants takes place.
Please write clearly in blue or black ink, place only one character in each box,
and use all uppercase letters; this form will be read by a computer.

On what date did these encounters occur?
Month Day Year

First name
Last name
Phone number - -
What is the participant's birth date? Month Day Year
Please list any additional programs or services the participant was referred to.

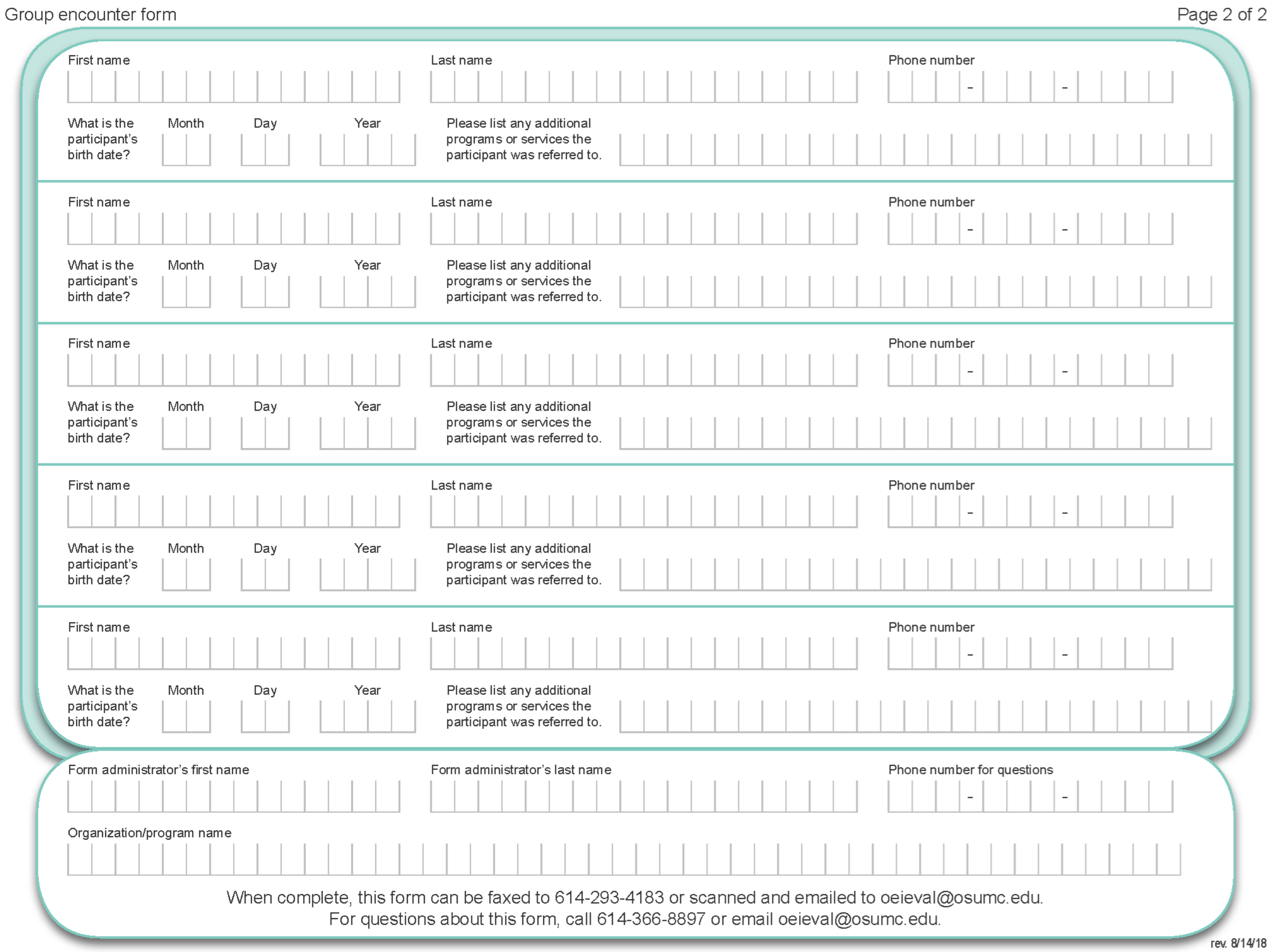
First name
Last name
Phone number - -
What is the participant's birth date? Month Day Year
Please list any additional programs or services the participant was referred to.

First name
Last name
Phone number - -
What is the participant's birth date? Month Day Year
Please list any additional programs or services the participant was referred to.

First name
Last name
Phone number - -
What is the participant's birth date? Month Day Year
Please list any additional programs or services the participant was referred to.

First name
Last name
Phone number - -
What is the participant's birth date? Month Day Year
Please list any additional programs or services the participant was referred to.

rev. 8/14/18



Group encounter form

Page 2 of 2

First name
Last name
Phone number - -
What is the participant's birth date? Month Day Year
Please list any additional programs or services the participant was referred to.

First name
Last name
Phone number - -
What is the participant's birth date? Month Day Year
Please list any additional programs or services the participant was referred to.

First name
Last name
Phone number - -
What is the participant's birth date? Month Day Year
Please list any additional programs or services the participant was referred to.

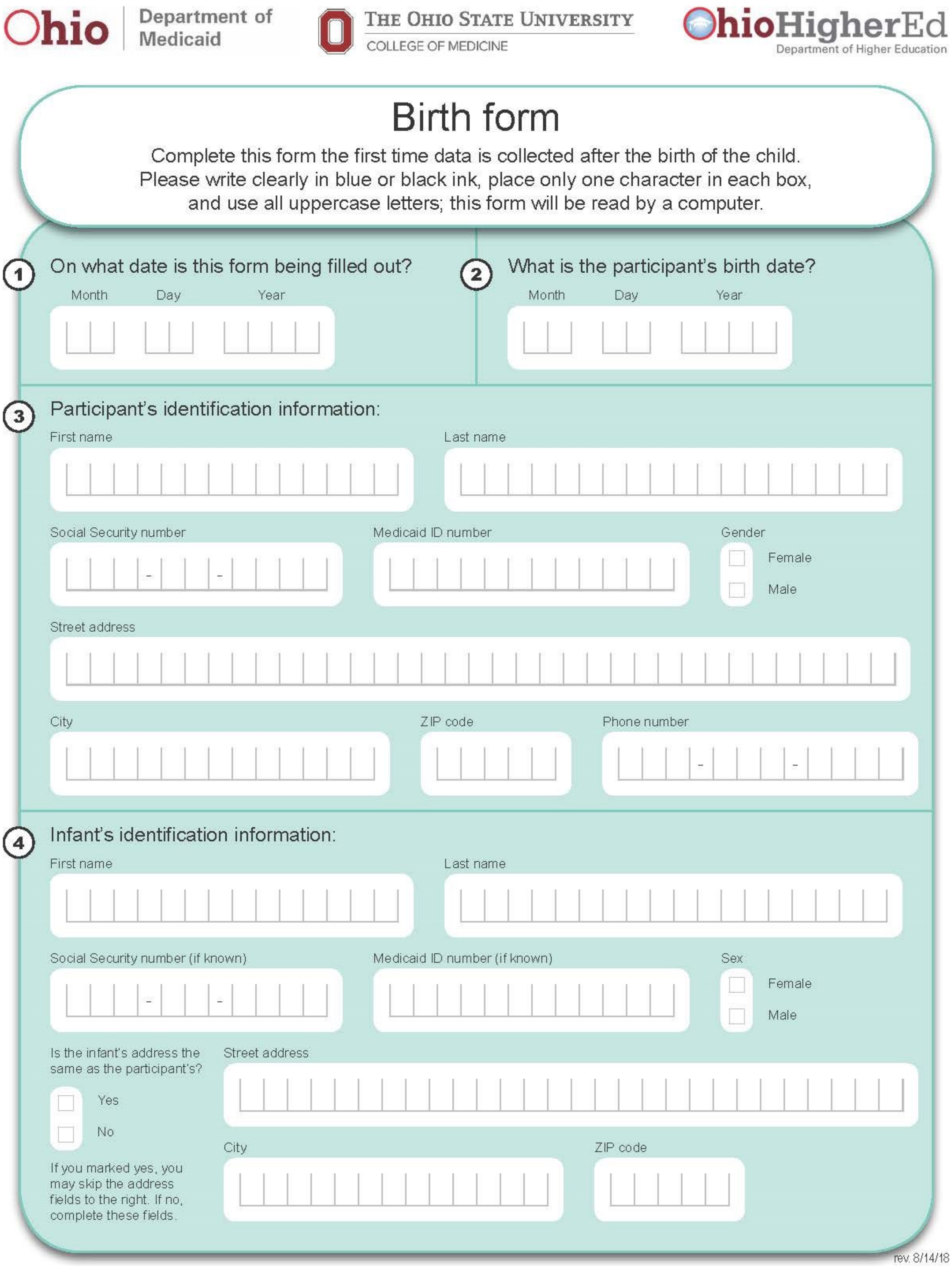
First name
Last name
Phone number - -
What is the participant's birth date? Month Day Year
Please list any additional programs or services the participant was referred to.

