QUANTIFYING DIABETES DISPARITIES RELATED TO AMERICAN INDIAN AND ALASKAN NATIVE RESIDENCY ON RESERVATIONS

by

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American Indians and Alaskan Natives (AI/AN) have the highest diabetes rate of any racial group in the United States. Rates range from 6.0% in some Alaskan Natives to 29.3% for tribes in Southern Arizona (Edwards and Patchell, 2009), suggesting that environmental and social effects may exacerbate health disparities. Due to the violent and traumatic events that created the reservation system, there are likely enduring conditions that deepen health disparities for AI/AN within these areas. Diabetes serves as the outcome of interest. The current thesis examines the correlation between living in a Census-designated American Indian Area (AIA) and having a diabetes diagnosis. Data from the 2015-2018 series of the National Survey on Drug Use and Health was run in logistic regression models to determine if residency in AIAs influences diabetes rates. These models quantify the severity of this inequality while controlling for other demographic factors such as age, family income, gender, education, and metropolitan status. The results show that AI/AN living in AIAs are anywhere between 1.595 - 1.764 times more likely to have diabetes than AI/AN outside of AIAs, depending on the controls. All models demonstrate statistical significance for the relationship between AIA and diabetes, showing that living in reservation-like areas

is correlated with conditions that likely contribute to diabetes disparities. Potential explanations for inequalities include lack of nutritious food sources, environmental stress, suboptimal prenatal conditions, and other socio-environmental conditions. This expands the current notion of factors that influence health, especially in the cultural context of AI/AN. These findings serve as a starting point for further qualitative research to explore social processes creating environmental inequalities and exacerbating health disparities. Exploring these mechanisms is crucial for creating effective policies and interventions that reduce diabetes disparities for AI/AN in their appropriate social contexts.

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Introduction

Individual vs social determinants of health: socio-ecological model

A large proportion of public health interventions focus on modifying individual-level behavior to improve health outcomes. For diabetes prevention, an example of individual-level intervention would be nutrition education to promote healthy dieting. Although these interventions may be helpful to some extent, they do not always account for environmental factors that complicate the intervention's effectiveness. For the aforementioned example, nutrition education is less effective if it does not address structural barriers in obtaining healthier foods. Thus, this individual-level intervention may be helpful in some contexts where individuals lack education about a topic, but ineffective when social structures make some healthy behaviors more unrealistic.

The socio-ecological model theorizes the interplay between various individual and environmental structures that influence health outcomes. Individuals are embedded within larger social systems, so accounting for interaction between individuals and their environment is important for understanding situations like the hypothetical example listed earlier. Most interventions do not address causes at the socio-environmental level. A systematic review of intervention approaches notes that 95% of articles describe individual-level activities, 67% describe interpersonal activities, but only 39% describe institutional-level activities (Golden and Earp, 2012). This means that a large majority of interventions target individual behavior, some seek to influence social networks through interpersonal intervention, and less seek to modify institutional structures and policies. Although designing larger-scale interventions may be more difficult, more people are advocating for multilevel focuses to create effective programs. Communityfocused interventions attempt to increase health services and empower disadvantaged groups (Golden and Earp, 2012). These may help address the social, cultural, and physical aspects of environments that influence health, specifically suited for each community's unique characteristics. This is especially important for marginalized groups such as AI/AN because living on reservations could create unique complications that require tailored interventions to reduce diabetes prevalence. Reservations would directly affect community-level factors because they influence the built environment and local conditions that impacts access to food and mental health services. The socio-ecological model pertaining to diabetes disparities is shown below in Figure 1.

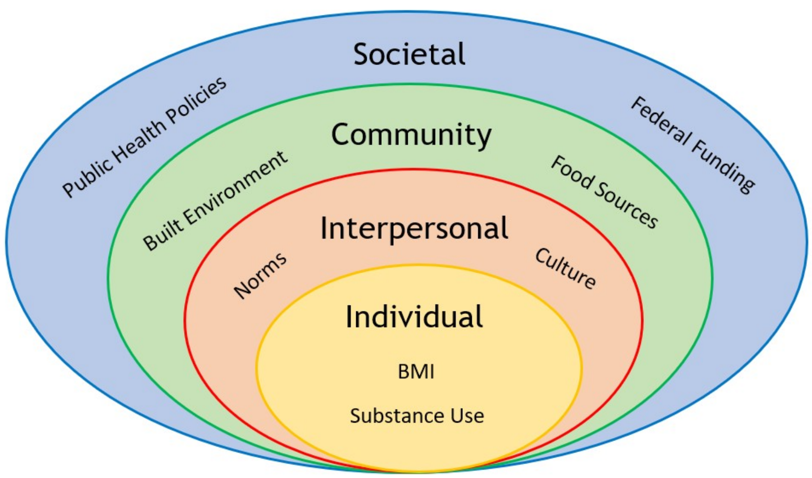

Figure 1: Socio-ecological Model For Diabetes in AI/AN Reservations

The socio-ecological model as it applies to diabetes outcomes in reservations. Includes factors in the societal, community, interpersonal, and individual levels that could influence diabetes risk and outcomes for AI/AN in these areas. Adapted from: "Models and Frameworks for the Practice of Community Engagement." Agency for Toxic Substances and Disease Registry. Retrieved May 21, 2020

Creating an enclave: history of reservations

AI/AN have a marginalized history in United States, as their traditional lands were seized during colonization. The result of this environmental degradation is deprivation, trauma, and poverty that has persisted in AI/AN tribes from generation to generation. In the 1830's, the U.S. government started systematically removing AI/AN from their traditional lands and relocating them through the Indian Removal Act. (Banner, 2005). This did not help reduce conflict between settlers and AI/AN as anticipated, so the U.S. government designated land to establish the first reservations in the 1850's (Dippel, 2014).

