SSM - Population Health 15 (2021) 100869

Contents lists available at ScienceDirect

SSM - Population Health

journal homepage: www.elsevier.com/locate/ssmph

Social determinants of the Latinx diabetes health disparity: A Oaxaca-Blinder decomposition analysis

Kate Cartwright

University of New Mexico, USA

ARTICLE INFO

Keywords:
Health inequities
Latinx/Latino/Hispanic health
Diabetes
Social determinants of health

ABSTRACT

Latinx people living in the U.S. report a disproportionately high prevalence of diabetes. This project builds on the existing social determinants of diabetes literature by examining factors associated with a greater likelihood of diabetes and investigates factors correlated with the Latinx/non-Latinx disparity. This project studies the adult sample (18 and older) from the 2010–2018 IPUMS Health: National Health Interview Survey (NHIS) data. Logistic regression analyses are used to examine the patterns between reporting Latinx identity and reporting diabetes with additional subgroup analyses of the Latinx and non-Latinx groups. Then, Oaxaca-Blinder decomposition is used to examine the patterns explaining the difference in self-reported diabetes between the Latinx and non-Latinx population for the whole sample and by age group.

The logistic regression analyses show that after adjusting for age and other key social determinants of health, Latinx individuals are approximately 64.5% (OR 1.645, [95% CI, 1.536–1.760]) more likely to report being diagnosed with diabetes than non-Latinx individuals. Individual characteristics of age, race, and smoking behaviors are identified as suppressors of the gap, and conversely, characteristics of income, education, and BMI all contribute to the Latinx diabetes disparity gap. The Oaxaca-Blinder decomposition results show that the measured social determinants of health characteristics explain a meaningful amount of the Latinx diabetes gap. Importantly, differences in education and income (which are more immediately actionable policy areas) make larger contributions to the gap than BMI or other health behaviors.

The Latinx epidemiological paradox is an enduring phenomenon where the U.S. Latinx population experiences a meaningfully longer life expectancy than their socioeconomic position would predict (Lariscy, Hummer, & Hayward, 2015; Markides & Coreil, 1986). However, at times the focus on this phenomenon masks the health disparities that Latinx communities experience. In fact, recent studies suggest that the U.S. Latinx epidemiological paradox is rapidly waning, due in part to COVID-19 (Sáenz & Garcia, 2021).[1] Scholarship points to the prior health disparities faced by Latinx people as a major contributor to the pandemic disparities and suggests that these pre-pandemic health disparities must be more thoroughly investigated to redress these health injustices (Sáenz & Garcia, 2021). While COVID-19 has brought renewed attention to Latinx health disparities, one of the most persistent Latinx health disparities is the disproportionately high prevalence of type 2 diabetes mellitus (diabetes). This paper responds to calls for additional disparities research by contributing to the Latinx diabetes disparity scholarship.

Diabetes is the most common disorder of the endocrine system, and it occurs when blood sugar levels in the body consistently stay above normal. Over 34.2 million people (over 10% of the population) in the U. S. have some form of diabetes in the U.S., of which more than 90–95% of cases are type 2 diabetes, and 88 million people, over 34% of the population, exhibit pre-diabetic symptoms (Centers for Disease Control and Prevention CDC, 2020. As of 2017, diabetes is the seventh leading cause of death overall in the U.S., but the fifth leading cause of death for Latinx people (CDC, 2020). The physical ramifications of diabetes are great, and the conditions associated with advanced stage diabetes include vision impairment, peripheral neuropathy, amputations, decreased mobility, and end stage renal failure. Also, diabetes is particularly debilitating in the population aged 65 and older, and over 26% of this

E-mail address: kcartwright@unm.edu.

[1] This paper mainly uses the term "Latinx" to be more inclusive of sex and gender in this investigation and discussion of U.S. Latinx health disparities, and sometimes use Hispanic and Latino, primarily when referring to the measures from the dataset. However, the term "Latinx" is not without limitations and controversies. Salinas (2020) articulates the complexity of Latinx/a/o with great nuance and suggests that all investigators of Hispanic/Latina/o/Latinx research make note of considerations behind selected terms.

https://doi.org/10.1016/j.ssmph.2021.100869
Received 28 March 2021; Received in revised form 7 July 2021; Accepted 8 July 2021
Available online 24 July 2021

population has been diagnosed with diabetes (CDC, 2020). The number of older individuals with diabetes is projected to grow rapidly as diabetes is being diagnosed at higher rates in the younger populations.