First name
Last name
Phone number - -
What is the participant's birth date? Month Day Year
Please list any additional programs or services the participant was referred to.

Form administrator's first name
Form administrator's last name
Phone number for questions - -
Organization/program name

When complete, this form can be faxed to 614-293-4183 or scanned and emailed to oeieval@osumc.edu.
For questions about this form, call 614-366-8897 or email oeieval@osumc.edu.

rev. 8/14/18



Ohio | Department of Medicaid
THE OHIO STATE UNIVERSITY
COLLEGE OF MEDICINE
OhioHigherEd
Department of Higher Education

Birth form

Complete this form the first time data is collected after the birth of the child. Please write clearly in blue or black ink, place only one character in each box, and use all uppercase letters; this form will be read by a computer.

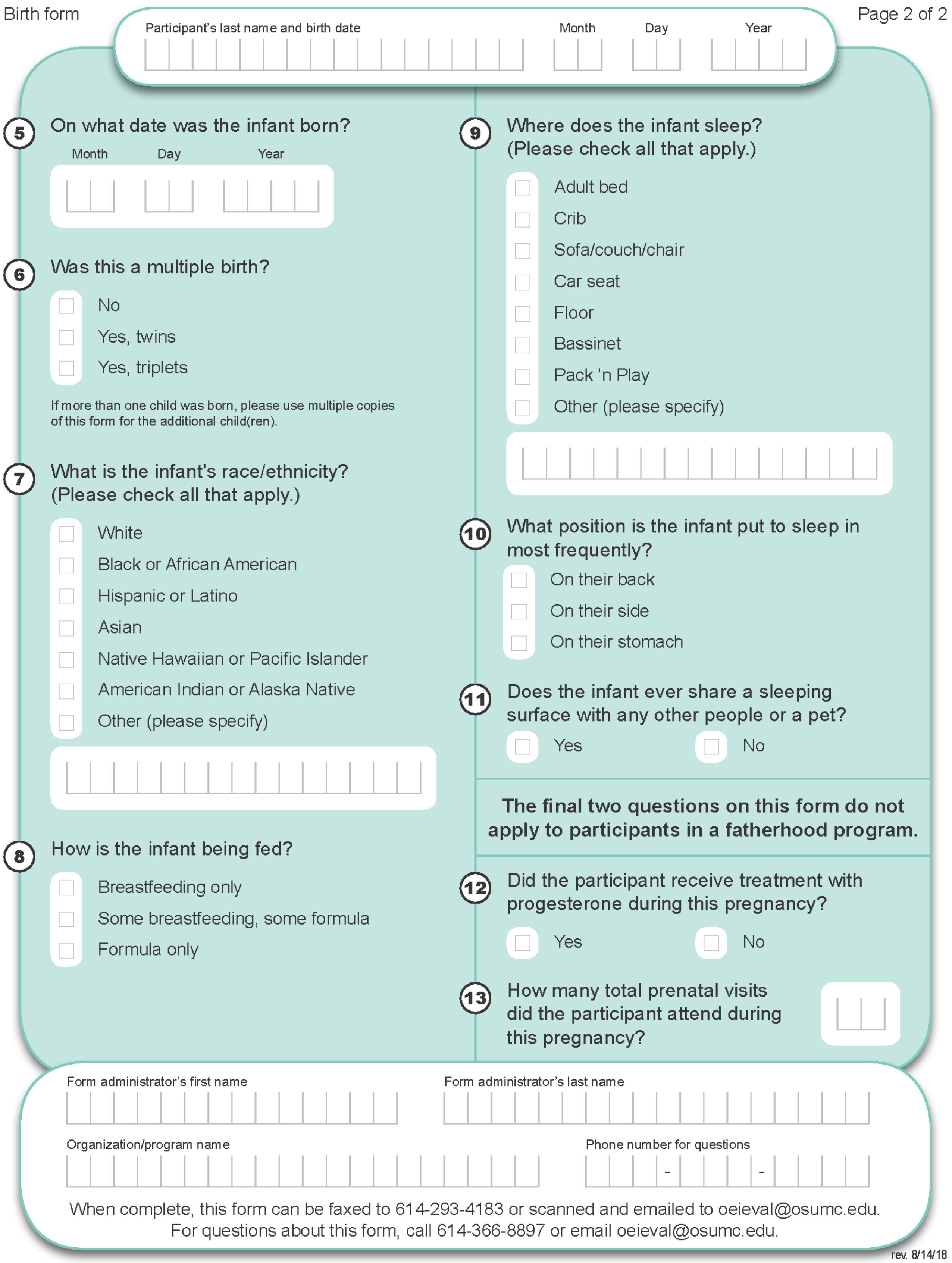
① On what date is this form being filled out?
Month Day Year

② What is the participant's birth date?
Month Day Year

③ Participant's identification information:
First name
Last name
Social Security number - -
Medicaid ID number
Gender
☐ Female
☐ Male
Street address
City
ZIP code
Phone number - -

④ Infant's identification information:
First name
Last name
Social Security number (if known) - -
Medicaid ID number (if known)
Sex
☐ Female
☐ Male
Is the infant's address the same as the participant's?
☐ Yes
☐ No
If you marked yes, you may skip the address fields to the right. If no, complete these fields.
Street address
City
ZIP code

rev. 8/14/18



Birth form

Page 2 of 2

Participant's last name and birth date | Month | Day | Year

⑤ On what date was the infant born?

Month | Day | Year

⑥ Was this a multiple birth?

- ☐ No
- ☐ Yes, twins
- ☐ Yes, triplets

If more than one child was born, please use multiple copies of this form for the additional child(ren).

⑦ What is the infant's race/ethnicity? (Please check all that apply.)

- ☐ White
- ☐ Black or African American
- ☐ Hispanic or Latino
- ☐ Asian
- ☐ Native Hawaiian or Pacific Islander
- ☐ American Indian or Alaska Native
- ☐ Other (please specify)

⑧ How is the infant being fed?

- ☐ Breastfeeding only
- ☐ Some breastfeeding, some formula
- ☐ Formula only

⑨ Where does the infant sleep? (Please check all that apply.)

- ☐ Adult bed
- ☐ Crib
- ☐ Sofa/couch/chair
- ☐ Car seat
- ☐ Floor
- ☐ Bassinet
- ☐ Pack 'n Play
- ☐ Other (please specify)

⑩ What position is the infant put to sleep in most frequently?

- ☐ On their back
- ☐ On their side
- ☐ On their stomach

⑪ Does the infant ever share a sleeping surface with any other people or a pet?