For the government, there were benefits to confining AI/AN into these concentrated lands. First, they could maximize land area for the growing population of settlers (Banner, 2005). Second, they could easily monitor AI/AN and prevent them from interfering with further colonization (Dippel, 2014). Some argue that segregation could also protect AI/AN from white settlers, but this policy did not guarantee that new AI/AN land was secure from further seizure.

Reservations remained in place until the 1950's, resulting in the termination era. Though individual tribes were terminated throughout the 19th and early 20th centuries, termination became the official policy for all tribes in 1953 (Wilkinson and Biggs, 1977). Congress attempted to assimilate AI/AN by removing them from their established reservations and integrating them into the rest of American society. This freed up tribal lands for further settlement, so the U.S. government reaped economic benefits (Wilkinson and Biggs, 1977). Termination and forced assimilation created several negative outcomes for AI/AN, including loss of remaining tribal lands, enfeeblement of culture and religion, and weakening family structures (Wilkinson and Biggs, 1977). These historical traumas have endured to create disparities in AI/AN populations today, including in socioeconomic status (SES) and health outcomes—both mentally and physiologically.

Indigenous self-determination became increasingly relevant in the U.S. government from the 1960s-1980s (Wilkins, 2011). Many tribes regained recognition during this time. As of 2016, there are 567 federally recognized tribes and 63 state-recognized tribes (Salazar, 2016). Federal recognition is coveted because it provides legal status and federal benefits to tribes, which is not guaranteed with state recognition. Not all recognized tribes have reservation land, but likely share similar disparities with AI/AN on reservations due to residential conditions in highly AI/AN-concentrated areas. This includes socio-environmental disparities that influence health outcomes, including in diabetes.

Historically high diabetes rates amongst AI/AN populations

AI/AN have higher rates of diabetes than any other racial group in the United States. The Indian Health Service (IHS) and National Health Interview Survey indicate that age-adjusted prevalence rate for type 2 diabetes in AI/AN populations is more than double that of the total U.S. population, with 25% of AI/AN males and 30% of AI/AN females diagnosed with diabetes (Benyshek et al. 2010). The CDC claims that diabetes is the 4th leading cause of death in the AI/AN population, behind heart disease, cancer, and unintentional injuries (Benyshek et al. 2010). This makes diabetes one of the top preventable chronic diseases for AI/AN. It is comorbid with obesity and cardiovascular disease, which disproportionately impacts AI/AN (Spanakis and Golden, 2014). Risk factors such as concentrated poverty, smoking, poor mental health, stress, and maternal pregnancy conditions can increase risk of diabetes (Kelley et al., 2015). AI/AN on reservations may be particularly vulnerable to chronic diseases because of destabilized food sources, psychosocial stressors from community conditions, and inadequate areas to exercise (Spanakis and Golden, 2014).

Before colonization in the U.S., AI/AN populations cultivated crops suitable for the growing seasons they lived in. After colonizers pushed AI/AN out of their traditional lands, their food sources were destabilized. Government food aid was not a sufficient replacement, as their supplies was low in nutritional value. Surveys from the 1920s and 1950s found that the AI/AN diet post-colonization consisted of canned meat, bread, sugar, and other non-traditional processed foods (Edwards and Patchell, 2009). The Food Distribution Program on Indian Reservations (FDPIR) serves as the primary food source for many tribes, providing monthly food packages to qualifying low-income households on reservations (Fox et al., 2004). Many were concerned that these packages lacked fresh produce and had high levels of fat, sodium, and sugar. They were updated in 1998, but still lack certain nutrients compared to dietary recommendations (Fox et al., 2004). As a result, malnutrition and nutritional deficiencies were common on reservations. By the 1990s, around ¼ of AI/AN households were food insecure (Edwards and Patchell, 2009). Lack of reliable nutritious food sources for AI/AN populations has resulted in increased rates of diabetes.

One specific case is the Pima tribe of Arizona, who practiced traditional agriculture and sold their crops to settlers, creating a successful commercial agriculture business. After Anglo and Mexican-American farmers started diverting water from the Gila River, the Pima's main source, the Pima's crop production dropped to nearly zero. Starvation and poverty set in shortly afterwards. The Pima diet shifted from a traditional diet to a high fat, high carb diet based on wheat flour, animal fats, sugar, and other processed foods (Benyshek et al. 2010). Caloric intake was initially low, but government nutrition programs increased caloric intake to excessive amounts. Diabetes rates increased with these nutritional deprivation trends to the point where 50% of Pima 30 to 64 years old have diabetes as of 2010, compared to 4% in the general population (Benyshek et al. 2010), (Fox et al., 2004). The Pima's history show how systematic malnutrition can lead to increased diabetes rates. Nutritional deprivation can specifically impact AI/AN populations on reservations if their community food sources are compromised.