Diabetes does not affect racial and ethnic groups at the same rates: 10.3% of the Latinx population has been diagnosed with diabetes compared to 9.4% of non-Hispanic whites (CDC, 2020). The total direct and indirect costs of diagnosed diabetes in the U.S. in 2017 were approximately $327 billion (CDC, 2020). The financial burden of disease is matched by the individual burden of disease. Not only are the symptoms of diabetes burdensome, but they exacerbate comorbid conditions. Too often experts' primary approach to reducing diabetes is by promoting changes in individual health behaviors; however, structural inequalities are inextricably linked with diabetes in society, as is evidenced by the patterns of who has the disease and how treatment differs between groups (Berwick, 2020; Brown et al., 2019; Harris & Pamukcu, 2020; McKinlay & Marceau, 2000). As many social factors contribute to developing type 2 diabetes (the focus of this study), it is important not only to understand but address social determinants to reduce diabetes disparities.

Unsurprisingly, many of the social determinants which contribute to the health disparities experienced by the U.S. Latinx population overlap with the social determinants of diabetes, including structural determinants (such as race and ethnicity) and more individual-level determinants (such as smoking) (Fenelon, Chinn, & Anderson, 2017; Lariscy et al., 2015; Marquez, Calman, & Crump, 2019; Rodríguez & Campbell, 2017; Sáenz & Garcia, 2021). The negative effects of diabetes on the Latinx community are monumental. As mentioned earlier, Latinx people are more likely to develop diabetes and to be diagnosed at younger ages (Avilés-Santa et al., 2017; Haw, Shah, Turbow, Egeolu, & Umpierrez, 2021). They are more likely to have disabilities related to diabetes and less likely to access and receive high quality care for diabetes; they are more likely to die from diabetes and diabetes-related conditions (such as end-stage renal disease) (Haw et al., 2021; Marquez et al., 2019; Rodríguez & Campbell, 2017). Though diabetes can be prevented and mitigated at many stages, Latinx communities face disparities at each of these stages. To better understand how social factors, structural and individual, influence Latinx diabetes, it is important to look at the body of work on Latinx health. Much of the work on Latinx social determinants of health comes from the Latinx paradox research.

The Latinx paradox literature shows that U.S. Latinx groups experience both benefits and consequences from a wide range of social determinants (Lariscy et al., 2015; Sáenz & Garcia, 2021). The early work on what was originally coined the "Hispanic paradox" noted how surprising the U.S. mortality outcomes were in relation to the U.S. Latinx's significantly and meaningfully lower education and income levels (Markides & Coreil, 1986). Subsequent research has identified some key explanatory factors for the paradox, including lower rates of smoking, related lower rates of cancer, supportive family networks, the healthy migrant theory, and more (Markides & Eschbach, 2005; Akresh & Frank, 2008; Lariscy et al., 2015). However, at times the focus on the Latinx paradox has masked real health problems the Latinx community faces (such as diabetes and chronic kidney disease) which are connected to a relatively disadvantaged socioeconomic status.

Investigating health disparities through the social determinants of health framework provides evidence for the structural sources of these inequities. In turn, the evidence contributes to the development of social and health policy that can best be implemented to improve equity efforts and decrease disease burden (Arcaya, Arcaya, & Subramanian, 2015; Solar & Irwin, 2010). As both the prevalence and severity of diabetes is linked with many social determinants of health, it is a condition that meets the assumptions for this framework (Avilés-Santa et al., 2017; Haw et al., 2021; Marquez et al., 2019; Rodríguez & Campbell, 2017). This paper uses Oaxaca-Blinder decomposition to further examine the social factors contributing to the diabetes disparity between Latinx and non-Latinx populations in the U.S. The Oaxaca-Blinder decomposition method allows empirical researchers to distinguish between outcome variations caused by differences in observable characteristics between two populations (if one group is on average older, the older group would be more likely to have diabetes) vs. differences in how those characteristics influence the outcome (the rate of diabetes diagnosis increases faster with age in one group than another group) (Blinder, 1973; Oaxaca, 1973). These are referred to as the *explained* and *unexplained* gaps, respectively. If the factors that contribute to the differences in the explained gap can be influenced by policymakers, the gap can be reduced through policy.

