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EXECUTIVE SUMMARY

The Infant Mortality Research Partnership (IMRP) is a collaboration between state agencies, researchers, and subject matter experts to bring rigorous and innovative methodological approaches to lowering infant mortality (IM) and preterm birth (PTB) in Ohio. In Phase I, a novel multi-agency linked dataset was created and cross-disciplinary research teams examined the obstetrical, other clinical, sociodemographic and contextual factors associated with IM and PTB, as well as the trends in their distribution across the State. In Phase II, researchers focused on 1) developing predictive models that could be used throughout the course of pregnancy to identify women and infants at high risk of suffering infant mortality and preterm birth; 2) examining the impact of neighborhood structural factors on preterm birth in urban settings and the spatial distributions of additional outcomes; 3) developing novel applications designed to help users better apply this work to clinical and public health practice and policy; and 4) exploring a place-based program evaluation approach to determine if such an approach added critical information in the evaluation process.

Major products of the Phase II IMRP include the following:

1. Twelve predictive models integrated into an interactive risk-calculator application to be used at the point-of-care.
2. An interactive web-mapping tool that allows users to examine the results of the spatial cluster analysis in conjunction with socio-economic data at the census tract-level.

Major contributions and findings of Phase II IMRP include the following:

1. **Expanded data integration**: In this phase, variables associated with census tract-level factors (the Ohio Opportunity Index), opioid use, interpregnancy interval, and congenital anomaly were added to the study dataset.

2. **Race and ethnicity have a complex association with infant mortality and preterm birth**. Maternal non-Hispanic Black (NHB) race/ethnicity was associated with increased odds of infant mortality in all individual models, even when variables associated with neighborhood-level factors were included. NHB mothers living in segregated NHB neighborhoods have higher odds of preterm birth than white mothers living in the same neighborhood type. Very high concentration NHB neighborhoods appear to offer a small protective effect for preterm birth, but this was only significant for NHW mothers.

3. **Maternal non-Hispanic Black race for women living in rural areas was not associated with increased odds of preterm birth**. However, NHB mothers living in urban areas had significantly increased risk for preterm birth.

4. **Medical complications and prior obstetrical history, including short interpregnancy intervals, are major risk factors for infant mortality and preterm birth**. Increasing access to quality prenatal care and primary care in Ohio may reduce infant mortality and preterm birth.
5. **Severe mental illness in the prenatal period is associated with infant mortality.** Interventions could be focused on improving the integration of mental health services with prenatal care.

6. **Living in an area with a high violent crime rate increases the risks of infant mortality and preterm birth.** Interventions to make neighborhoods safer could have an impact on the health of women and infants in Ohio.

7. **Place-based evaluation approaches, using vital statistics and Medicaid data, can provide critical information for program design and evaluation at the local level.**

## SECTION 1: INTRODUCTION AND BACKGROUND

### 1.0 Background and Rationale

The infant mortality rate (IMR), defined as the number of deaths in the first year of life per 1,000 live births, reflects not only maternal and infant health but also the overall health of a community, state, or nation (1). In the United States, the IMR has progressively declined in recent years to reach 5.8/1,000 in 2017, a rate below the Healthy People 2020 goal (2). However, the IMR for non-Hispanic Black (NHB) infants in many U.S. states and cities is more than twice as high as for non-Hispanic White (NHW) infants.

In 2017, Ohio had one of the higher reported IMRs in the United States (3). A variety of strategies, including national, statewide, and community-based initiatives, have been undertaken to reduce both the overall IMR in Ohio and narrow its racial disparity. In 2017, Ohio’s rate had improved to 7.2/1,000 from 7.4/1000 in 2016; however, the NHB IMR increased to 15.6/1000 while the NHW IMR dropped to 5.3/1000, widening an existing disparity (4). Previous work has suggested that up to one third of this disparity may reflect Ohio’s reporting of pre-viable live births as liveborn, a disproportionate number of which are NHB infants (5).

To reduce this disparity, The Ohio Department of Health (ODH) joined the national Institute for Equity in Birth Outcomes initiative and designated the nine counties and communities in which the majority of Ohio’s NHB babies are born as Ohio Equity Institute (OEI) communities. Building on the Ohio Department of Health Infant Mortality Reduction plan and the Ohio Commission on Infant Mortality report, legislators enacted S.B. 332. Also known as the Infant Mortality Reduction Bill, it contains provisions that address factors known to affect infant mortality. For example, it supports strategies to reduce premature births by increasing availability and use of progesterone therapy, and to reduce unintended pregnancies via long-acting reversible contraceptives (LARC). The State Health Improvement Plan for 2017-2019 includes a strong focus on maternal and infant health to achieve health equity and reduce infant mortality. To examine the specific risk factors for different populations as well as individual risks, a more coordinated effort, grounded in Ohio-specific data, was needed.
Infant mortality is a complex problem with varied contributing factors that are themselves often interacting, and as such effective solutions require a multi-pronged, multi-sector approach (6). Poor birth outcomes such as preterm birth (PTB, defined as birth prior to 37 weeks gestation), very preterm birth (<32 weeks), low birth weight (LBW, defined as weight <2500 grams), very low birth weight (<1500 grams) and infant mortality have long been understood as the result of medical risk factors (high blood pressure, diabetes, short cervix, etc.), and factors related to social and behavioral health (e.g., socioeconomic status, racism, neighborhood characteristics, access to prenatal care, smoking, alcohol or drug abuse). Researchers and policymakers alike increasingly recognize the role of structural and institutional factors (i.e., social determinants of health) that directly and indirectly impact maternal and child health, as well as their relationship to medical, psychosocial, and demographic risk factors (7, 8). By identifying these complex, contributing factors of infant mortality and the interactions among them, a more effective set of interventions responsive to the various populations and geographic regions across the state of Ohio, can be developed and implemented (9, 10).

The need for a statewide research collaboration to address this public health issue was identified by the Ohio Legislature, the Governor’s Office of Health Transformation (OHT), and the Ohio Departments of Medicaid (ODM), Health (ODH), and Higher Education (ODHE). The Infant Mortality Research Partnership was launched in this spirit. The IMRP project design incorporated multiple methodologies to span multiple domains and levels. The design was intended to explicitly model nuance in infant mortality risk factors (i.e. move beyond poverty as the primary risk factor), as well as capture a cohesive and more comprehensive portrait of the complexity of infant mortality.

The Ohio Colleges of Medicine Government Resource Center (GRC) was charged with administering the IMRP. Phase I of the IMRP consisted of three teams who approached the problem of infant mortality from the diverse perspectives of geospatial distribution, systems dynamic modeling, and predictive modeling. These teams made significant strides to understand the complex factors associated with risk of infant mortality. Phase II of IMRP continued with two teams with expertise in geospatial modeling and point-of-care predictive models with a greater focus on creating actionable and usable tools. These two teams worked together to share resources and tools to better integrate their work. This report focuses on the findings of Phase II of the IMRP.