☐ Yes ☐ No

The final two questions on this form do not apply to participants in a fatherhood program.

⑫ Did the participant receive treatment with progesterone during this pregnancy?

☐ Yes ☐ No

⑬ How many total prenatal visits did the participant attend during this pregnancy?

Form administrator's first name

Form administrator's last name

Organization/program name

Phone number for questions - -

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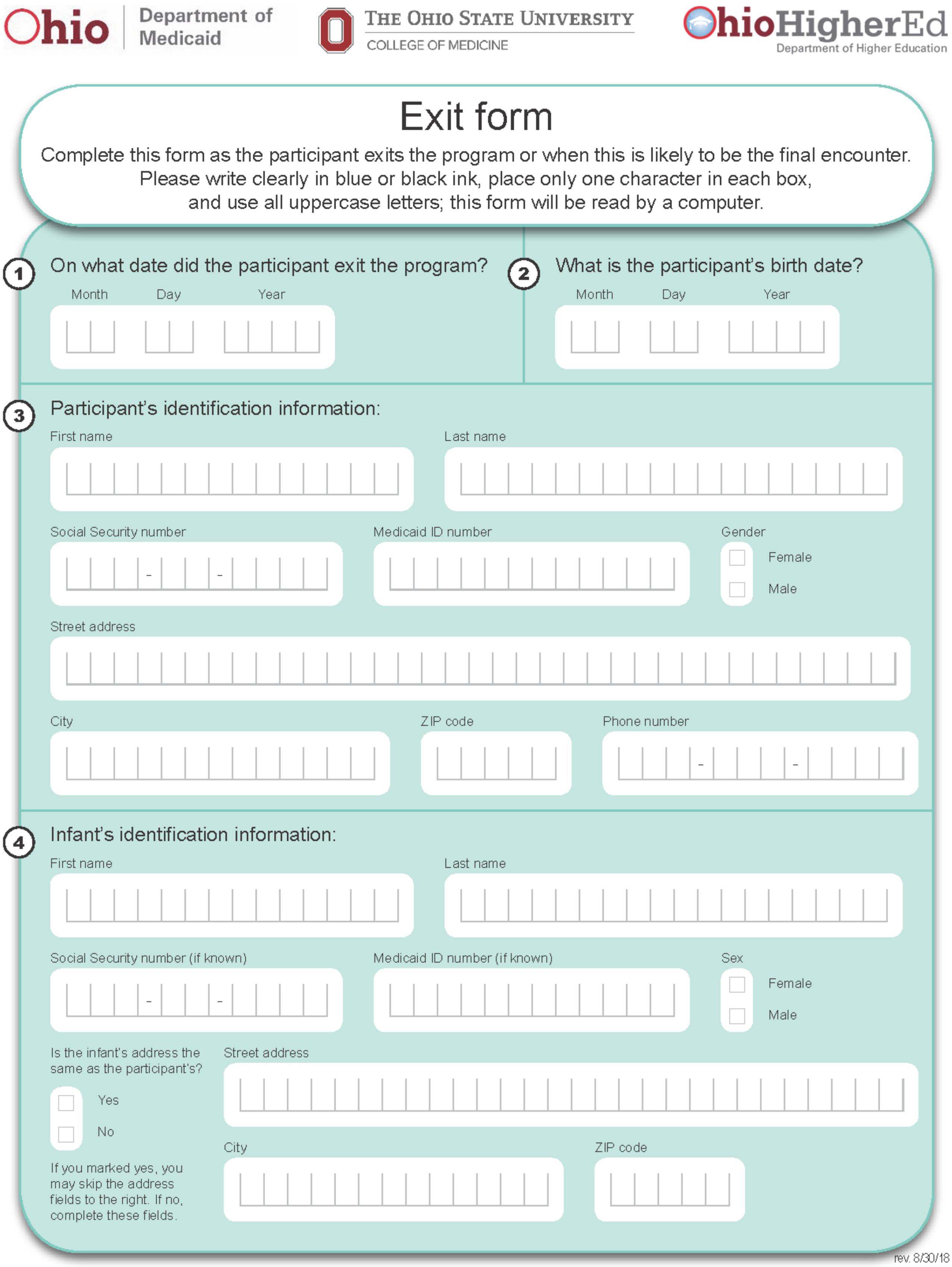
For questions about this form, call 614-366-8897 or email oeieval@osumc.edu.

rev. 8/14/18



Ohio Department of Medicaid
The Ohio State University
College of Medicine
OhioHigherEd
Department of Higher Education

Exit form

Complete this form as the participant exits the program or when this is likely to be the final encounter. Please write clearly in blue or black ink, place only one character in each box, and use all uppercase letters; this form will be read by a computer.

① On what date did the participant exit the program?

Month Day Year

② What is the participant's birth date?

Month Day Year

③ Participant's identification information:

First name

Last name

Social Security number - -

Medicaid ID number

Gender

☐ Female

☐ Male

Street address

City

ZIP code

Phone number - -

④ Infant's identification information:

First name

Last name

Social Security number (if known) - -

Medicaid ID number (if known)

Sex

☐ Female

☐ Male

Is the infant's address the same as the participant's?

☐ Yes

☐ No

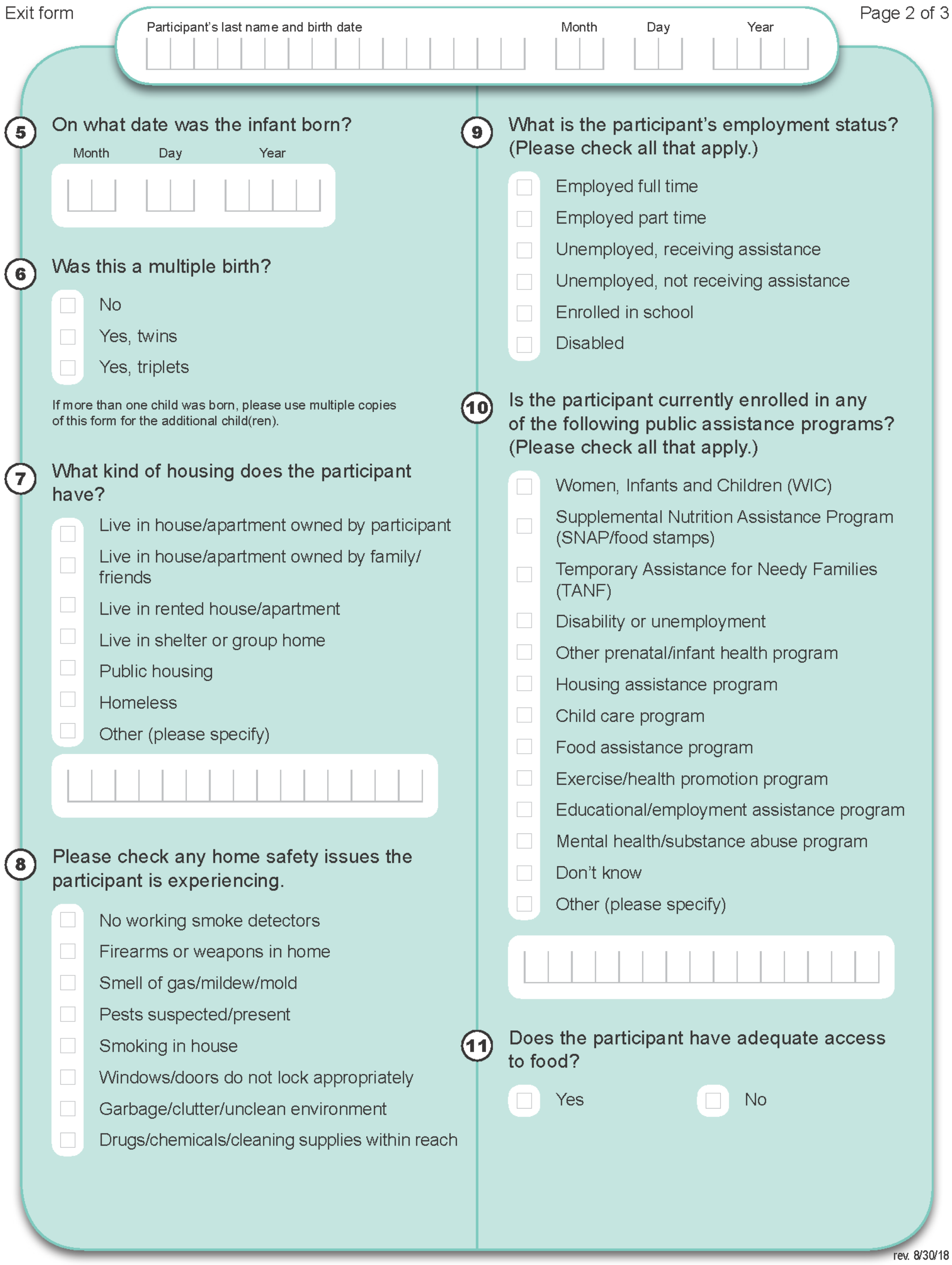
If you marked yes, you may skip the address fields to the right. If no, complete these fields.