Based on the literature investigating the Latinx epidemiological paradox, the Latinx diabetes disparity, and the social factors influencing diabetes, the project's hypotheses predict (1) that structural factors will be the primary factors contributing the diabetes disparity between Latinx and non-Latinx groups; (2) that for some factors, such as age and racial composition, if the U.S. Latinx population had the same characteristics as their non-Latinx peers, they would have even higher rates of diabetes; and (3) for other factors, such as income and education, if the U.S. Latinx population had the same characteristics as their non-Latinx peers, they would have lower rates of diabetes.

Methods

Data and sample. This investigation into the U.S. Latinx diabetes disparity uses the publicly available IPUMS Health: National Health Interview Survey data (NHIS), managed by the Minnesota Population Center at the University of Minnesota (Blewett, Rivera Drew, King, & Williams, 2019). The National Health Interview Survey (NHIS) is a nationally representative health survey conducted by the National Center for Health Statistics under the Centers for Disease Control and Prevention (CDC) (Blewett et al., 2019). Since 1997, the NHIS has included an extensive range of demographic and socioeconomic characteristics, which allow for thorough analyses of social determinants of health, as well as age, ethnicity, and nativity.

The nationally representative sample design of the NHIS, with strategic oversampling of select minority groups makes this dataset well-suited for the study of general patterns and national level trends related to the population of U.S. Latinx people. While some datasets focus solely on the population of specific age groups, the immigrant population, or are race and ethnicity focused, the broad, the nationally representative design allows for comparative data analyses between groups, such as non-Latinx people and Latinx people or native born and foreign-born residents. NHIS allows for robust cross-group analysis. Each year, the sample includes somewhere between 50,000 and 85,000 individuals. A common strategy for data analysis is to pool years of cross-sectional data for analysis to analyze groups that comprise relatively small proportions of the U.S. population. The sample for this project pools data from 2010 to 2018. To be included in the sample, participants must be 18 years of age or older.

Dependent variable. The key outcome variable for this study is diabetes. The measure for diabetes is a self-report of having received a diabetes diagnosis from a doctor. While this question does not differentiate between type 1 and type 2 diabetes, most researchers use this variable as a measure of type 2 diabetes since 90–95% of adults who self-report diabetes have been diagnosed with type 2 (CDC, 2020; Oza-Frank & Narayan, 2010). This variable is a dichotomous variable.

Independent variable. The key input variable for this study is Latinx ethnicity. The NHIS uses the same operationalization of race and ethnicity as the U.S. Office of Management and Budget (OMB)—the survey asks participants if they consider themselves to be Hispanic or Latino, and if they answer in the affirmative, they are asked to identify their representative Hispanic or Latino identity group (which includes ethnicity of origin). Race and ethnicity scholars note that the use of the OMB categories, which are used across most government and government-adjacent social science research frequently leads to the essentializing of racial and ethnic groups, which may result in perpetuating or exacerbating the inequalities (Gómez & López, 2013; Knight, Roosa, & Umaña-Taylor, 2009). These limitations of quantitative methods and techniques is particularly disheartening considering that many of these projects aim to improve racial health equity. Quantitative research relies upon the fixed-response racial and ethnic categories. While this is useful for understanding the patterns of inequality across large groups, there are also conceptual limitations to this that most quantitative researchers do not acknowledge in the development of their methods, their analysis, nor in their discussion of limitations.

Critical race scholars have challenged researchers employing quantitative methods to be very intentional in how they measure race and ethnicity, to articulate these decisions in their research, and to exercise great caution in making generalizations and making conclusions based on their results (Knight et al., 2009; Zuberi and Bonilla-Silva, 2008). While these challenges should be acknowledged in all race and ethnicity research, it is particularly important to heed these cautions while conducting health research. Even with overwhelming evidence that race is not biological, but a social construct, researchers continue to treat racial and ethnic identification as a biological characteristic in their research by failing to justify the use of and unpack the variables carefully (Gómez & López, 2013; Zuberi and Bonilla-Silva, 2008).

While exploring trends using Latinx ethnicity identifies important patterns, it is important to remember that the U.S. Latinx population, regardless of nativity, is diverse (Borrell, Menendez, & Joseph, 2011; Fenelon et al., 2017; Rotermann, 2011; Zsembik & Fennell, 2005). In order to critically examine research methods and the social issue of Latinx health disparities simultaneously, Knight et al. (2009) challenge all who study Latinx health and well-being to investigate who comprises the social group "Latinx" in any study, and especially quantitative studies, where often sweeping generalizations about Latinx people are made. To begin to account for this diversity, the cultural heritage of respondent's Latinx ethnicity is also measured and included in the descriptive and regression analyses. Responses are coded as: Not Hispanic/Spanish origin, Mexican (all Mexican heritage categories recoded as one category), Puerto Rican, Cuban/Cuban American, Dominican, Other Hispanic (all non-specified types including multiple Hispanic recoded as one category), and Central or South American. Due to sample sizes, many groups are still conflated in this measure. The consequences of this are addressed in the discussion. However, the inclusion of these categories shows how various cultures of origin influence health outcomes for U.S. Latinx people and how any research on Latinx health needs to account for diversity.