AI/AN are likely to experience stress and trauma related to historical loss of land, systematic attacks on culture, and poverty, which can influence diabetes outcomes. The most common mental health diagnoses for AI/AN are alcohol dependency and Post-Traumatic Stress Disorder (PTSD), though prevalence varies by tribe (Beals et al., 2005). Alcohol impacts biological mechanisms by reducing glucose intake into cells, leading to high blood glucose—characteristic of diabetes (Jiang et al., 2013). PTSD is associated high levels of obesity and metabolic irregularities, which also causes diabetes (Scherrer et al., 2019). PTSD and alcohol dependency are strongly correlated, so compounding biological effects from these conditions greatly increase diabetes risk. PTSD rates are 2 to 3 times higher for AI/AN compared to the general population (Sarche and Spicer, 2008). According to the National Comorbidity Survey, AI/AN in poor rural communities may have a higher risk of PTSD and alcohol dependency than the general survey sample (Beals et al., 2005). They are also more likely to drink heavily than other groups (Whitesell et al., 2012). Smoking is correlated with stress and increases risk for diabetes, with rates varying by tribe. Some tribes may use tobacco for cultural reasons, such as in the North Plains, so they have a higher smoking rate than Southwest tribes (44% vs 21%) (Dennis and Momper, 2012). As a result, it is difficult to characterize diabetes risk for AI/AN generally because risk factors are not consistent for each tribe. However, the overall trend of mental health diagnoses and alcohol/tobacco use correlates with increased diabetes rates. These mental health disparities may be exacerbated by the high rate of per-capita violent victimization for AI/AN (Sarche and Spicer, 2008). Though individual rates of trauma are already high, the interconnected culture of reservations makes it so trauma is shared throughout the community instead of staying within the individual's immediate family (Sarche and Spicer, 2008). Thus, frequent traumatic incidents in the community can greatly increase individual stress, potentially leading to higher amounts of alcohol and tobacco use. Reservations may have higher rates of substance use and mental health disorders due to living in a stressful environment, though there is not substantial research on reservation/non-reservation disparities.

Concentrated poverty and neighborhood effects on reservations may also increase risk for developing diabetes. Over 25% of AI/AN live in poverty—double that of the general population (Sarche and Spicer, 2008). For some tribes, this rate can be as high as 40% (Sarche and Spicer, 2008). Concentrated poverty is correlated with poorer health outcomes. AI/AN from areas with higher median household income have 35% lower risk of having diabetes than those from low neighborhood income areas (Jiang et al., 2018). Since reservations are generally known to have high rates of poverty and unemployment, this would likely increase the risk of developing diabetes. Past studies have shown that living in areas with high concentrations of AI/AN—such as reservations—are less effective at reducing BMI and increasing physical activity (Jiang et al., 2018). This could be due to neighborhood characteristics, since lifestyle interventions are ineffective in areas with many neighborhood disadvantages. If an area is unsafe for exercise and has no accessible exercise facilities, then it is difficult to increase physical activity. Ideal exercise environments are more likely to be in higher SES areas, which may partially explain why these areas are more effective at reducing BMI and increasing health food consumption (Jiang et al., 2018). These disparities may relate to the fact that low-income neighborhoods contain more racial minorities, which correlate to less allocation of resources. Regardless, neighborhood SES and resources are correlated with health outcomes, so reservation areas with lower SES and higher concentrations of racial minorities may have higher rates of diabetes.

Intrauterine factors, or conditions within the uterus, influence likelihood to have diabetes later in life. Maternal factors such as nutrition and stress influence development in the womb, with adverse conditions leading to increased risk of insulin resistance and type 2 diabetes (Jiang et at., 2013). Disadvantages in the social environment can become embodied before birth, thereby creating health disparities through social inequalities. Maternal stress creates hormones that can result in insulin resistance in offspring (Jiang et at., 2013). Poor nutrition, whether that be through malnutrition or overnutrition, alters biological mechanisms in mice and lead to insulin resistance (Jiang et at., 2013). This includes having low protein, high protein, and high fat maternal diets during pregnancy, since this causes disturbances in crucial development periods. Living in reservations may include geographic isolation that makes it more difficult to access fresh foods at grocery stores. Poverty makes it difficult to afford healthy options as well, so AI/AN may turn to processed food subsidies, if available. Lower birth weights may result in negative health outcomes, as shown in twin studies, where the twin with a lower birth weight is more likely to have diabetes (Benyshek et al. 2010). Additionally, glucose intolerance is most prominent amongst babies gestated under famine conditions during the third trimester of pregnancy, where 21% of them had impaired glucose tolerance or were diabetic (Benyshek et al. 2010). Given the increased barriers in accessing traditional food sources, this makes AI/AN especially susceptible to having unideal diets during pregnancy in comparison to other races. Social inequalities and risk factors can even extend to exacerbate health disparities even prenatally.

Despite several documented health disparities between AI/AN and other races, there is not as much research on intersectional disparities within the AI/AN community. Less studies have compared the disparities between AI/AN living on and off reservations. It is difficult to generalize AI/AN population health because risk factors vary by tribe and partially depend on each tribe's unique history and local context. Though diabetes inequalities appear differently in each tribe, there are likely general inequalities that create overall trends. Quantifying the relationship between reservation habitation and diabetes amongst AI/AN can open up avenues of research into disparities that may exist for AI/AN living on reservations.