Street address

City

ZIP code

rev. 8/30/18



Exit form

Participant's last name and birth date Month Day Year

Page 2 of 3

⑤ On what date was the infant born?

Month Day Year

⑥ Was this a multiple birth?

- ☐ No
- ☐ Yes, twins
- ☐ Yes, triplets

If more than one child was born, please use multiple copies of this form for the additional child(ren).

⑦ What kind of housing does the participant have?

- ☐ Live in house/apartment owned by participant
- ☐ Live in house/apartment owned by family/ friends
- ☐ Live in rented house/apartment
- ☐ Live in shelter or group home
- ☐ Public housing
- ☐ Homeless
- ☐ Other (please specify)

⑧ Please check any home safety issues the participant is experiencing.

- ☐ No working smoke detectors
- ☐ Firearms or weapons in home
- ☐ Smell of gas/mildew/mold
- ☐ Pests suspected/present
- ☐ Smoking in house
- ☐ Windows/doors do not lock appropriately
- ☐ Garbage/clutter/unclean environment
- ☐ Drugs/chemicals/cleaning supplies within reach

⑨ What is the participant's employment status? (Please check all that apply.)

- ☐ Employed full time
- ☐ Employed part time
- ☐ Unemployed, receiving assistance
- ☐ Unemployed, not receiving assistance
- ☐ Enrolled in school
- ☐ Disabled

⑩ Is the participant currently enrolled in any of the following public assistance programs? (Please check all that apply.)

- ☐ Women, Infants and Children (WIC)
- ☐ Supplemental Nutrition Assistance Program (SNAP/food stamps)
- ☐ Temporary Assistance for Needy Families (TANF)
- ☐ Disability or unemployment
- ☐ Other prenatal/infant health program
- ☐ Housing assistance program
- ☐ Child care program
- ☐ Food assistance program
- ☐ Exercise/health promotion program
- ☐ Educational/employment assistance program
- ☐ Mental health/substance abuse program
- ☐ Don't know
- ☐ Other (please specify)

⑪ Does the participant have adequate access to food?

☐ Yes ☐ No

rev. 8/30/18

Exit form

Page 3 of 3

Participant's last name and birth date ______ Month ____ Day ____ Year ____

12 How many well-child medical visits did the participant and child attend to check on the child's heath? ____

13 How many ER/urgent care visits were attended for the child or participant since the child's birth? ____

14 If the answer to #13 was more than zero, what were the reasons for the visit/visits?

15 Has the child received recommended immunizations?

☐ Yes ☐ No

16 When the participant is away from home, where does the child or children go for child care?

☐ Family
☐ Friends
☐ Licensed child care provider
☐ Other (please specify)

The final two questions on this form do not apply to participants in a fatherhood program.

17 How many postpartum medical visits did the mother attend to check on her health? ____

18 Is the father involved in the care of the infant?

☐ Yes ☐ No

Form administrator's first name ______

Form administrator's last name ______

Organization/program name ______

Phone number for questions ___ - ___ - ____

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RESEARCH ARTICLE

Health Disparities Among Sexual and Gender Minority Adults in Ohio

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ABSTRACT

Background: Many documented disparities associated with health behaviors and access to health care impact the health outcomes of sexual and gender minorities (SGM). The current study aimed to gain insight into the health disparities experienced by SGM adults living in Ohio to obtain data to plan future health-related programs.

Methods: A secondary data analysis was conducted using 2018 Ohio Behavior Risk Factor Surveillance System (BRFSS) data. Health behaviors, health care access, and health outcomes were analyzed by sexual orientation (n=11 301) and gender identity (n=11 426) to determine health disparities faced by sexual minority males, sexual minority females and transgender individuals.

Results: Significant SGM health disparities in Ohio are related to substance use (ie, binge drinking, current smoking status, e-cigarette use, and marijuana use); poor physical and mental health status; lack of health care coverage; and experiencing COPD, emphysema, or chronic bronchitis (all $p < 0.001$). In addition, fewer sexual minority females reported being within recommended breast cancer screening guidelines than heterosexual females ($p < 0.05$).

Conclusion: Sexual and gender minority adults in Ohio report disparities associated with several health behaviors and access to health care. These findings may be due to factors at the patient level (eg, experiencing minority stress), provider level (eg, implicit bias), system level (eg, discrimination), and/or society level (eg, lack of legal protections). Study results will be used to plan health campaigns and programs targeted to SGM adults and providers to achieve health equity for the SGM population in Ohio.

Keywords: Sexual and gender minorities; Health status disparities; Health behavior; Substance-related disorders; BRFSS; Secondary analysis

INTRODUCTION

Sexual and gender minorities (SGM) in the United States (US) are disproportionately impacted by many disparities that can negatively impact health outcomes. Some health behaviors are well-established as being disproportionately high among SGM, such as smoking, heavy alcohol consumption, not attaining enough sleep, not exercising within recommended guidelines, and not using certain preventive health screenings.[1-4] For example, sexual minority (SM) women are less likely to utilize cervical cancer screenings (eg, the Papanicolaou test).[2-4] Sexual and gender minorities report they often avoid utilizing health care due to anticipated discrimination.[5]

There are also numerous adverse health outcomes that disproportionately impact SGM, such as having a normal body weight being less prevalent among SM women than heterosexual women.[1,6] Disparities have also been documented for physical health symptoms (eg, pain, insomnia) and physical health conditions (eg, diabetes, asthma, hypertension, cancer, and stroke).[6,7] In contrast, other studies found no significant differences in disease diagnoses including hypertension, diabetes, high cholesterol, or heart disease.[8,9] Sexual minorities are also disproportionately impacted by mental health disparities such as having a higher prevalence of a major depressive episode and generalized anxiety disorder compared to their heterosexual peers.[10]

Despite the growing body of evidence documenting SGM health disparities in the US, important gaps in public health professionals' knowledge persist. For example, marijuana and e-cigarette use is currently rising in popularity in the general population with limited information available about its use among SGMs.[11,12] Public health professionals also need more information about SGM's health care coverage, their utilization of preventive health screenings, and their ability to access health care. These health-related issues and others may contribute to the disparities documented for various health outcomes.