1.1 Data Used for the IMRP

This initiative employed an innovative approach to identify the causes of infant mortality and to determine the best mix of interventions to reduce the IMR. Driving this multi-method, interdisciplinary approach was the construction of a multidimensional dataset. Thanks to a multi-agency effort, facilitated by data preparation, linkage and management by GRC, infant mortality researchers had access to comprehensive, linked datasets that included physical and mental health variables, indicators of numerous social determinants of health, and data on the utilization of some community and government programs. (See Table 1 for the full list of available datasets.) This application of big data to the pervasive, complex problem of infant mortality enabled researchers to develop more accurate models of the factors impacting risk,
and the interventions that can improve maternal and child health outcomes across the state of Ohio.

1.2 Overview of the Methodology

The IMRP Phase II comprised two complementary research teams, each conducting data analyses toward answering one of the partnership’s key questions.

Table 1: Datasets Used by the IMRP Research Teams

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Source/URL</th>
<th>Teams that used dataset</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medicaid Claims</td>
<td>Ohio Department of Medicaid</td>
<td>GEO, PM</td>
</tr>
<tr>
<td>Women of Reproductive Age (WRA)</td>
<td>grc.osu.edu/Projects/MEDTAPP/WomenOfReproductiveAge</td>
<td>GEO, PM</td>
</tr>
<tr>
<td>Ohio Vital Statistics -Births</td>
<td>odh.ohio.gov/healthstats/vitalstats/vitalstatsmainpage.aspx</td>
<td>GEO, PM</td>
</tr>
<tr>
<td>Ohio Vital Statistics -Deaths</td>
<td>odh.ohio.gov/healthstats/vitalstats/vitalstatsmainpage.aspx</td>
<td>GEO, PM</td>
</tr>
<tr>
<td>American Community Survey</td>
<td>census.gov/programs-surveys/acs/news/data-releases.html</td>
<td>GEO</td>
</tr>
<tr>
<td>Ohio Business Listings</td>
<td>infousa.com/product/business-lists/</td>
<td>GEO</td>
</tr>
<tr>
<td>USDA Food Deserts</td>
<td>ers.usda.gov/data-products/food-access-research-atlas/download-the-data/</td>
<td>GEO</td>
</tr>
<tr>
<td>Foreclosure data</td>
<td>huduser.gov/portal/datasets/nsf_foreclosure_data.html</td>
<td>GEO</td>
</tr>
<tr>
<td>Homicide deaths 2007-2014</td>
<td>odh.ohio.gov/healthstats/vitalstats/vitalstatsmainpage.aspx</td>
<td>GEO</td>
</tr>
</tbody>
</table>

Abbreviations: GEO: spatiotemporal; PM: individual predictive model; USDA: United States Department of Agriculture.

GRC oversaw all aspects of the IMRP initiative, coordinated project communications and activities, and developed and implemented methodologies to link the majority of the project datasets together. GRC provided ongoing support to research teams as they began analyzing these project data and conducted intensive reviews of their interim and final project outputs. Most teams conducted their analyses and developed their interactive outputs within the technological infrastructure GRC developed and supported for the project.

The IMRP aimed to improve understanding of the factors contributing to infant mortality and preterm birth in Ohio, building a foundation from which to design and implement targeted interventions. Teams took into account factors recognized in research literature as consequential to IM and PTB. These factors span multiple levels, as illustrated by the socio-ecological framework (see Figure 1) (11). The individual predictive models and multilevel spatiotemporal models addressed individual and organizational risk factors. The spatiotemporal models included community-level risk factors. By using these models together, the project aimed to include the most relevant factors at each of these levels that contribute to infant mortality and preterm birth.
1.2.1 Researchers' Roles and Deliverables

The two teams in Phase II worked together closely. This collaboration was facilitated through semi-monthly joint team meetings, semi-monthly GRC-led team meetings and quarterly executive committee meetings. To aid in collaborative work, the two teams shared a project manager. Each team was also responsible for providing a section for the Methodology Report encapsulating their full study design, methods, and results, as well as a summary contribution to this Final Report. A brief overview of the teams' goals and approaches is provided below, and more detailed summaries, including their primary results are provided in subsequent sections of this report.

1.2.1.1 Spatiotemporal Analysis of Infant Mortality and Preterm Birth in Ohio

Guided by the recognition that “place matters” for individual-level outcomes including health and well-being, this team utilized geospatial methods to identify the Ohio communities with the highest rates of infant mortality, incorporating measures of the social determinants of health, access to care, and areas of insufficient healthcare service availability. Researchers were able to identify clusters in Ohio where women had an elevated risk of experiencing poor birth outcomes, after adjusting for demographic composition. They integrated key neighborhood characteristics such as racial segregation and neighborhood crime rates, measuring risk defined by factors from the women's communities of residence as well as their own characteristics. In addition to identifying geographic areas of high risk, the team demonstrated how spatial data can be used as an aid in targeting interventions and evaluating interventions’ impact: Researchers examined a place-based and temporal evaluation approach to determine if the approach might add key information for local programming decisions. This was done through an analysis of neighborhood data in Franklin County.
1.2.1.3 Individual Predictive Modeling of Preterm Birth and Infant Mortality

This IMRP team’s primary research activity was developing predictive models that could be used at the point of care by healthcare providers, toward identifying patients at high risk of infant mortality or preterm birth. The team worked to bring together patient and area level risk factors into one model, by incorporating the Ohio Opportunity Index into the models. The main product developed by this group is a risk calculator application that integrates these models into an interactive and usable application. This application is designed to be used at the point of care and to help policymakers identify possible impacts of targeted interventions on the Medicaid population. In order to respond to the needs of these different groups, the application underwent and iterative design process and multiple usability tests with potential stakeholders.

1.3 References


SECTION 2: SPATIOTEMPORAL ANALYSIS OF INFANT MORTALITY AND PRETERM BIRTH IN OHIO

2.1 Introduction and Objectives

Geography plays a major role in the dynamics of health. People, and the factors that lead to both positive and adverse health outcomes, are dispersed -- often unevenly -- across communities and regions (1). This dispersion leads to distinct spatial patterns of many health outcomes, including low birth weight and preterm birth, infant mortality, and a variety of birth defects. The availability of geographic data provides policymakers and public health officials with the capability to perform two unique types of analysis: 1) finding areas of high or low incidence worthy of further investigation, and 2) examining the spatial relationship between health outcomes on the one hand, and population and contextual factors on the other (2,3).

This study used mapping and spatial analysis to identify high-risk communities in Ohio that can be targeted for intervention and resource allocation, and to provide a deeper understanding of why these communities are high risk. These efforts addressed three major objectives:

1) Examine individual-level and area-level risk factors associated with infant mortality and preterm birth in Ohio.
2) Focus on preterm birth to mothers living in urban areas to examine the area-level factors associated with this outcome.
3) Examine spatial patterns and clusters of infant mortality, preterm birth, Neonatal Abstinence Syndrome (NAS) and maternal opiate use in Ohio.
4) Demonstrate how spatial analytic techniques can be used for program planning and evaluation using the CelebrateOne neighborhoods in Franklin County as an example.