Methods

Survey Data

Data from the 2015-2018 series of the National Survey on Drug Use and Health (NSDUH) was analyzed to determine statistical correlations between living in an AIA and diabetes rates amongst AI/AN. Aggregating multiple years of data collection ensures sufficient sample size. The annual survey is taken by the U.S. Department of Health and Human Services through the Substance Abuse and Mental Health Services Administration, which measures use of drugs (prescription and illegal), alcohol, tobacco, substance use disorder care, mental health disorders, and more. The survey includes questions about clinical health, such as if participants have been diagnosed with diabetes. This data can support public health programs by identifying community health disparities and treatment needs. Professional interviewers conduct surveys in person, with the first data collected in 1971. The annual data collection makes the NSDUH an ideal dataset for analysis because it provides a large representative sample throughout several years.

Outcome of Interest

The outcome of interest is diabetes, and whether the participant has a diagnosis. A specific survey question asks about general health conditions such as heart condition, cancer, HIV/AIDS, and diabetes. Participants self-report on whether a doctor or health care professional has diagnosed the participant with any of the conditions, selecting either “yes” or “no.” If participants do not have any of the conditions listed, they would self-report as having none of the conditions, coded as a “legitimate skip.” For the purposes of this research, the “legitimate skip” responses are recoded as “no” responses, since they indicate an absence of diabetes diagnosis. Responses coded as “bad data,” “don’t know,” “refused,” and “blank,” were excluded from the logistic regression models. Thus, after recoding, the only participants included in the models responded with either a “yes” or “no” response.

Main Predictor

The main predictor is living in an “American Indian Area” (AIA), which indicates concentrated areas of AI/AN populations. The Census specifies five types of AIAs, including federally-recognized American Indian reservations (AIRs), state-recognized American Indian reservations (SAIRs), Oklahoma tribal statistical areas (OTSAs), tribal designated statistical areas (TDSAs), and state designated tribal statistical areas (SDTSAs). The U.S. federal government designates AIR land for AI/AN tribes holding federal recognition. SAIRs are state-established reservations for tribes recognized by the state but not federally. OTSAs are intended to indicate former AI reservation land existing before Oklahoma statehood, which is still considered for statistical purposes. TDSAs include federally-recognized tribes without reservation land, intended to represent contiguous areas containing individuals that identify with the tribe. SDTSAs are identified for state-recognized tribes without reservation land, including geographic areas with large concentrations of tribe members. These AIAs are mutually exclusive and serve as indicators for reservation-type areas, the effect of interest.

AIA was chosen as a main predictor because it includes “pseudo-reservation” areas. This indicator is more inclusive than only looking at recognized reservations because it accounts for AI/AN tribes without recognized reservation land, who may share similar outcomes from residency in predominantly AI/AN areas. AI/AN living within these AIAs will be compared to those living outside these areas to see if living in concentrated AI/AN areas are correlated with diabetes disparities. This indicator is more inclusive and comprehensive than looking at federally-recognized tribal land alone because many tribes do not have federal recognition, though they may share similar environmental conditions and health outcomes. This provides a better understanding of how an enclave effect of racial minorities can influence health outcomes, making the AIA an ideal predictor for diabetes rates.

Control Variables

Control variables include gender, age, education, family income and metropolitan status. Gender is coded with males as the reference variable, where "male" = 0 and "female" = 1. Age is split into 5 categories, with the age group "50+" serving as the reference variable, and the other groups coded as "12-17" = 1, "18-25" = 2, "26-34" = 3, and "35-49" = 4. The 50+ age group was chosen as the reference variable because it would predictably have the highest prevalence of diabetes, as chronic disease rates generally increase with age. Education was recoded and split into 4 categories, with "less than HS degree" serving as the reference variable, "HS degree" = 2, "some college" = 3, and "college/secondary degree" = 4. College/secondary degrees include associate's, bachelor's, master's, and doctorate degrees. Within the dataset's codebook, the variable for highest achieved education was coded to distinguish between each grade level in high school, so these categories were combined into the reference variable. Family income includes "< $10,000" as the reference variable, with the remaining categories being “$10,000-$19,999” = 2, “$20,000-$29,000” = 3, “$30,000-$39,000” = 4, “$40,000-$49,000” = 5, “$50,000-$74,999” = 6, and “≥ $75,000” = 7. Metropolitan status has “large metro” as the reference variable, with “small metro” = 2, and “nonmetro” = 3.

The education and family income variables include imputed data, which means that respondents did not input those responses. Instead, this missing data is estimated based on responses to other survey questions. Two versions of the education and income data exist: one with imputed data and one with reported data only. Both were analyzed in two separate sets of models.

Analysis

Six total logistic regression models were run. Logistic regression models best fit the data because the outcome of interest is binary, meaning there are two responses: having a diabetes diagnosis and not having one. All data management and statistical analyses were conducted using R. Models 1A-3A contain imputed data and Models 1B-3B exclude imputed data. Models 1A and 1B include the main predictor only, looking at AIA vs diabetes rates amongst AI/AN without controlling for other variables. Models 2A and 2B look at AIA vs diabetes rates while controlling for gender, age, education, and family income. Controlling for these variables accounts for imbalances in the demographics spread, ensuring that AIA is the only effect creating trends in the outcome. It also minimizes confounding effects and isolates the main predictor to best determine statistical relationships. For example, the average age of people living in AIAs may be disproportionately older, so failing to control for this variable would make it appear that residency in AIAs is correlated with higher diabetes rates, when this effect is actually caused by age of population living in this area. After controlling for all these variables, it can be determined if living in an AIA directly relates to diabetes rates. Models 3A and 3B still look at AIA vs diabetes and contain the same controls as Models 2A and 2B, but now controls for metropolitan status. Controlling for metropolitan status removes effects that rural or urban environments may have on diabetes rates, since reservation land tends to lie in rural areas. The results of all models were compared to see if significant correlations still appear after adding more controls.