This project uses the NHIS fixed-response measures of Latinx ethnicity (the key independent variable) and race (as a control). This study begins by measuring Latinx identity with self-reported identification based off fixed-response category. To prevent essentializing a "Latinx effect," a range of variables including ethnicity of Latinx origin, nativity status, and racial identification are added to the descriptive analyses and logistic regression models to demonstrate the importance of the heterogeneity of the Latinx population. The Oaxaca Blinder decomposition models use a dichotomous measure of Latinx ethnicity as the decomposition model compares characteristics across groups, and the non-Latinx group does not have the characteristic of detailed Latinx origin group. The dichotomous Latinx variable sets up the comparisons to unpack the factors influencing the diabetes disparity between U.S. Latinx and non-Latinx populations.

Control variables. The models control for a variety of individual demographic characteristics, health and health-behaviors, and acculturation measures. The demographic controls include *age*, treated as a continuous variable. *Sex* is measured as a dichotomous female/male category. *Race* is measured by the OMB definition and responses are grouped into white, Black, Asian, Native American, and other. As previously noted, these categories are very broad, and findings related to race should be treated with nuance and not reductively. In this study, race is kept as a separate category to show the diversity of the U.S. Latinx people. This allows the study to investigate how additional racial identification influences the disparity.

Other demographic controls include socioeconomic status measures. *Education* (measured as less than high school, high school diploma, GED or equivalent, some college, Associate degrees, Bachelor's degrees, graduate degrees, and unknown). Of racial and ethnic groups, people of Latinx heritage have the lowest high school completion rate in the U.S., so having additional information about education gives some insight to the return on different levels of education in relation to the diabetes disparity (Carnevale & Fasules, 2017; Whitaker et al., 2014). This is a categorical variable, and the omitted category is less than high school. *Income* is measured as a percentage of the Federal Poverty Level (FPL) (coded as less than 100% of the FPL, between 100% and 199% of the FPL, between 200% and 399% of the FPL, above 400% of the FPL, and unknown). This is a categorical variable, and the omitted category is income below the FPL.

The *number of people in an individual's household* is a proxy for socioeconomic status and it is also an indicator of social connectedness. This variable is treated as a continuous variable. Marital status is another good measure for social connectedness and is strongly connected to health outcomes in adults, including diabetes (Manfredini et al., 2017; Ramezankhani, Azizi, & Hadaegh, 2019; Robles, Slatcher, Trombello, & McGinn, 2014). The survey responses are regrouped into "Married" (married, spouse present) and "Not-Married" (married, spouse not in household; widowed; divorced; separated; never married; and unknown). This is a dichotomous variable and "Not Married" is the omitted category. The models control for variability related to *geographic* factors measured as region of residence; the regions are categorized into four groups: the Northeast, the North Central/Midwest, the South, and the West. This is a categorical variable, and the omitted category is the Northeast.

The health and health-behavior controls include a few key measures. *Body mass index (BMI)* is included as obesity is highly correlated with diabetes and other health conditions (Arias-Gastélum et al., 2020). BMI is a controversial measure particularly in race and ethnicity studies as BMI does not capture different average body compositions across racial and ethnic groups and due to the tendency to overstate findings related to analyses using BMI (Gutin, 2018). While scholars should be cautious about interpreting findings related to BMI this imperfect measure is still useful in capturing some overall health information in relation to diabetes (Gutin, 2018; Oza-Frank & Narayan, 2010). BMI is a continuous variable. *Smoking* is measured as current smokers, former smokers, never smoked, and unknown. This is a categorical variable and current smokers is the omitted category. Finally, *health Insurance* correlates with many health outcomes. For this study, a broad proxy indicates if an individual has health coverage. This is measured as not covered, covered, and unknown. This variable is treated as categorical and having health coverage is the omitted category.