Previous work investigated health disparities among SGMs in Ohio for physical health status, mental health status, smoking prevalence, and excessive drinking prevalence.[13] The current study expands upon this previous work by investigating additional health disparities such as substance use, utilization of preventive health screenings, and various health outcomes.[13] We focused our investigation on Ohio, as this state's SGM population is estimated to be 4.3% of the total state population, and the SGM population has a varied profile in terms of socioeconomic status, race/ethnicity, and urban/rural residence.[14,15] In addition, Ohio ranks 25th in the nation for public support of SGM rights and acceptance.[14] Ohio's history of SGM discrimination is evident through lawsuits challenging Ohio's ban on same-sex marriage, which led to the 2015 US Supreme Court decision declaring state-level bans on same-sex marriage unconstitutional.[14] As part of minority stress theory, stigma, prejudice, and discrimination experienced by SGM creates a stressful environment that can partially explain many of the health disparities among this population.[16] Currently, Ohio does not have nondiscrimination statutes that include sexual orientation or gender identity as protected individual characteristics.[14] Thus, this study was conducted to document health disparities among adults in Ohio in order to have evidence to develop public health education campaigns and programs targeted to SGM adults and providers to achieve health equity for the SGM population in Ohio.

METHODS

Data Source

The current study used the 2018 Behavioral Risk Factor Surveillance System (BRFSS) to determine the health behaviors and health outcomes among SGMs living in Ohio.[17] The BRFSS is an annual random-digit-dialing state-based telephone survey administered to noninstitutionalized adults aged 18 years or older by health departments in all 50 states, District of Columbia, Guam, and Puerto Rico in collaboration with the Centers for Disease Control and Prevention (CDC).[18] In 2018, the combined response rate (landline and cellular) for individuals surveyed in Ohio was 51.7% (N = 12 763).[19] As part of the sexual orientation and gender identity module, self-report data were collected from 11 529 individuals on their sexual orientation, and 11 518 indicated their gender identity. Individuals who responded "I do not know" or "refused" were excluded from the analysis resulting in analytic samples of 11 301 who reported sexual orientation and 11 426 who indicated their gender identity.

Measures

Sexual Orientation and Gender Identity

To collect sexual orientation data, participants were asked, "Which of the following best represents how you think of yourself?" (gay or lesbian, straight, bisexual, something else). Participants were also asked, "Do you consider yourself to be transgender?" If they reported "yes," they were then asked, "Do you consider yourself to be male-to-female, female-to-male, or gender nonconforming?" Due to the small numbers of responses in some categories, sexual orientation was collapsed into 4 categories (ie, straight male, SM male, straight female, and SM female), and gender identity was collapsed into 2 categories (ie, transgender and cisgender). The SM categories included individuals who identified as gay, gay/lesbian, bisexual, or something else. Transgender included individuals who indicated transgender (male-to-female or female-to-male) and gender nonconforming. Respondents' birth sex was collected from a single item with responses of male or female.

Demographic Variables

We used CDC-derived variables calculated to classify respondents for income, level of education completed, age, and race/ethnicity.[20] The variable for income included 5 categories (eg, <$15 000, $15 000 to <$25 000, $25 000 to <$35 000, $35 000 to <$50 000, and $50 000 or more). Level of education completed included 4 categories (eg, did not graduate high school, graduated high school, attended college or technical school, and graduated from college or technical school). Age contained 6 levels (eg, 18-24 years, 25-34 years, 35-44 years, 45-54 years, 55-64 years, and 65 years or older). Lastly, the variable for race/ethnicity contained 5 categories (eg, White non-Hispanic, Black non-Hispanic, other race non-Hispanic, multiracial non-Hispanic, and Hispanic).

Health-Related Variables

Substance use was assessed for 4 outcomes: binge drinking, smoking status, current e-cigarette use, and marijuana use. Binge drinking was defined as males having 5 or more drinks on 1 occasion and females having 4 or more drinks on 1 occasion in the past 30 days. We recoded smoking to include current smoker (smoked at least 100 cigarettes in their lifetime and now smoke every day or some days), former smoker (smoked at least 100 cigarettes in their lifetime and currently do not smoke), and individuals who reported never smoking. Current e-cigarette use was indicated as current use (using every day or some days) and no current use. Marijuana use was coded as any use in the past month (yes, no).

Health care access was examined among respondents aged 18 to 64 years with 2 variables. First, health care coverage was defined as having health insurance, prepaid plans such as health maintenance organization (HMOs), or government plans such as Medicare or Indian Health Services.[21] Second, we examined whether participants reported a routine checkup within the past year (any time less than 12 months ago), within the past 5 years, or more than 5 years ago (including never).

Receiving a preventive health screening included having been tested for HIV, receiving 1 or more of the recommended colorectal cancer screenings within the recommended time interval among respondents aged 50 to 75 years,[22] having a prostate cancer screening within the past 2 years asked of male respondents aged 40 years and older, receiving a Pap smear within the past 3 years asked of female respondents aged 21 to 65 years with an intact cervix, and receiving a mammogram within the past 2 years asked of female respondents aged 40 years and older.

A CDC-derived variable was used for body mass index (BMI) categorizing participants as underweight (<18.5), normal weight (18.5 to <25.0), overweight (25.0 to <30.0), or obese (≥30.0). Leisure time physical activity was a CDC-derived variable indicating physical activity in the past 30 days other than a regular job. CDC-derived variables were also used for self-report health status, physical health status, and mental health status. For physical and mental health status, respondents reported if they had no days, 1 to 13 days, or 14 or more days when their physical or mental health was not good. Additional health outcomes were self-reported history of coronary heart disease (CHD) or myocardial infarction (MI); skin cancer; other types of cancer; chronic obstructive pulmonary disease (COPD), emphysema, or chronic bronchitis; and diabetes. Due to small cell sizes, individuals who reported having diabetes during pregnancy were excluded from the analysis.

Statistical Analysis

For substance use, health care access, preventive health screenings, and health outcomes, the proportion of participant responses were calculated by sexual orientation and by gender identity. Chi-square tests were conducted to analyze the association between all outcome variables by sexual orientation and by gender identity. We compared SM females to straight females, SM males to straight males, and transgender individuals to cisgender individuals. Analyses were conducted using SPSS Statistics software (SPSS Inc, version 27). Statistical significance was set at $p < 0.05$.

RESULTS

The analytic sample reported that 40.4% identified as a straight male, 1.6% as an SM male, 55.4% as a straight female, and 2.5% as an SM female. In addition, 99.4% identified as cisgender and 0.6% as transgender. The majority of respondents for all sexual orientations and gender identities were White non-Hispanic and were aged 55 years or older (Table 1).

Table1. Demographic Characteristics of Ohio Adults who Participated in the BRFSS in 2018