Figure 2 depicts the data-cleaning process, including the number of respondents excluded during each step. Data from the 2015-2018 NSDUHs were appended after sub-setting the race variable for AI/AN, so only respondents identifying as AI/AN (N = 3363) were included in the appended dataset. Respondents were dropped from the regression models if they did not have a “yes” or “no” response to having diabetes after recoding. The remaining respondents (N = 3286) were included in Models 1A-3A. To test for robustness, respondents with imputed data for education and family income were dropped and the remaining sample (N = 2876) was included in Models 1B-3B. Table 1 shows respondent demographics in the starting sample before the data cleaning process in Figure 2.

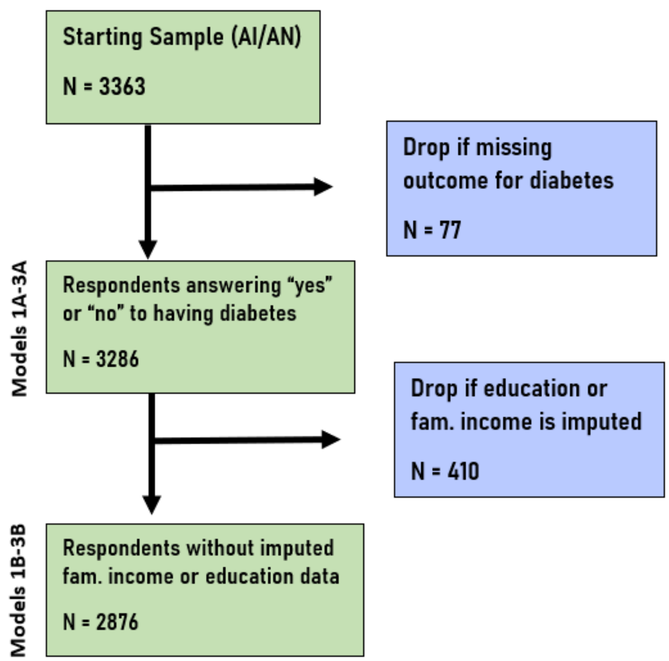

Figure 2: Data Cleaning

Depicts the process for sub-setting data in the regression models. After removing missing data for the outcome of interest, subset data was used for Models 1A-3A. To test for robustness, imputed data was dropped and the remaining data was used in Models 1B-3B.

Table 1: Respondent Demographics

	Full Sample		AIA = yes		AIA = no	
	N	%	N	%	N	%
Demographics						
Gender						
Male	1623	48.260	580	17.247	1043	82.753
Female	1740	51.740	618	18.376	2745	81.624
Age						
12-17	834	24.799	309	9.188	3054	90.812
18-25	874	25.989	311	9.248	3052	90.752
26-34	568	16.890	207	6.155	3156	93.845
35-49	680	20.220	225	6.690	3138	93.310
50+	407	12.102	146	4.341	3217	95.659
Education						
Less than HS Degree	416	12.370	104	3.092	3259	96.808
HS Degree	940	27.951	347	10.318	3016	89.682
Some College	649	19.298	225	6.690	3138	93.310
College/Secondary Degree	416	12.370	104	3.092	3259	96.908
Family Income						
< $10,000 (REF)	531	15.789	229	6.809	3134	93.191
$10,000-$19,999	688	20.458	247	7.345	3116	92.655
$20,000-$29,999	454	13.500	193	5.739	3170	94.261
$30,000-$39,999	379	11.270	124	3.687	3239	96.313
$40,000-$49,999	315	9.367	114	3.390	3249	96.610
$50,000-$74,999	407	12.102	141	17.247	3222	82.753
≥ $75,000	589	17.514	150	18.376	2745	81.624
Metro Status						
Large Metro	484	14.392	28	9.188	3054	90.812
Small Metro	1060	31.519	203	9.248	3052	90.752
Nonmetro	1819	54.089	967	6.155	3156	93.845

Results

All models indicate a statistically significant correlation between living in an AIA and having a diabetes diagnosis within AI/AN populations. The magnitude of disparity varies depending on the controls. Table 2 shows results of logistic regression models including imputed data. When looking at the main predictor and the outcome of interest without controls, Model 1A finds that AI/AN living in an AIA are 1.595 times more likely to have diabetes than AI/AN living outside of an AIA. This probability is found through the odds ratio, listed in the first column of each model's results. P-values less than 0.05 are considered statistically significant. The data in Models 1A-3A yields a p-value of <0.001, making it statistically significant. Model 2A finds that disparities caused by AIA are greater than represented in the first model. After controlling for gender, age, education, and family income, Model 2A shows that AI/AN living in an AIA are 1.764 times more likely to have diabetes than AI/AN living outside of an AIA. This means that within cohorts in the same categories for gender, age, education, and family income, the disparity for those living in an AIA is even greater than when looking at AIA status alone. In Model 3A, AI/AN living in AIAs are 1.725 times more likely than those outside an AIA to have diabetes. The odds ratio in Model 3A decreased in comparison to Model 2A, meaning that metropolitan status likely contributes some effects that influence likelihood of having diabetes. The differences were not formally tested for statistical significance, serving instead as a qualitative observation of changing odds ratios between models.