2.2 Methods

This study used a combination of Geographic Information Systems (GIS), geovisualization and mapping, and statistical modeling to examine the spatial patterns of infant mortality and preterm birth in Ohio. In order to conduct a spatial analysis, all Ohio birth and infant death records were geocoded so data could be displayed on a map. Once records were geocoded, each record was assigned a census tract in the GIS and merged with a variety of area-level data (e.g., median household income or OB/GYNs per capita). Then, using multilevel models (MLMs) and spatial cluster analysis, two primary outcomes were examined: infant mortality and preterm birth. This report presents results for the Medicaid Women of Reproductive Age (WRA) cohort; the Methodology Report includes analyses of the full Ohio birth cohort.

Multilevel models are used when observations in a data set are nested or grouped (4,5). For example, observations such as residents of the same census tract tend to be more alike than data from individuals selected at random across tracts. These within-group similarities require statistical models that account for this phenomenon. This study used multilevel models to estimate the probability of infant mortality or preterm birth event as a function of both individual-level (e.g., age, education, hypertension, etc.) and area-level (e.g., racial concentration, residential stability, poor housing, etc.) factors.
The spatial scan statistic is one of the main epidemiological tools to detect the presence and locations of geographic clusters of health events (6). This method tests whether there is an elevated risk (e.g., more cases than would be expected) within a specific geographic area as compared to outside that area. In this case, using the observed number of infant deaths or preterm birth cases, an expected number was calculated based on: 1) population density or 2) population density by maternal age, race/ethnicity and education. Adjusting for population density assured that the reported clusters were not merely due to a large number of births in an area. Additional adjustment for maternal characteristics also ensured that clusters were not simply reflecting uneven distributions of populations with known risk factors, such as a large concentration of NHB mothers. Results of the scan statistic were mapped using the GIS. Relative risk is reported for all clusters with a p-value < 0.05.

This work includes a case study to demonstrate how spatially and temporally referenced data can be used to support program evaluation or planning activities. A formal program evaluation, that establishes causal links between programs and changes in birth outcomes, was not conducted. Rather, the case study shows, for limited geographic areas, how to use vital record and Medicaid data to examine whether key maternal characteristics and infant outcomes changed over time.

2.3 Key Findings

Figure 2 shows rate maps for infant mortality (Panel A) and preterm birth (Panel B) for the Medicaid WRA cohort. There are a higher proportion of low-income and NHB mothers in the Medicaid WRA cohort.

Figure 2: Spatially Smoothed Rate Maps of: A) Infant Mortality (Per 1,000 Births) and B) Preterm Birth, Medicaid WRA Cohort 2008-2015
The patterns look similar between the two maps; all major cities have concentrations of high infant mortality and preterm birth, and there is a distinct dark band of higher rates (especially for preterm birth) in the Appalachian counties and the rural area north of Columbus. At the same time, there are some areas where IM and PTB rates don’t match (e.g., relatively high IM but low PTB), such as Portage County between Akron and Youngstown. Some of these differences are related to small numbers in rural areas, such that even a few IM events leads to a very high rate when mapped. Alternatively, these could be areas where IM is not related to preterm birth or preterm babies are effectively cared for, so an early birth does not lead to mortality.

**Figure 3: Adjusted Odds Ratio (OR) and 95% Confidence Interval (CI) for the Effect of Area Level NHB Concentration, Medicaid WRA**

There is an Elevated Risk for Infant Death and Preterm Birth in Neighborhoods with a High Concentration Of NHB Residents

The teal dots in Figure 3 show the increase in odds of infant mortality from living in NHB-concentrated neighborhoods. Compared to neighborhoods with 0% to 24% NHB residents, the odds of an infant death in neighborhoods with 50% to 74% NHB residents were approximately 15% greater. The dark blue dots show this same relationship for preterm birth. The odds were approximately 5% higher for preterm birth in neighborhoods with 50% to 74% NHB residents compared to neighborhoods with 0% to 24% NHB residents.

**Area-Level Socioeconomic and Structural Variables Help Explain Much of the Effect of Living in a High Concentration NHB Neighborhood on Infant Mortality**

Figure 4 shows the results of two different models for infant mortality. The teal dots show the effect of living in a high concentration NHB neighborhood when no other neighborhood factors are considered. The dark blue dots indicate the effect of living in a high concentration NHB.
neighborhood when additional socioeconomic/structural factors are considered (e.g., residential stability, food deserts, and health providers). For all neighborhoods, the odds decrease when the model adjusts for socioeconomic/structural factors; in the 75% to 100% NHB neighborhoods adjustment for these factors yields a decrease from a 8% greater odds of infant mortality to 2% (not significant). This holds true for preterm birth as well (Figure 5). When socioeconomic/structural factors are considered (dark blue dots), the odds of preterm birth for women living in a high concentration NHB neighborhood decreases from 5% greater odds to 5% decrease in odds. This is consistent with previous research showing that neighborhoods with a high NHB concentration also have fewer resources, such as quality housing, healthy food, and health care providers (8,9).

**Figure 4: Infant Mortality Model: The Impact of Adjusting for Socioeconomic & Structural Factors on the Effect of Racial Composition**

![Graph](image)

*Adjusted OR and 95% CI for effect of area-level NHB concentration on infant mortality for models including racial composition only (teal) and racial composition and socioeconomic/structural variables (blue), Medicaid WRA cohort 2008-2015*
Figure 5: Preterm Birth Model: The Impact of adjusting for Socioeconomic and Structural Factors on the Effect of Racial Composition

Living in an Ethnically Isolated Community is Protective While Living in an Area with High Violent Crime Increases Risk for Infant Mortality and Preterm Birth

While socioeconomic and structural factors as a group mitigate the negative effect of living in a highly concentrated NHB area, individually these factors have very small independent effects on infant mortality and preterm birth (Figure 6). For example, living in an ethnically isolated community (e.g., high concentration of non-English speakers and a large foreign-born population) decreases odds of infant mortality by 4% (teal dots) and 3% for preterm birth (dark blue dots). Prior research suggests this may be because there is more social support in an ethnically isolated community (10,11). Living in an area with a high homicide rate increased odds of infant mortality by 14% and odds of preterm birth by 7%. Other interesting findings include the increased odds of PTB and IM of living in a food desert; though neither are statistically significant, the elevated odds of both outcomes implies healthy food options are important for positive birth outcomes.
Figure 6: Infant Mortality and Preterm Birth Model: The Effect of Socioeconomic & Structural Factors on Preterm Birth