Demographic characteristics	Sexual orientation				Gender identity	
	Straight Male (n=4571) n (%)	SM Male[a] (n=183) n (%)	Straight Female (n=6265) n (%)	SM Female[b] (n=282) n (%)	Transgender (n=70) n (%)	Cisgender (n=11 356) n (%)
Sex						
Male	4571 (100)	183 (100)	0	0	30 (42.9)	4750 (41.8)
Female	0	0	6265 (100)	282 (100)	40 (57.1)	6606 (58.2)
Income level						
Less than $15 000	300 (7.4)	21 (12.7)	612 (11.5)	38 (16.7)	8 (14.0)	979 (10.0)
$15 000 to <$25 000	643 (15.8)	41 (24.8)	1096 (20.7)	66 (28.9)	15 (26.3)	1861 (19.0)
$25 000 to <$35 000	455 (11.2)	25 (15.2)	664 (12.5)	30 (13.2)	10 (17.5)	1184 (12.1)
$35 000 to <$50 000	639 (15.7)	18 (10.9)	732 (13.8)	29 (12.8)	7 (12.3)	1415 (14.5)
$50 000 or more	2027 (49.9)	60 (36.4)	2201 (41.5)	65 (28.5)	17 (29.8)	4350 (44.4)
Education level						
Did not graduate high school	289 (6.3)	15 (8.2)	399 (6.4)	22 (7.8)	7 (10.0)	735 (6.5)
Graduated high school	1712 (37.5)	62 (33.9)	2188 (35.0)	107 (37.9)	27 (38.6)	4101 (36.2)
Attended college or technical school	1202 (26.3)	45 (24.6)	1816 (29.0)	82 (29.1)	23 (32.9)	3148 (27.8)
Graduated from college or technical school	1359 (29.8)	61 (33.3)	1852 (29.6)	71 (25.2)	13 (18.6)	3351 (29.6)
Age						
18-24 years	265 (5.8)	19 (10.4)	215 (3.4)	36 (12.8)	7 (10.0)	531 (4.7)
25-34 years	434 (9.5)	24 (13.1)	453 (7.2)	45 (16.0)	8 (11.4)	950 (8.4)
35-44 years	468 (10.2)	19 (10.4)	585 (9.3)	40 (14.2)	5 (7.1)	1112 (9.8)
45-54 years	689 (15.1)	24 (13.1)	978 (15.6)	34 (12.1)	11 (15.7)	1718 (15.1)
55-64 years	1113 (24.3)	41 (22.4)	1450 (23.1)	42 (14.9)	14 (20.0)	2650 (23.3)
65 years or older	1602 (35.0)	56 (30.6)	2584 (41.2)	85 (30.1)	25 (35.7)	4395 (38.7)
Race/Ethnicity						
White non-Hispanic	4030 (89.4)	157 (87.2)	5562 (89.7)	223 (80.2)	62 (88.6)	10 005 (89.2)
Black non-Hispanic	248 (5.5)	11 (6.1)	394 (6.4)	17 (6.1)	3 (4.3)	675 (6.0)
Other non-Hispanic	77 (1.7)	3 (1.7)	82 (1.3)	9 (3.2)	3 (4.3)	173 (1.5)
Multiracial non-Hispanic	83 (1.8)	5 (2.8)	89 (1.4)	15 (5.4)	0	196 (1.7)
Hispanic	69 (1.5)	4 (2.2)	75 (1.2)	14 (5.0)	2 (2.9)	164 (1.5)

(N=11 301 who reported sexual orientation and N=11 426 who reported gender identity)
[a] Sexual minority (SM) male: identifying as gay, bisexual, or something else
[b] Sexual minority (SM) female: identifying as gay/lesbian, bisexual, or something else

Substance Use

Sexual minority males (18.2%) and SM females (13.2%) had larger proportions of individuals who engaged in binge drinking compared to their heterosexual counterparts; $\chi^2 (3, N = 11\,162) = 214.41$, $p < .001$ (Table 2). No association was found between binge drinking and gender identity. Sexual minority males (31.1%) and SM females (25.4%) had larger proportions of respondents who reported being current smokers compared to straight males (19.6%) and straight females (17.7%); $\chi^2 (6, N = 11\,231) = 162.19$, $p < .001$. No association was found between smoking status and gender identity. Sexual minority females (10.0%) and SM males (6.6%) had a greater proportion that currently used e-cigarettes compared to their straight peers; $\chi^2 (3, N = 11\,291) = 52.02$, $p < .001$. Sexual minority males (17.1%) and SM females (11.7%) had a significantly greater proportion of individuals who used marijuana in the past month compared to straight males (7.9%) and straight females (3.8%); $\chi^2 (3, N = 11\,253) = 140.49$, $p < .001$. Due to small cell sizes, a chi-square value could not be calculated to determine the association between current e-cigarette use and gender identity, and marijuana use and gender identity.

Health Care Access

Sexual minority males (11.1%) and SM females (9.7%) had the largest proportion of respondents who did not have health care coverage compared to straight males (8.2%) and straight females (5.6%); $\chi^2 (3, N = 6898) = 23.31$, $p < .001$ (Table 3). Due to small cell sizes, a chi-square value could not be calculated to determine the association between health care coverage and gender identity. Straight females (87%) and SM females (85.6%) had a greater proportion of respondents who received a routine checkup within the past year compared to straight males (79.9%) and SM males (80.4%); $\chi^2 (6, N = 11\,211) = 114.53$, $p < .001$. No association was found between time since last routine checkup and gender identity.

Preventive Health Screening

A significant association was found between HIV testing and sexual orientation; $\chi^2 (3, N = 10\,936)=127.48$, $p < .001$ (Table 4). Sexual minority males (55.8%) had the largest proportions of individuals who had ever been tested for HIV compared to SM females (43.4%), straight males (25.4%), and straight females (25.4%). No association was found between HIV testing and gender identity. Out of respondents aged 50 to 75 years, a significantly larger proportion of straight females (71.1%) and SM females (72.7%) received the recommended colorectal cancer tests compared to straight males (68.0%) and SM males (65.5%); $\chi^2 (3, N = 6042) = 7.80$, $p = .05$. No association was found between the following: colorectal cancer screening and gender identity, prostate cancer screening and sexual orientation, and prostate cancer screening and gender identity.

Additionally, no statistically significant relationship was found between cervical cancer screening and sexual orientation. Due to small cell sizes, a chi-square value could not be calculated to determine the association between cervical cancer screening and gender identity. There was a significant disparity with a larger proportion of straight females (74.8%) aged 40 years or older receiving mammograms within the past 2 years compared to SM females (67.0%); $\chi^2 (1, N =5390) = 5.53$, $p = .019$. An even wider gap emerged when analyzing the association between breast cancer screening and gender identity; $\chi^2 (1, N = 5477) = 4.40$, $p =. 036$. A larger proportion of cisgender females (74.6%) aged

Table 2. Association of Substance Use Behaviors by Sexual Orientation and by Gender Identity Among Ohio Adults who Participated in the BRFSS in 2018

Behaviors	**Sexual orientation**					**Gender identity**		
	Straight Male (n=4571) n (%)	SM Male[b] (n=183) n (%)	Straight Female (n=6265) n (%)	SM Female[c] (n=282) n (%)	χ^2	Transgender (n=70) n (%)	Cisgender (n=11 356) n (%)	χ^2
Binge drinking [a]					214.41***			0.20
Yes	762 (16.9)	33 (18.2)	487 (7.9)	37 (13.2)		9 (13.4)	1312 (11.7)	
No	3737 (83.1)	148 (81.8)	5715 (92.1)	243 (86.8)		58 (86.6)	9906 (88.3)	
Smoking status					162.19***			1.47
Current smoker	892 (19.6)	56 (31.1)	1102 (17.7)	71 (25.4)		17 (24.3)	2109 (18.7)	
Former smoker	1501 (33.0)	54 (30.0)	1518 (24.4)	77 (27.6)		19 (27.1)	3164 (28.0)	
Never smoked	2150 (47.3)	70 (38.9)	3609 (57.9)	131 (47.0)		34 (48.6)	6010 (53.3)	
Current e-cigarette use					52.02***			-
Yes	190 (4.2)	12 (6.6)	178 (2.8)	28 (10.0)		6 (8.6)	405 (3.6)	
No	4374 (95.8)	171 (93.4)	6086 (97.2)	252 (90.0)		64 (91.4)	10 939 (96.4)	
Marijuana use in past month					140.49***			-
Yes	357 (7.9)	31 (17.1)	237 (3.8)	33 (11.7)		11 (15.9)	650 (5.8)	
No	4190 (92.1)	150 (82.9)	6007 (96.2)	248 (88.3)		58 (84.1)	10 654 (94.2)	

(N=11 301 who reported sexual orientation and N=11 426 who reported gender identity)
*=p ≤ .05
**=p < .01
***=p < .001
[a] Use in the past month
[b] Sexual minority (SM) male: identifying as gay, bisexual or something else
[c] Sexual minority (SM) female: identifying as gay/lesbian, bisexual or something else
-A chi-square value could not be calculated due to low cell size

Table 3. Association of Health Care Access by Sexual Orientation and by Gender Identity Among Ohio Adults who Participated in the BRFSS in 2018