These overall trends demonstrate how living in an AIA increases risk of diabetes for AI/AN. Table 3 shows Models 1B-3B, which tests for robustness by fitting the same controls as Models 1A-3A, but without imputed data. If the trends in Table 2 are also present in Table 3, findings are strengthened because the trends persist even in data where participants reported all demographic information. Models 1B-3B show statistical significance for AIA vs diabetes, which means that AI/AN living in AIA have a higher likelihood of having a diabetes diagnosis. The same general trend appears in Models 1B-3B compared to Models 1A-3A, with the odds ratio increasing when adding all controls excluding metropolitan status, then decreasing again after metropolitan status is included.

The odds ratios of models listed in Table 3 are all less than their corresponding models in Table 2. In Model 1B, the odds ratio is 1.584, as compared to 1.595 in Model 1A. In Model 2B, the odds ratio is 1.703, which is less than the ratio of 1.764 in Model 2A. In Model 3B, the odds ratio is 1.665, compared to the ratio of 1.725 in Model 3A. This trend between Models 1A-3A and Models 1B-3B shows that the diabetes disparity for AI/AN in AIAs is reduced after excluding imputed data, but the findings are still statistically significant and strengthen evidence for a health disparity. All models show varying magnitudes of diabetes disparity for AI/AN living within AIAs, indicating that there is an overall disparity within AI/AN populations dependent on residential environment.

Table 2: Logistic Regression Models with Imputed Data

	Model 1B				Model 2B				Model 3B			
Variables	OR	B	SD	p	OR	B	SD	p	OR	B	SD	p
AIA	1.584	0.46	0.134	**<0.001**	1.703	0.533	0.146	**<0.001**	1.665	0.51	0.315	**<0.001**
Gender												
Male (REF)					-	-	-	-	-	-	-	-
Female					1.287	0.252	0.139	0.198	1.288	0.253	0.146	0.082
Age												
17-Dec					0.04	-3.21	0.353	**<0.001**	0.04	-3.213	0.354	**<0.001**
18-25					0.048	-3.036	0.299	**<0.001**	0.048	-3.035	0.299	**<0.001**
26-34					0.124	-2.091	0.248	**<0.001**	0.124	-2.091	0.249	**<0.001**
35-49					0.533	-0.629	0.166	**<0.001**	0.534	-0.627	0.166	**<0.001**
50+ (REF)					-	-	-	-	-	-	-	-
Education												
Less than HS Degree (REF)					-	-	-	-	-	-	-	-
HS Degree					0.843	-0.171	0.213	0.421	0.839	-0.176	0.213	0.409
Some College					1.002	0.002	0.227	0.992	1	3.24E-05	0.227	1
College/ Secondary Degree					1.017	0.016	0.255	0.949	1.018	0.002	0.255	0.945
Family Income												
< $10,000 (REF)					-	-	-	-	-	-	-	-
$10,000-$19,999					1.143	0.134	0.227	0.556	1.141	0.132	0.227	0.561
$20,000-$29,999					0.781	-0.247	0.269	0.359	0.781	-0.247	0.269	0.358
$30,000-$39,999					0.776	-0.254	0.273	0.352	0.775	-0.255	0.273	0.351
$40,000-$49,999					0.514	-0.666	0.329	**0.043**	0.514	-0.666	0.329	**0.043**
$50,000-$74,999					0.578	-0.548	0.29	0.058	0.579	-0.547	0.29	0.059
≥ $75,000					0.706	-0.348	0.259	0.179	0.712	-0.339	0.26	0.192
Metro Status												
Large Metro (REF)					-	-	-	-	-	-	-	-
Small Metro									1.058	0.057	0.237	0.811
Nonmetro									1.09	0.087	0.239	0.717

Table 3: Logistic Regression Models without Imputed Data

	Model 1A				Model 2A				Model 3A			
Variables	OR	B	SD	p	OR	B	SD	p	OR	B	SD	p
AIA	1.595	0.467	0.128	**<0.001**	1.764	0.568	0.139	**<0.001**	1.725	0.545	0.154	**<0.001**
Gender												
Male (REF)					-	-	-	-	-	-	-	-
Female					1.195	0.179	0.139	0.198	1.197	0.18	0.139	0.195
Age												
17-Dec					0.042	-0.03	0.202	**<0.001**	0.042	-3.18	0.348	**<0.001**
18-25					0.05	0.083	0.218	**<0.001**	0.05	-2.994	0.28	**<0.001**
26-34					0.117	0.083	0.218	**<0.001**	0.117	-2.147	0.241	**<0.001**
35-49					0.551		0.202	**<0.001**	0.552	-0.594	0.158	**<0.001**
50+ (REF)					-	-	-	-	-	-	-	-
Education												
Less than HS Degree (REF)					-	-	-	-	-	-	-	-
HS Degree					0.97	-0.03	0.202	0.88	0.967	-0.034	0.203	0.867
Some College					1.086	0.083	0.218	0.704	1.086	0.082	0.218	0.867
College/ Secondary Degree					1.086	0.083	0.218	0.58	1.149	0.139	0.244	0.571
Family Income												
< $10,000 (REF)					-	-	-	-	-	-	-	-
$10,000-$19,999					1.127	0.119	0.217		1.128	0.12	0.217	0.58
$20,000-$29,999					0.771	-0.26	0.26	0.317	0.771	-0.26	0.26	0.316
$30,000-$39,999					0.868	-0.141	0.256	0.582	0.87	-0.139	0.257	0.588
$40,000-$49,999					0.442	-0.815	0.322	**0.011**	0.443	-0.813	0.322	**0.012**
$50,000-$74,999					0.585	-0.537	0.278	0.054	0.586	-0.534	0.278	0.055
≥ $75,000					0.731	0.119	0.217	0.209	0.737	-0.305	0.251	0.224
Metro Status												
Large Metro (REF)					-	-	-	-	-	-	-	-
Small Metro									1.006	0.006	0.227	0.98
Nonmetro									1.058	0.057	0.227	0.803