Urban models of preterm birth indicate that the increase in risk of living in a non-Hispanic black neighborhood is not consistent across maternal race. Figure 7 shows that NHB women have approximately the same probability of a preterm birth regardless of how segregated their neighborhood is. We can compare the probabilities and the 95% confidence intervals between groups; if they do not overlap then we assume there is a significant difference between groups. So, for example, NHW women have a smaller probability of preterm birth if they live in a highly segregated black neighborhood (9.4%) compared to NHB and Hispanic women in the same neighborhood (12.3% and 12.1%, respectively). Highly segregated neighborhoods with a large NHB population appear to have a moderate protective effect against preterm birth for both white and black mothers, but this relationship is only statistically significant for white mothers. A NHW mother living in a neighborhood with >75% black residents, the probability of preterm birth is approximately 9.4% compared to 10.8% for a NHW woman in a <25% black neighborhood. This may suggest that white women are able to access services target in highly segregated neighborhoods better than NHB women.
There are spatial clusters of infant mortality in major cities that are the result of the spatial distribution of maternal age, race, and education. Figure 8 shows clusters of infant mortality in Cleveland, Columbus, and Cincinnati (Panel A). These clusters disappear when the clusters are adjusted for maternal characteristics, suggesting that the concentration of high risk populations in these areas drives the higher than expected rates of infant mortality in Ohio’s urban centers.

**Spatial Patterns of Preterm Birth are Related to Other Factors in Addition to Demographics**

Figure 9 shows clusters in Cleveland, Canton, Youngstown, Columbus, Dayton, and Cincinnati. The clusters in Canton, Youngstown, and Dayton disappear with adjustment for age, race, and education, but clusters in Cleveland, Columbus, and Cincinnati persist and new clusters appear in Appalachian counties and rural areas south and east of Columbus in the counties of Ross, Perry, and Morgan. Targeted intervention that specifically considers the needs of these rural communities, may be necessary to address the higher than expected preterm rates in these counties.
Figure 8: Spatial Clusters of Infant Mortality: A) Unadjusted and B) Adjusted for Maternal Age, Race and Education. Medicaid WRA Cohort 2008-2016

Spatial clusters of higher than expected NAS and maternal opioid use are found in rural southern and eastern areas of the state. Figure 10 shows that maternal opioid use also had distinct clusters of higher risk to the north of Columbus and Cincinnati. These clusters are calculated by comparing the observed count of NAS and maternal opioid use in
each area to what would be expected given the number of births in that area and the overall rate of NAS and opioid use in the state. For example, women living in Scioto County, contained in the large dark brown cluster, had 2.14 times greater risk of a NAS birth and 2.0 times greater risk of maternal opioid use, compared to women living in the rest of the state. The northern areas of the state, including Cleveland, Canton, Akron, and Youngstown had lower than expected rates of NAS compared to the rest of the state.

**Figure 10: Spatial Clusters of: A) Neonatal Abstinence Syndrome and b) Maternal Opioid Use, WRA cohort 2012-2016**

Spatial and temporal Medicaid and vital records data at the neighborhood level provides information not easily obtained from other sources and provides important information. Examining maternal demographics of women giving birth by neighborhood and year showed that a smaller percentage of all mothers were below age 20 years and lacked a high school degree in 2017. Also, more of these new mothers were covered by Medicaid prior to conception, many for up to 12 months prior to pregnancy. These data also reveal that within the OEI neighborhoods the pattern of preterm birth since 2010 showed an initial decrease in preterm, but an increase in preterm during the last two years.

2.4 Implications/Conclusions

- The spatial distribution of infant mortality within the Ohio’s Medicaid population is largely driven by differences in population composition across the state. The spatial clusters in the state are centered in large cities, in neighborhoods with concentrated NHB populations. The multilevel models support this and show that some of the Black-White disparity in infant mortality risk can be explained by neighborhood racial composition and structural characteristics.
The OEI counties currently cover the areas with clusters containing high infant mortality, suggesting that the state is already appropriately targeting the highest risk areas. The results of the case study of the OEI counties do not indicate a reduction in poor birth outcomes to date, though additional years of data are needed to monitor the impact as programs only began in 2014. The study design does not allow for causal inference regarding the effect of this targeted intervention strategy.

Efforts to reduce infant mortality in the state should continue to target OEI counties, and areas within those counties having concentrations of disadvantaged NHB residents. At the same time, multilevel models suggest a few other potential points of intervention, most of which are related to the inequities in social and health services in NHB communities. For example, further investigation into the effects of neighborhood violence, poor housing, transportation availability, employment opportunities, and drug abuse will likely reveal additional opportunities for individual- and community-level interventions.

The spatial distribution of preterm birth is not entirely related to the distribution of the NHB population. Spatial clusters persist in urban areas even after adjustment for maternal age, race, and education. Further, new clusters in rural areas were revealed. These rural areas are not currently a target of the OEI program, so a new focus on Marion, Ross, Perry, and Morgan counties may be necessary to address the higher than expected preterm birth rates in these counties. The OEI counties were chosen specifically to address racial inequities. The data-informed approach used here shows additional spatial inequities that extend beyond the current reach of the OEI communities. Expanding efforts into areas outside OEI counties with higher than expected preterm birth rates would increase the overall population health impact.

As the opioid crisis continues to affect the state, there are areas of particularly high NAS and maternal opioid use that could be targeted for specific opioid-related interventions. Spatial cluster analysis suggests two particular regions where the risk of an opioid-related birth is nearly two times greater than the rest of the state. Clearly, these areas could be the focus of mental health and substance abuse programs for mothers.

The case study suggests that examining small-area variation in maternal demographics, and a variety of birth outcomes can assist OEI counties in evaluating their impact on communities. Since the Ohio OEI initiative uses a place-based approach, targeting very specific zip codes within larger communities and exploring methods for placed-based evaluation is important. Both neighborhood demographics and birth outcomes have changed over time in ways that may help OEI communities shift the geographic focus of their programs.

2.5 References

SECTION 3: PREDICTIVE MODELING: INDIVIDUAL PREDICTIVE MODELING OF PRETERM BIRTH AND INFANT MORTALITY

3.1 Introduction and Objectives

The goal of this section of the IMRP was the development of predictive models to allow for personalized risk prediction and improved communication between pregnant women and their healthcare providers. The principal study objective was reducing the IMR for Ohio’s Medicaid and at-risk populations by developing accurate, point-of-care predictive models that identify women and infants at high risk of suffering an infant death or premature birth. The models incorporate data from key time points to allow estimation of risk prior to pregnancy, at the end of the first trimester, in mid-pregnancy, and at birth. The models were then implemented in an interactive risk calculator for use at the point of care and by policy makers to better investigate the impact of factors on the risk of infant mortality and preterm birth.

3.2 Methods

To create the databases, death certificate information was merged with data from the birth certificates. The result was merged with the WRA study cohort, along with Managed Care Plans for mothers and babies at delivery.