Health care access	**Sexual orientation**					**Gender identity**		
	Straight Male (n=4571) n (%)	SM Male[a] (n=183) n (%)	Straight Female (n=6265) n (%)	SM Female[b] (n=282) n (%)	χ^2	Transgender (n=70) n (%)	Cisgender (n=11 356) n (%)	χ^2
Health care coverage					23.31***			-
Yes	2683 (91.8)	112 (88.9)	3447 (94.4)	177 (90.3)		40 (90.9)	6403 (93.1)	
No	241 (8.2)	14 (11.1)	205 (5.6)	19 (9.7)		4 (9.1)	478 (6.9)	
Routine checkup					114.53***			3.20
Within past year	3618 (79.9)	144 (80.4)	5419 (87.0)	238 (85.6)		56 (80.0)	9468 (84.1)	
Within past 5 years	580 (12.8)	20 (11.2)	578 (9.3)	28 (10.1)		7 (10.0)	1207 (10.7)	
5 or more years ago, or never	329 (7.3)	15 (8.4)	230 (3.7)	12 (4.3)		7 (10.0)	588 (5.2)	

(N=11 301 who reported sexual orientation and N=11 426 who reported gender identity)
*= p ≤ .05
**= p < .01
***= p < .001
[a] Sexual minority (SM) male: identifying as gay, bisexual, or something else
[b] Sexual minority (SM) female: identifying as gay/lesbian, bisexual, or something else
-A chi-square value could not be calculated due to low cell size.

Table 4. Association of Preventive Health Screening Behaviors by Sexual Orientation and by Gender Identity Among Ohio Adults Who Participated in the BRFSS in 2018

Behaviors	**Sexual Orientation**					**Gender Identity**		
	Straight Male (n=4571) n (%)	SM Male[d] (n=183) n (%)	Straight Female (n=6265) n (%)	SM Female[e] (n=282) n (%)	χ^2	Transgender (n=70) n (%)	Cisgender (n=11 356) n (%)	χ^2
HIV testing					127.48***			1.35
Yes	1121 (25.4)	101 (55.8)	1537 (25.4)	119 (43.4)		22 (32.4)	2870 (26.1)	
No	3301 (74.6)	80 (44.2)	4522 (74.6)	155 (56.6)		46 (67.6)	8112 (73.9)	
Colorectal cancer screening					7.80*			0.42
Yes[a]	1682 (68.0)	55 (65.5)	2409 (71.1)	72 (72.7)		22 (64.7)	4228 (69.8)	
No[a]	791 (32.0)	29 (34.5)	977 (28.9)	27 (27.3)		12 (35.3)	1826 (30.2)	
Prostate cancer screening in past 2 years[b]					1.05			0.43
Yes	1343 (39.1)	55 (43.7)	...	...		5 (31.3)	1400 (39.3)	
No	2091 (60.9)	71 (56.3)	...	...		11 (68.8)	2161 (60.7)	
Cervical cancer screening in past 3 years[c]					3.23			-
Yes	...	...	2235 (80.7)	109 (74.7)		11 (64.7)	2339 (80.4)	
No	...	...	534 (19.3)	37 (25.3)		6 (35.3)	571 (19.6)	
Breast cancer screening in past 2 years[b]					5.53*			4.40*
Yes	...	...	3899 (74.8)	120 (67.0)		20 (58.8)	4058 (74.6)	
No	...	...	1312 (25.2)	59 (33.0)		14 (41.2)	1385 (25.4)	

(N=11 301 who reported sexual orientation and N=11 426 who reported gender identity)
*=p ≤ .05
**=p < .01
***=p < .001
[a] Ages: 50 to 75 years
[b] Ages: 40 years and older
[c] Ages: 21 to 65 years
[d] Sexual minority (SM) male: identifying as gay, bisexual, or something else
[e] Sexual minority (SM) female: identifying as gay/lesbian, bisexual, or something else
-A chi-square value could not be calculated due to low cell size.
...Not Applicable

40 years or older received a mammogram within the past 2 years compared to transgender individuals (58.8%).

Health Outcomes

Sexual minority males (30.2%) and SM females (28.5%) had an increased proportion of respondents who indicated fair or poor health status compared to straight males (21.8%) and straight females (21.0%); χ^2(3, N = 11 275) = 17.37, p = .001 (Table 5). A significant association was observed between physical health status and sexual orientation; χ^2(6, N = 11 123) = 79.10, p < .001. Sexual minority males (22.3%) and SM females (22.4%) had the largest proportion of individuals who indicated they experienced 14 days or more of poor physical health. Sexual minority males (22.3%) and SM females (26.8%) had greater proportions of individuals who experienced 14 or more days of poor mental health compared to straight males (10.5%) and straight females (14.7%); χ^2(6, N = 11 150)= 271.08, p < .001. No association was found between the following: health status and gender identity, physical health status and gender identity, and mental health status and gender identity.

A significant association was demonstrated between BMI and sexual orientation; χ^2(9, N = 10 722) = 180.50, p < .001. Sexual minority females (40.3%) had the largest proportion and SM males (27.6%) had the smallest proportion of individuals considered to be obese (BMI ≥ 30.0). No association was found between BMI and gender identity; χ^2(3, N = 10 828) = 1.46, p = .693. Straight females (30.9%) and SM females (34.8%) had larger proportions of respondents who did not engage in leisure time physical activity outside of work in the past 30 days compared to their male counterparts; χ^2(3, N = 11 282) = 31.27, p < .001. No association was found between leisure time physical activity and gender identity.

A significant association was found between skin cancer and sexual orientation; χ^2(3, N = 11 281) = 9.68, p = .022. Sexual minority males (12.0%) had the largest proportion who had skin cancer in their lifetime, while SM females (4.6%) had the lowest percentage. No association was found between skin cancer and gender identity. A significant relationship was also demonstrated between other types of cancer and sexual orientation; χ^2(3, N = 11 276) = 31.24, p < .001. Straight females (11.7%) had the highest percentage of individuals who had other types of cancer besides skin cancer in their lifetime, and straight males (8.4%) had the lowest. Sexual minority males (10.9%) and SM females (10.0%) had similar proportions. No significant association was observed between other types of cancer and gender identity.

Straight males (14.4%) and SM males (15.9%) had a larger proportion of individuals who had a CHD or MI compared to their female counterparts; χ^2(3, N = 11 205)=75.22, p < .001. No association was found between CHD or MI and gender identity. Sexual minority males (15.8%) and SM females (16.4%) had larger proportions of individuals who have had COPD, emphysema, or chronic bronchitis compared to straight males (10.3%) and straight females (12.9%); χ^2(3, N = 11 267) = 24.02, p < .001. No association was found between COPD, emphysema, or chronic bronchitis and gender identity. No significant association was found between diabetes and sexual orientation, and between diabetes and gender identity.

DISCUSSION

The findings from the current study indicate the many health disparities experienced by the SGM population in Ohio. Consistent with previous research,[1,7,8,10,13,23] significant disparities were found for physical and mental health status, and substance use (ie, binge drinking, current smoking status, and marijuana use) among SM males and SM females. Additionally, a significant disparity emerged for e-cigarette use among SM females and SM males. Aligning with previous research,[1,6,8] the current study also found SM females to have the largest proportion of individuals to be classified as obese. Contrasting previous research,[1] the current study found SM females to have a significantly greater proportion of individuals who reported no leisure time physical activity in the past 30 days compared to their heterosexual peers. The lack of partaking in leisure time physical activity could partially explain the greater proportion of SM females classified as obese.