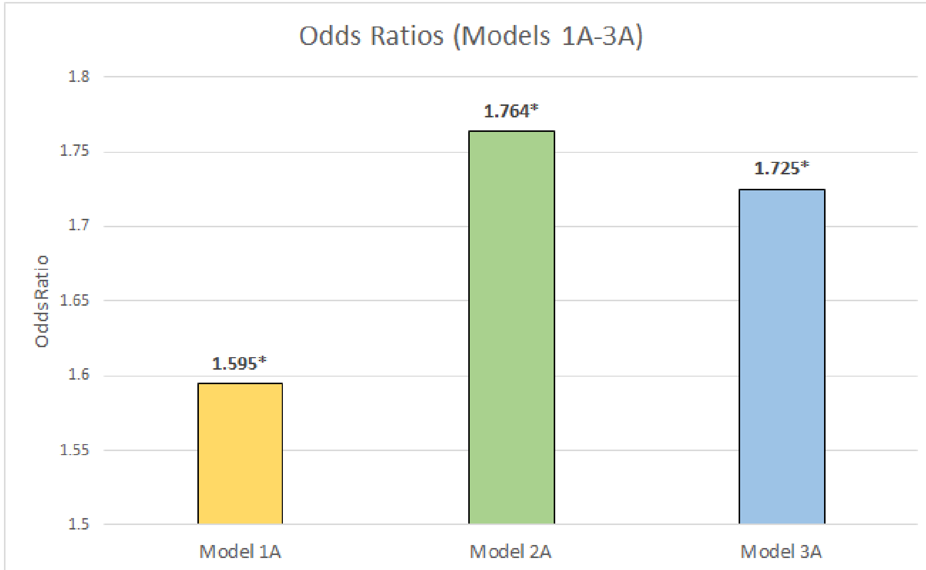

Figure 3: Odds Ratios (Models 1A-3A)

Compares the odds ratios for models containing imputed data. Statistically significant values are indicated by asterisks. Data demonstrates that AI/AN in AIAs are between 1.595-1.764 times more likely to have diabetes than those outside of these areas.

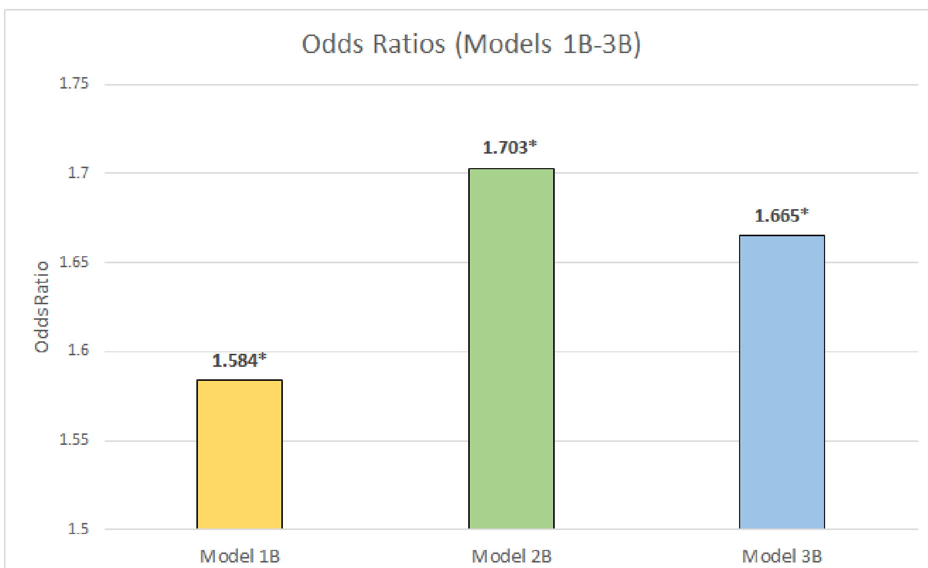

Figure 4: Odds Ratios (Models 1B-3B)

Compares the odds ratios for models without imputed data. Statistically significant values are indicated by asterisks. Data demonstrates that AI/AN in AIAs are between 1.584-1.703 times more likely to have diabetes than those outside of these areas.