Twelve logistic regression models were created. The models considered information available at six different timeframes: pre-pregnancy, end of first trimester (13 weeks), mid-pregnancy (20 weeks), end of second trimester (28 weeks), birth, and 6 weeks postpartum. Using appropriate timeframes, the models examined five different outcomes: preterm birth, very preterm birth, one-day mortality, infant mortality, and post-neonatal infant mortality. The same general modeling strategy was employed for all 12 models(1). This report focuses on the Infant Mortality Model (model 11), that estimated the probability of an infant death using all factors known at birth and presents summary findings from models 1-5 that modeled factors from pre-pregnancy and the end of the first trimester (Table 3). The development, validation, and detailed discussion of models 1-12, along with a list of all variables used and their prevalence in the population, can be found in the Methodology Report. All models are available for use in the Infant Mortality Risk Calculator developed as part of the IMRP project.

The Infant Mortality Model (model 11) estimates the probability of infant mortality for an individual woman given characteristics included in the model. In addition, this study calculates the standardized mortality ratios (SMR) and associated confidence intervals for each county in Ohio (2). The SMR is defined as:

\[
SMR = \frac{\text{Observed } \# \text{ deaths}}{\text{Expected } \# \text{ deaths}}
\]
### 3.3 Key Findings

Twelve models were developed at six time periods. Their performance ranged from acceptable to excellent discrimination (Table 1), with models at later time periods generally performing better. Specifically, both our models at birth (models 10 and 11) had excellent discrimination with area under the ROC >0.80. All of these models showed good calibration with a Hosmer-Lemeshow test p-value of >0.05.

**Table 1: Outcomes, Timeframes, and Logistic Regression Model Performance**

<table>
<thead>
<tr>
<th>Model</th>
<th>Timeframe</th>
<th>Outcome</th>
<th>Calibration¹</th>
<th>Discrimination²</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Pre-pregnancy</td>
<td>1-day mortality</td>
<td>.40</td>
<td>.64</td>
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*Yellow = Acceptable, Light Green = Good, Dark Green = Excellent

1. P-value of Hosmer-Lemeshow test with G=10 groups, corrected for large samples.
2. Area under the Receiver Operating Characteristic (ROC) curve.

Figure 1 shows the covariates and odds ratios included in the final Model 11.
Figure 1: Odds Ratios (95% CI) for Predictors for Infant Mortality Model

Odds ratios (95% CI) for predictors in Infant Mortality model

Demographics
Race/Ethnicity
NH White
NH Black
Hispanic
Other

Maternal Education
No high school degree
High school degree
Some college
College or more

Opportunity index (ten unit increase)

Obstetric history
Previous pre-term birth
Previous live births now dead
Pregnancy interval
<18 months
18-59 months

Medical risk
Mother’s smoking status
Never a smoker
Stopped smoking during pregnancy
Smoked during pregnancy
Severe mental illness

Prenatal care
Trimester initiated prenatal care
1st trimester
2nd or 3rd trimester

Pregnancy/baby
Multiple birth
Poor fetal growth
Gestational age (One week increase)

Congenital anomaly

Green = Protective   Red = Risk factor
The variables included in this model, when considered together, are a useful tool for estimating the probability of infant mortality for an individual woman. This does not imply that variables in the model are primary or even secondary causes of infant mortality; rather, they may be proxies for causative factors. For example, having a previous preterm birth by itself is unlikely to be protective of infant mortality; rather, this variable is likely a proxy for the receipt of more intensive prenatal care and clinical oversight. This model is not intended to investigate the effect of individual risk factors on the outcome, and should not be used alone to determine which interventions would be helpful.

The major risk factors highlighted in model 11 include:

**Maternal demographics:**

- NHB race/ethnicity and not having completed high school are each associated with increased odds of infant mortality
- Increasing maternal age is associated with reduced odds of infant mortality in younger women. A one year increase in age is associated with a more pronounced reduction of the odds for younger mothers. For mothers over 36 a one year increase in age is associated with a slight increase in the odds of infant mortality. See Figure 2
- An increase in the opportunity index, indicating more available community resources is associated with an decreased odds of infant mortality even when adjusted for other demographic variables

**Figure 2: Probability of Infant Mortality by Mother’s Age**
Obstetric history

- A history of a previous live birth, now dead and a pregnancy interval <18 months are associated with an increased odds of infant mortality

Maternal comorbidities and health history:

- Smoking during pregnancy is associated with increased odds of infant mortality
- Diagnosis of severe mental illness in the prenatal period is associated with increased odds of infant mortality.

Factors related to the pregnancy and baby:

- Poor fetal growth and a pregnancy with multiples is associated with increased odds of infant mortality
- Increasing gestational age is protective of infant mortality
- A congenital anomaly is a major risk factor for infant mortality. 43% of these deaths occurred within the first day of birth. Although this is a major risk factor, only 0.6% of all babies were born with a congenital anomaly

Using the model described above, one can estimate the risk of infant mortality in an individual woman. For example, consider the two hypothetical women:

Case 1: The patient is a 28-year-old Hispanic woman presenting for prenatal care at 10 weeks gestation. This is her third pregnancy. She has had two prior vaginal deliveries at 38 and 39 weeks gestation of a boy and girl, both normally grown. Her last pregnancy ended 2 years ago, and she has been using low dose oral contraception. This pregnancy was planned. She reports that in her last pregnancy she was diagnosed with gestational diabetes at 30 weeks gestation. She followed the recommended program of diet and exercise and did well. The patient reports that she is married, and her family lives in a subsidized rental property on the southwest corner of Franklin County. Her husband works in construction. She has never smoked or used drugs; however, she has had a history of mild depression. She left high school in the 11th grade but has competed her G.E.D. and works as a nurse’s aide in an assisted living community.

The patient’s pregnancy proceeds uneventfully. She is found to be Group B strep negative at 36 weeks gestation. She delivers a 3500 gram male infant vaginally at 39 weeks gestation. The patient and her baby leave the hospital 36 hours after birth. She is seen in her obstetrician’s office for follow-up 6 weeks after delivery and is doing well.
Case 2: The patient is a 19-year-old NHB woman presenting for prenatal care at 18 weeks' gestation. This is her second pregnancy. Ten months ago, her first pregnancy, resulted in a vaginal delivery at 26 weeks' gestation after the onset of spontaneous preterm labor. That infant, a boy, weighed 800 grams and spent 3 months in the NICU before being discharged home. The infant was found dead in his mother's bed at 4 months of age. The patient reports she was seriously depressed after that loss. She was told to see someone for this, but did not.

The patient explains that she left school in 10th grade. She has smoked since high school and continues to smoke. She denies substance abuse. The patient lives with her mother in northeast Columbus but reports that she has to move in with friends every few months. She is employed intermittently at a distribution warehouse.