Novel contributions to the literature include the finding that there were disparities for experiencing COPD, emphysema, or chronic bronchitis among SM males and SM females. As tobacco smoking is the most common cause of COPD, the greater proportion of SM females and SM males who are current smokers could help explain the disparity for experiencing COPD, emphysema, or chronic bronchitis.[24] Supporting previous research,[8,9] the current study found limited differences between SGM and their heterosexual peers in reporting cardiovascular disease diagnoses like CDH or MI and diabetes, but found SMs were more likely to report cardiovascular risk factors such as substance use, increased BMI, and poor mental health. The significant difference found in reporting CDH or MI was between all males and females.

A significant disparity was demonstrated for breast cancer screening with a larger proportion of straight females reported receiving a mammogram within the past 2 years compared to SM females. Another new finding was an even wider disparity for gender identity with a significantly larger proportion of cisgender females receiving a mammogram in the past 2 years than transgender individuals. One possible explanation for this disparity is that transgender individuals may avoid seeking routine health care due to anticipated discrimination.[5] A critical finding is the disparity that emerged for health care coverage among SM males and SM females. The disparity in health care coverage can limit access to care, which could partially explain the disparity in preventive health screenings.

Limitations

Telephone surveys were used to collect data for the 2018 BRFSS data set. It is important to note that telephone surveys exclude

Table 5. Association of Health Outcomes by Sexual Orientation and by Gender Identity Among Ohio Adults who Participated in the BRFSS in 2018

Health outcomes	Sexual orientation					Gender identity		
	Straight Male (n=4571) n (%)	SM Male[c] (n=183) n (%)	Straight Female (n=6265) n (%)	SM Female[d] (n=282) n (%)	χ^2	Transgender (n=70) n (%)	Cisgender (n=11 356) n (%)	χ^2
Health status					17.37**			0.05
Excellent, very good, or good	3566 (78.2)	127 (69.8)	4943 (79.0)	201 (71.5)		54 (77.1)	8866 (78.3)	
Fair or poor	992 (21.8)	55 (30.2)	1311 (21.0)	80 (28.5)		16 (22.9)	2462 (21.7)	
Physical health status					79.10***			0.40
No days physical health was not good	2887 (64.1)	99 (55.3)	3621 (58.8)	117 (42.2)		38 (56.7)	6752 (60.5)	
1-13 days physical health was not good	939 (20.8)	40 (22.3)	1543 (25.0)	98 (35.4)		17 (25.4)	2624 (23.5)	
14 days or more physical health was not good	680 (15.1)	40 (22.3)	997 (16.2)	62 (22.4)		12 (17.9)	1793 (16.1)	
Mental health status					271.08***			5.22
No days mental health was not good	3325 (73.8)	98 (54.7)	3796 (61.4)	119 (42.5)		43 (63.2)	7388 (65.9)	
1-13 days mental health was not good	711 (15.8)	41 (22.9)	1482 (24.0)	86 (30.7)		10 (14.7)	2331 (20.8)	
14 days or more mental health was not good	471 (10.5)	40 (22.3)	906 (14.7)	75 (26.8)		15 (22.1)	1485 (13.3)	
BMI					180.50***			1.46
Underweight (<18.5)	45 (1.0)	3 (1.7)	115 (2.0)	7 (2.7)		0	173 (1.6)	
Normal weight (18.5 to <25.0)	953 (21.2)	49 (27.1)	1702 (29.5)	95 (36.1)		15 (23.4)	2822 (26.2)	
Overweight (25.0 to <30.0)	1849 (41.1)	79 (43.6)	1836 (31.8)	55 (20.9)		25 (39.1)	3821 (35.5)	
Obese (≥30.0)	1655 (36.8)	50 (27.6)	2123 (36.8)	106 (40.3)		24 (37.5)	3948 (36.7)	
Leisure time physical activity in past 30 days					31.27***			0.17
Yes	3360 (73.7)	132 (72.1)	4321 (69.1)	184 (65.2)		8027 (70.8)	48 (68.6)	
No	1202 (26.3)	51 (27.9)	1934 (30.9)	98 (34.8)		3310 (29.2)	22 (31.4)	
Skin cancer					9.68*			0.57
Yes	455 (10.0)	22 (12.0)	607 (9.7)	13 (4.6)		5 (7.1)	1114 (9.8)	
No	4105 (90.0)	161 (88.0)	5651 (90.3)	267 (95.4)		65 (92.9)	10 223 (90.2)	
Other types of cancer					31.24***			1.67
Yes	384 (8.4)	20 (10.9)	733 (11.7)	28 (10.0)		4 (5.7)	1184 (10.5)	
No	4177 (91.6)	163 (89.1)	5518 (88.3)	253 (90.0)		66 (94.3)	10 145 (89.5)	
CHD or MI[a]					75.22**			0.58
Yes	654 (14.4)	29 (15.9)	577 (9.3)	23 (8.3)		6 (8.6)	1294 (11.5)	
No	3874 (85.6)	153 (84.1)	5641 (90.7)	254 (91.7)		64 (91.4)	9966 (88.5)	
COPD, emphysema, or chronic bronchitis[b]					24.02***			0.36
Yes	471 (10.3)	29 (15.8)	803 (12.9)	46 (16.4)		10 (14.3)	1354 (12.0)	
No	4085 (89.7)	154 (84.2)	5445 (87.1)	234 (83.6)		60 (85.7)	9967 (88.0)	
Diabetes					0.53			0.82
Yes	788 (17.3)	31 (16.9)	1018 (16.5)	41 (15.0)		10 (14.5)	1908 (17.0)	
No	3680 (80.6)	146 (79.8)	5038 (81.7)	228 (83.2)		58 (84.1)	9118 (81.1)	
Prediabetes or borderline	96 (2.1)	6 (3.3)	110 (1.8)	5 (1.8)		1 (1.4)	217 (1.9)	

(N=11 301 who reported sexual orientation and N=11 426 who reported gender identity)
*= p ≤ .05
**= p < .01
***= p < .001
[a] Coronary heart disease (CHD) or myocardial infarction (MI)
[b] Chronic obstructive pulmonary disease (COPD)
[c] Sexual minority (SM) male: identifying as gay, bisexual, or something else
[d] Sexual minority (SM) female: identifying as gay/lesbian, bisexual, or something else

individuals who do not have access to phones and individuals who have prepaid phones. Another limitation is that sexual orientation and gender identity variables are only part of the optional BRFSS modules, which hinders the ability of researchers to fully understand SGM health disparities across different regions.

Condensing the SM and transgender variables allowed for greater cell sizes and power needed for statistical analyses, but it limited the ability to analyze differences within sexual and gender identities. Notably, there were only 70 transgender individuals in the sample, so some analyses may have been underpowered to detect significant effects. A limitation of the current study is the lack of ability to analyze the interactions between SGM individuals and other intersecting identities, such as race, due to small sample sizes.

PUBLIC HEALTH IMPLICATIONS

The most critical SGM health disparities in Ohio are related to greater substance use (ie, binge drinking, current smoking status, e-cigarette use, and marijuana use); poor physical and mental health status; experiencing COPD, emphysema, or chronic bronchitis; lack of health care coverage; and reduced rates of receiving breast cancer screenings. These SGM disparities are likely due to several factors, including experiencing minority stress, anticipated discrimination, and a lack of legal protections.[5,16,25-29] Public health action is critically needed to better understand and address these disparities. Education campaigns and programs targeted to SGM to address health issues such as substance use, mental health, and preventive screenings are vital. Additionally, programs aimed toward reducing bias among health care providers in Ohio may reduce anticipated discrimination among SGM and thereby increase their utilization of health care and preventive screenings. Establishing legislation that outlaws discrimination toward SGM in Ohio could also reduce the health disparities found by lessening the stigma, prejudice, and discrimination faced by this population. The Ohio Fairness Act is an example of legislation that seeks to clarify in Ohio that it is illegal to discriminate based on one's sexual orientation or gender identity, but it has yet to pass into law.[30] Legal protections establishing the equal rights of SGM individuals and outlawing discrimination are critical to create lasting change in reducing SGM disparities.

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