Discussion

There are many health disparities between AI/AN and other racial/ethnic groups in the United States, but further disparities dependent on demographics and social environments may exist within these populations. AI/AN may face health disparities related to historical and contemporary marginalization, including forced relocation onto government-designated reservations. This historical trauma could contribute to poor health outcomes, yet additional disparities within the AI/AN population may potentially lead to diabetes disparities based on residential context. Though many AI/AN live on reservations, many others live in urban and suburban settings. If there is a disparity in diabetes rates between AI/AN living in AIAs or reservation-like land, there are likely effects in the social environment that contribute to overall health outcomes. All logistic regression models find that AI/AN living in AIAs have a higher likelihood of having diabetes than those living outside of AIAs. These findings were consistent while controlling for several other demographic factors such as gender, age, education, and family income. The test for robustness strengthens evidence for this disparity because it excludes imputed data. Thus, it is likely that there are effects within AIAs and reservation-like areas that create health disparities and can increase risk of having diabetes.

Future Research

Given these findings, more research on area-level effects is needed to determine exactly why AI/AN have a higher risk of having diabetes when living in AIAs. Disparities could be related to an “enclave effect,” where having high concentrations of AI/AN living within a specific area of land correlates with social effects that increase risk of adverse health outcomes such as diabetes. Environmental conditions could be related to conditions such as differing food sources, since reservations may be disproportionately located in food deserts. There could also be adverse effects related to concentrated poverty and internalized stress for those living on reservations. Stress can weaken immune systems, result in poorer health outcomes, and is correlated to substance use and poor mental health outcomes—also increasing diabetes risk. These conditions can influence maternal health and create unideal intrauterine factors, which increases diabetes risk for newborns from the start. These explanations can come together to create a more complete picture of why health disparities exist in AIAs, but researchers will need to conduct specific case studies to determine social conditions that contribute to these disparities. They will also need to compare local conditions with AI/AN living outside of AIAs, especially to find factors outside of AIAs that are more optimal for health. Finally, they should compare conditions between tribes in different states and geographical areas, since diabetes rates range greatly from tribe to tribe.

The regression models in this study did not compare diabetes rates between specific geographical regions, so analyzing disparities within AI/AN living in AIAs can reveal qualitative factors impacting AI/AN health. If there are explanations relating to social conditions, this can help determine the main factors for diabetes disparities among AI/AN populations, as well as how social environments shape their general health outcomes. Qualitative data is needed to contextualize these quantitative findings and provide a better idea of what public health interventions are needed to reduce these disparities.

Limitations

Several limitations exist within the data, both in terms of data collection design and the use of self-reported data. First, the survey does not distinguish between Type 1 and Type 2 diabetes, leading to an incomplete profile of health conditions in the findings. In Type 1 diabetes, the body is unable to produce insulin, while in Type 2 diabetes, the body becomes insulin-resistant due to diet, stress, weight, and other factors. The main causes of these diabetes types can differ, which changes the ideal type of intervention to reduce these disparities. Failing to distinguish between these conditions removes context that is crucial for determining which factors contribute most to these health disparities, especially if one type is diabetes is more prevalent within or outside of AIAs. Another limitation exists in rates of diabetes diagnosis because many individuals may not have a formal diagnosis of diabetes from a healthcare worker, but may still have the condition, nonetheless. Organizational structures may make it more difficult for AI/AN to access healthcare if they live in certain areas, resulting in underdiagnosis. Diabetes rates may also change depending on geographic area and could vary region by region. AI/AN populations have a wide range of diabetes rates, so generalized findings may not accurately depict disparities for certain tribes. More research is needed on area-level effects and structural conditions shaping health in order to accurately identify AI/AN most at risk for diabetes. This includes case studies and historical analyses on how neighborhood setup and environmental-based factors influence food sources, mental health and substance use, and maternal health disparities for specific reservations. Given the small sample size for respondents living in AIAs and the limited scope of survey questions surrounding built environment, determining most influential causes of diabetes in AIAs could not be done with current limitations in the data.

Conclusion

Although there are limitations in the findings, the results are still compelling because it substantially demonstrates a health disparity between AI/AN in AIAs and those living outside of AIAs. The results are generalizable for the AI/AN population because it comes from a representative sample. The data within both sets of models have many respondents and spans through four years of data collection. This large sample size generates a more accurate average when looking at overall trends, reducing the likelihood of outliers skewing the data. The logistic regression models also demonstrate a substantially higher likelihood of AI/AN living in AIAs to have diabetes, and the results in all models are statistically significant. This was true in the initial models containing imputed data, but also appeared in the models without imputed data. The test for robustness strengthens the validity of the findings, where AI/AN living in AIAs may be as high as 1.764 times more likely than AI/AN outside of AIAs to have diabetes. All results demonstrate a diabetes disparity within AI/AN populations that depend on residency in reservation-like areas, despite all limitations. Further research can help fill in knowledge gaps due to design limitations within these results, providing more social context for analyzed trends.

Diabetes disparities between AI/AN in AIAs and those outside of AIAs can now be quantified through odds ratios found in these models. There is a clearly established health disparity related to living on reservation-type land, but more research is needed to understand causes for these disparities. Future research will need to look at qualitative environmental factors and area-level effects specific to a tribe or region to supplement quantitative findings. This can include differing access to food sources, community stress levels, mental health disparities, and various other factors. Due to the variability of conditions surrounding each tribe, specific comparisons are needed to explain disparities existing between tribes living in AIAs. Public health organizations will need to address qualitative factors that create diabetes disparities for AI/AN living in AIAs. By doing so, policies and interventions can effectively mitigate diabetes disparities in AI/AN and have potential to create successful prevention measures.

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