The patient is offered weekly 17-OH progesterone injections to reduce her risk of recurrent preterm birth. She is also followed by a Maternal-Fetal Medicine specialist for her high-risk pregnancy. However she fails to attend clinic regularly because she is working and lacks transportation and receives only 2 progesterone injections. She is hospitalized for severe depression at 22 weeks, but misses her follow-up counseling appointment. At 28 weeks gestation, she delivers a 1000 gram female infant vaginally after the onset of spontaneous preterm labor. She did receive corticosteroids 48 hours before birth. The baby develops moderate respiratory distress syndrome (RDS) and remains in the neonatal intensive care unit (NICU) for 10 weeks before discharge home.

Using the Infant Mortality Model one can estimate the probability of infant mortality for each of these patients. For Case 1, one would use as model inputs the woman’s Demographics: age (28), race/ethnicity (Hispanic), education (no high school degree), Ohio Opportunity Index (88.25), Obstetric history: previous live births now dead (no), parity (one or more), pregnancy interval (18-59 months), previous preterm birth = no), Pregnancy baby: trimester initiated prenatal care (first); multiple birth (no), poor fetal growth (no), gestational age (39 weeks), congenital anomaly (no). These factors would give her an estimated probability of infant mortality of 0.18%.

For Case 2, one would use as model inputs the woman’s Demographics: age (19), race/ethnicity (NHB), education (High school degree), opportunity index (57.77); Obstetric history: previous live births now dead (yes), parity (one or more), pregnancy interval (<18 months), previous preterm birth = no), Pregnancy baby: trimester initiated prenatal care (second), multiple birth (no), poor fetal growth (no), gestational age (28 weeks), congenital anomaly (no). These factors would give her an estimated probability of infant mortality of 39.05%.

The Infant Mortality Model (Model 11) is intended to be used at birth. The IMRP dataset contained a rich array of data that enabled the construction of a powerful model including all
factors prior to birth. However, other models developed in this study are designed to be used earlier in the course of pregnancy. These models can help to identify women at higher and lower levels of risk at a point where interventions may help to prevent preterm birth, itself a major risk factor for infant mortality. Table 4 shows the variables included in all 12 predictive models. In table 3 we show how Models 1-5 (detailed in the Methodology Report) can be used to calculate the estimated probability of various outcomes using the factors available in the cases above.

**Table 2: Variables included in all 12 models**

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Infant Mortality Research Partnership
### Table 3: Estimates of the Probabilities of Case 1 and Case 2 for Models 1-5

<table>
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<tr>
<th>Model #</th>
<th>Timeframe</th>
<th>Outcome</th>
<th>Estimate of the probability for case 1</th>
<th>Estimate of the probability for case 2</th>
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<td>8.54%</td>
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<td>6-weeks after birth</td>
<td>Post-neonatal infant mortality</td>
<td>0.12%</td>
<td>19.26%</td>
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</tbody>
</table>

The models themselves should not be used to suggest specific interventions. However, the high probabilities of negative outcomes for the second case provide an objective measure of the patient’s high-risk condition. Given that 0.86% of infants in the development dataset died, an estimated probability of 39% from the Infant Mortality Model is a highly significant risk. The patient in Case 2 would fall within the top quintile of risk in the dataset. Similarly, 1.81% of infants in the developmental dataset had a very preterm birth, so a risk of almost 14% is striking. Such high risks could be used as evidence in the counseling of the patient and could trigger the obstetrician to pursue more intensive interventions. In this specific example, the obstetrician might refer the patient for mental health and social support services earlier in the course of her pregnancy, ultimately leading to a healthier pregnancy and baby.
Given the number of models, and variables included in each of these models, calculating risk by hand is not feasible. As such, we developed an interactive calculator that allows the user to input a mother’s characteristics and see her estimated probabilities of the outcomes of interest at each time period (Figure 3). Usability was evaluated with three in-person sessions including a session with 11 maternal fetal medicine specialists, OSU Family medicine faculty, and at a booth at the annual conference of the Ohio Collaborative to Prevent Infant Mortality (OCPIM). Usability testing involved participants following a protocol using simulated data to evaluate participant comprehension of the tool’s function. Participants were also asked their impressions of the tool, whether and how they might use it in their practice, and what changes they would want to see in the tool to increase its usefulness. This feedback was used as an input to continued tool development.

**Figure 3: Screenshot of point-of-care tool**

These models can also be used to identify areas with higher or lower infant mortality than the model would predict by calculating SMR. Figure 4 shows the SMR for all 88 counties in Ohio. Counties whose confidence interval lies completely below the horizontal ‘unity line’ have lower observed infant mortality than the model predicts, while those whose confidence interval lies entirely above the unity line have higher observed infant mortality than predicted by the model. This same type of analysis can also be done for other categorizations such as managed care plans.
The work presented here is the first step to fully leverage the IMRP data for predictive modeling. This study provides strong evidence that these data can be used to reliably estimate probabilities of relevant infant mortality and preterm birth outcomes. Future work could focus on incorporating additional covariates from other available datasets, using the models at the point of care to inform clinical practice, and testing these models on more recent data.

3.4 References

SECTION 4: DISCUSSION

4.1 Putting Results into Context

The first phase of IMRP brought together three very different methodological approaches to large-scale data analysis toward addressing the problem of infant mortality in Ohio. In Phase II the two teams have worked collaboratively to develop usable tools for policy makers and clinicians.

A principal value of this project lies in the tools that have been created for policymakers and healthcare professionals. These tools can help stakeholders investigate the causes of infant mortality and develop strategies to address these issues. This innovative approach gives policymakers powerful analytical tools to make a difference in the lives of Ohio mothers and their babies.

There are several important themes to highlight in this report, presented here in terms of the level in which they fall within the socio-ecological model.

4.1.1 Individual-Level

Maternal Demographics, Infant Mortality, and Preterm Birth

Each year in Ohio, nearly 1,000 infants die before reaching their first birthday, and a disproportionately large number of them, nearly 40%, are NHB infants. This disparity is evident in the findings of the IMRP; however, the results of the IMRP’s work also show that this is a complex issue that deserves a more nuanced approach.

NHB race/ethnicity was associated with increased odds of infant mortality in the individual predictive model (Figure 1) even when adjusted for age, maternal comorbidities and obstetrical history. In fact, race was a significant factor in all 12 predictive models. Education was also associated with infant mortality in all of the models. In the Infant Mortality Model, detailed above (section 4.3), those without a high-school diploma had the highest odds of infant mortality, when adjusted for all other factors in the model.

Similarly, the spatiotemporal model showed that spatial clusters are concentrated in urban neighborhoods with high concentrations of NHB residents. Compared to neighborhoods with <25% NHB residents, the odds of an infant death in neighborhoods with >75% were approximately 20% greater. The odds were increased for preterm birth as well. The multi-level models (see Table 2.8, Methodology Report) showed NHB race and not completing high school to be significantly associated with infant mortality.

Interestingly, spatial clusters of infant mortality in major cities disappear when adjusted for maternal age, race and education, suggesting a much more complex role of race in infant mortality. In contrast, premature birth clusters do not disappear in most large urban areas when models adjust for maternal age, race, and education.
Prior Obstetrical History, Medical Complications, Infant Mortality and Preterm Birth

In addition to demographics and community-level factors, an individual woman’s obstetrical and medical history was also found to be associated with infant mortality.

Obstetrical History and Pregnancy characteristics: The individual-prediction Infant Mortality Model (Figure 1, Section 3) showed that diagnosis of poor fetal growth and congenital anomaly were associated with increased odds of infant mortality. Parity was included in the 8 of the 12 models and interpregnancy interval was included in 4 of the models. In the majority of the 12 models, previous preterm birth and previous live birth, now dead, were associated with the outcomes of interest. In the models intended for use after birth, gestational age, infant transferred and an infant in the NICU were strong predictors of the outcome.

Medical history: Medical and mental health history was found to be associated with infant mortality in the individual predictive models. Smoking during pregnancy was associated with increased odds of infant mortality (Figure 1). Smoking status, pre-pregnancy diabetes, hypertension and BMI were included in a majority of the very preterm and preterm birth models. Diagnosis of severe mental illness in the prenatal period was associated with increased odds of infant mortality but was not included in the preterm birth models.

Opiate addiction was included in half of the models as a predictor of preterm and very preterm birth. Maps of material opiate use and NAS clearly indicate areas of the state where a significantly higher proportion of mothers struggle with opiate addiction.

4.1.2 Organizational-Level

Access to Prenatal Care, Appropriate Postnatal Care, Infant Mortality and Preterm Birth

Prenatal Care Initiation: The individual predictive models also showed the impact of pre- and postnatal care. The week of initiation of the first prenatal care visit was associated with the outcome of infant mortality (Figure 1) with a later initiation being associated with increased odds of infant mortality.

4.1.3 Community-Level

The Association Between Social Determinants, Infant Mortality and Preterm Birth

Results showed that social factors such as housing and exposure to high crime areas are extremely important in influencing infant mortality. The spatiotemporal models showed that once area-level socioeconomic and structural variables are taken into account, much of the effect of living in a high concentration NHB area dissipates. These models also suggested that living in an area with a high crime rate increases the risk of infant mortality and preterm birth. This is a novel finding with significant implications for statewide interventions and policy.

Furthermore, models of preterm birth that focused on urban populations demonstrate that NH white mothers and NH black mothers experience neighborhoods quite differently. The interaction of maternal race and neighborhood segregation indicates that NH black mothers...
have a higher risk of preterm birth than NH white mothers living in the same (highly segregated black) neighborhood. This suggests that NH black mothers may struggle with issues such as institutional racism, weaker social networks, or higher levels of stress than white mothers.

In Phase II of IMRP, the researchers combined efforts to include a census-tract level variable in the individual predictive models. The Ohio Opportunity Index measures a series of community level resources such as transportation, education, employment, housing, health, access and crime. A higher score implies more access to these resources. The specific census-tract score for each woman was associated with the outcome in seven of the twelve models, even when adjusted for other demographic variables. This suggests that community level resources are important factors in the health of pregnant women and their infants.

4.1.4 Policy-Level

The Impact of Ohio’s Current Interventions on Infant Mortality and Preterm Birth

The case study examined how Ohio’s vital records and Medicaid data can be used to assist place-based interventions such as the OEI initiatives examine the changing demographics of their target populations and whether population-level changes in key birth outcomes have occurred over time. In the case of Franklin County, the demographic composition of their target zip codes are changing, suggesting they need to consider focusing on new zip codes to reach the population most in need of their services. Analysis of trends in birth outcomes suggest that while poor birth outcomes initially declined, there has been an uptick over the past few years. This type of analysis suggests that access to small-area data from Medicaid and vital records is a valuable tool as place-based interventions around the state attempt to understand their impact on the communities they serve.

The Role of Gestational Age

A large fraction of infant deaths occurred at pre-viable gestational ages. Specifically, analyses found that 11.60% (549/4,733) of infant deaths occurred before or on their 20th week of gestation. Infants born at such an early gestational age would not be expected to survive given limits to currently available medical interventions.

Ohio had the 7th highest proportion of infant deaths <20 weeks gestation (7.7%) according to CDC Wonder data from 2010-2014. When infant deaths less than 20 weeks are excluded, Ohio’s IMR drops to 6.9 per 1,000 live births, compared to the reported 7.5 per 1,000. This issue has been discussed previously. A study of Ohio live births at 16-22 weeks gestation from 2006-2012 found that these births accounted for 0.25% of all live births, but 28% of all infant mortality for NHW newborns and 45% for NHB newborns. In addition to the contribution to the overall IMR, the racial disparity in pre-viable live births may explain much of the IMR disparity between NHW and NHB infants.

On the policy level, these findings suggest that interventions aimed at decreasing preterm labor, (e.g. improving pre-pregnancy maternal health, early prenatal care, increasing inter-pregnancy interval) especially in communities at highest risk, will likely have a significant impact on both Ohio’s IMR and in its racial infant mortality disparity.
4.2 Implementing the IMRP models

The work done by the IMRP is innovative. Instead of reporting static findings, the teams created dynamic and interactive models that can be used by policymakers and healthcare professionals to continue to investigate factors associated with infant mortality. The following are some (but not all) of the ways these models could be used to impact policy and care for individual Ohio women.

Identify high-risk areas in Ohio

- The spatiotemporal clustering allows policymakers to visualize areas at highest risk, as well as identify areas at high risk after adjusting for known risk factors. Once known risk factors are taken into account, rural counties in Appalachia are shown to be at increased risk. Many of these counties are not specific targets of OEI initiatives and may be areas for expansion.

- Cluster analysis also indicates several regions of the state with higher than expected risk for maternal opiate use and NAS. Such information could be used to begin place-based, targeted interventions around maternal opioid use.

Implement point-of-care individual models

- Calculate individual risk: The final logistic regression models can be used in a calculator that can estimate the probability of an outcome (e.g., infant mortality) based on a woman’s individual factors (see section 3.3). This could be used by a healthcare provider to help counsel an individual woman or by policymakers for hypothesis generation to consider which risk factors might be important to address.

Estimate impact of interventions

- Estimate risk with changes in the prevalence of covariates: The predictive models (section 3) can be used to estimate the change in the probability of an outcome corresponding to changes in the level of a covariate. For example, if the prevalence of smoking pre-pregnancy was reduced, how might this change the expected number of infant deaths?

Assess performance

- Use Standardized Mortality Ratios to compare counties and managed care plans: By calculating the SMR for counties and Medicaid managed care plans in Ohio, policymakers can more accurately identify counties that have lower or higher infant mortality than predicted.

4.3 Putting It All Together: The Infant Mortality Reduction Analytics Dashboard

The models discussed in this report have been incorporated into the Infant Mortality Reduction Analytics Dashboard to create a set of dynamic tools that can help users at ODH and ODM better understand and evaluate factors related to infant mortality in the state of Ohio. These tools were built in a web-based application so that they could be disseminated among the state sponsors to help inform policy decisions. In the future, certain functions of the dashboard could also be used by healthcare providers to assess risk in their patients at the point of care.
The geographic models allow users to visualize spatial clusters and relevant geographic layers of infant mortality on a map of Ohio, track the impact of interventions over time to decrease infant mortality, and identify high and low performing counties. The individual predictive models enable users to estimate the risk of relevant outcomes for individual women and infants over the course of pregnancy, and display standardized infant mortality rates for each managed care plan. For more information, please visit grc.osu.edu/projects/IMRP.

4.4 Strengths of the Partnership

This partnership was an innovative approach to large-scale data analytics to address a significant public health issue. The strengths of this approach included:

- **Robust methods:** Results and common themes can be compared across multiple, established methods to further assess the robustness of the findings.

- **Ongoing communication and feedback:** Regular in-person meetings, conference calls, and webinars enabled the research teams as well as ODM, ODH, ODHE and GRC to provide continued constructive criticism and feedback.

- **Iterative improvements:** The research teams have been able to continuously improve and update their models with current and expanded data from Phase 1 to Phase 2 of the study.

- **Transdisciplinary collaboration:** The researchers on this project include obstetricians, pediatricians, geographers, informaticians, public health practitioners, and experts in statistical modeling. Their shared expertise along the research continuum helps us to translate our findings to policy makers and the bedside.

4.5 Limitations of the Work

The nature of this type of research posed challenges during the course of the partnership:

4.5.1 **Data Limitations**

The IMRP leveraged data collected for operational and public health uses throughout the state of Ohio. As with any project that uses data collected for other purposes, there were expected and unexpected challenges related to data accuracy and completeness.

4.5.1.1 **Missing and Inaccurate Data**

There were discrepancies between similar variables among datasets used by IMRP researchers. For example, birth weight was available from multiple data sources, sometimes with different values for the same birth. There were also discrepancies between the date of death across some of the datasets. These are common challenges when using data collected for other purposes; however, they complicated the process of linking the data to additional files. This issue was exacerbated by the lack of a unique, cross-dataset woman and baby identifier (e.g. Social Security Numbers are not available within all study datasets). In addition, some of the
variables within data sources were not reliably collected, including those about important topics such as smoking cessation and breastfeeding support, and thus could not be used in the analyses.

One of the IMRP’s ancillary contributions was exploring some of these data issues to facilitate future work in this area.

4.5.1.2 Completeness of the Datasets
Despite a wealth of data available to project researchers, there are some risk factors across all levels of the socio-ecological model that are not easy to capture. For example, at the individual level, data were not available for measures of women’s stress levels, their trust in the healthcare system, or their perceptions and experiences of racism. At the interpersonal level, data were not available for what kind of family or peer support women receive. At the organizational level, data were not available about women’s interactions with mental health care providers or social service agencies (e.g. how hard it is to obtain help from organizations). From the community level, data about clean air and water and ‘walkability’ of women’s community were not available in this phase of the project. Finally, at the public policy level there were insufficient data or results from prior studies on the impacts of housing policies, safety net policies, institutionalized racism, and changes in the healthcare system on infant mortality, PTB, or their antecedents.

In addition, available datasets were limited to live births. This limited the study’s ability to model poor pregnancy outcomes in the state of Ohio.

4.5.2 Dynamic Risk Factors
The factors influencing infant mortality are dynamic, and some are changing rapidly and without high quality data that allow integrating them in models. Phenomena such as Medicaid expansion and the opioid epidemic in Ohio pose challenges to constructing and validating models such as those presented in this report. To address this challenge, ongoing modeling and engagement between researchers and policymakers will be essential.

4.6 Recommended Next Steps
The IMRP aimed to use Ohio’s data to better understand infant mortality in Ohio and to develop tools to inform policy and practice. There are many ways that the results mentioned in this document as well as in future IMRP work may inform policy and interventions. A few of these include:

- While common challenges face all Ohio counties and neighborhoods, each is also unique and will require locally-informed interventions.

- The research teams collectively demonstrated the importance of addressing the social determinants of health in resource-scarce communities if infant mortality is to be reduced. These include, but are not limited to: segregation and structural racism, violent crime,
food security, housing stability, education, safe sleep programs and access to health care for women and children before, during and after pregnancy.

- Expanding and integrating mental health care services with perinatal medical care to address the strong association between serious mental health conditions and infant deaths.

- Explicit investigation of the impact of maternal opioid use on preterm birth and low birthweight that might ultimately impact the infant mortality rate in the state.

- While these results have clear implications for policymakers and community leaders from many disciplines (e.g. housing, business, justice department), the findings from the IMRP could also be disseminated to practitioners to improve their practice at the individual level. Health and social service professionals could benefit from translational science in this regard, in order to ensure they are equipped with a robust understanding of the multiple, intersecting factors contributing to infant mortality. This could ensure they are able to appropriately and effectively identify and address some of the factors impacting infant mortality, or mobilize the necessary community resources if needed.

- Expanded data collection: The IMRP researchers identified several risk factors that were not well represented in the dataset. This may have been because the data are not currently collected or that they just were not available in the datasets for the project. Some examples include:
  - Data on exact location of Section 8 / federal housing.
  - Air and water quality data. These are available but are time intensive to process for modeling.
  - Noise and urban greenness data.
  - Records reflecting fetal death or pregnancy loss that would give a broader picture of infant mortality and maternal health in Ohio.
  - A single unique identifier across all datasets for mothers and babies to avoid the challenges of probabilistic linking.
  - All residential addresses not just annual addresses.
  - Qualitative information from the Fetal Infant Mortality Review.
  - Walkability scores of Ohio streets and traffic counts.
  - Immigration status in history (important to address disparities among refugee, recent and long-term immigrants).
  - Opioid overdose rates at the census tract level.

The addition of these variables in future IMRP work would likely give a more accurate representation of the environment in which women in Ohio live.

- Multiple initiatives have been implemented to improve birth outcomes in the state. However, there is not a robust inventory of these interventions. This inventory should include the geographic reach, a description of the intervention, adjustments made that
tailor the intervention to specific populations, and information on the fidelity of implementation.

While the infant mortality rate in Ohio has recently been reduced, it remains a significant public health problem. The findings in this report and other IMRP outputs provide insights and direction to focus and enhance efforts aimed at reducing the number of infants in Ohio dying before their first birthday.

4.7 References

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**Abbreviations:** GRC: Ohio Colleges Of Medicine Government Resource Center; OSU: The Ohio State University; PI: Principal Investigator; PM: Project Manager; C: Coordinating; G: Geospatial; I: Individual Predictive Modeling;