As more than half of U.S. Latinx people are born outside of the U.S., it is important to consider how these differences affect health (Brown, 2018; Reyes & Garcia, 2020; Riosmena, Everett, Rogers, & Dennis, 2015). The acculturation measures include *nativity* and *language of the interview*. Nativity is measured by U.S. born, non-U.S. born, and unknown, and U.S. born is the omitted category. Language of interview captures one facet of English proficiency. This variable is coded as a dichotomous variable (interview taken in English only or interview taken in another language/combination of another language and English). The Latinx region and country of origin (discussed prior as a facet of Latinx identity) also gives information about specific cultural identification.

To control for social dynamics specific to each sample, *survey year* is included, as is consistent with other studies (Langellier, Chen, Vargas-Bustamante, Inkelas, & Ortega, 2016; Whitaker, 2014). This variable is constructed based on the year of participation.

Analytical design. As the goal of this paper is to better understand the factors that contribute to the diabetes disparity in Latinx populations, the analyses use the Oaxaca-Blinder decomposition technique. This method was originally developed to determine which factors explain the gender wage gap, and over the last few years has been increasingly utilized to better understand health inequities (Blinder, 1973; Oaxaca 1973). Oaxaca-Blinder decomposition is a regression-based method that determines the degree to which any disparity in a characteristic of a sample mirrors differences in the observed characteristics of a sample, and identifies important factors associated with the disparity (Chen & Rizzo, 2010; Idler & Cartwright, 2018; Kino & Kawachi, 2020; Langellier et al., 2016). An advantage of this technique is that it specifically explores the factors that explain the gap or the disparity in an outcome variable.

The analysis begins with descriptive statistics of the whole sample, the Latinx sample, and the non-Latinx sample. Then, the analysis moves to logistic regression models examining the association between being Latinx and reporting a diabetes diagnosis, including controls for key demographics, health-related behaviors and characteristics, and acculturation measures. The final analyses decompose the disparity and explain the contributing factors of the difference in diabetes between Latinx and non-Latinx groups.

After estimating the logistic regressions for Latinx people and non-Latinx people separately, the Oaxaca-Blinder technique decomposes these regressions into explained differences (differences based on the observable characteristics included in the regressions) and unexplained differences that are caused by unobserved differences (differences in the regression coefficients) between the groups. This is achieved by constructing a *counterfactual equation* where the intercept and coefficient of the Latinx logistic regression equation is replaced with those from the non-Latinx logistic regression equation. The non-linear decomposition analysis methods adjust for the logistic regression models (Jann, 2008; Sinning, Hahn, & Bauer, 2008). The results are then interpreted in the context of the following question: if the Latinx subsample had the same observable characteristics as the non-Latinx subsample, would they have the same rate of reported diabetes? All analyses were completed using Stata 16 (StataCorp, 2019).

Results

Descriptive statistics. Table 1 summarizes the descriptive statistics of the weighted whole sample, the Latinx sample, and the non-Latinx sample. After cleaning the data and applying the sampling strategy, the final sample included 257,763 observations. In the whole sample, 9.6% report being diagnosed with diabetes, which is almost the same as the non-Latinx sample, with 9.5% reporting. Of the Latinx sample, 10.4% report being diagnosed with diabetes. At first glance, this 0.9 percentage point gap may seem negligible. However, even this difference means that Latinx people' risk is 10% greater than non-Latinx people. These numbers closely align with the numbers reported by the CDC in 2020 (where 9.4% of non-Hispanic white respondents reported a diabetes diagnosis compared to 10.3% of Hispanic respondents) (CDC, 2020). Moreover, due to some differences in key variables between the samples, even these statistics indicate that this gap is much greater than these initial numbers show. The most meaningful differences between the Latinx sample and the non-Latinx sample are in the difference in age, education, poverty, and language. The two groups are statistically significantly different from each other when comparing all key variables with exception of the composition of sex (females/males) in each group (see Table 1, Column 4). The average age of the Latinx sample is approximately 43 years old compared to the average age of nearly 50 years old of the non-Latinx sample. As one's likelihood of developing diabetes increases with age, this age difference indicates that the Latinx group is on track to have even higher rates of diabetes as this group ages, and these descriptive statistics suggest that the disparity will be much greater after controlling for age in the multivariate models. On average, the Latinx population has lower levels of education. In this sample, about 30% of Latinx people have not finished high school or its equivalent, compared to about 10% of non-Latinx people. This is consistent with other studies which show that Latinx people have some of the

Table 1
Participant characteristics: Percent or mean (SD).

Characteristics	Whole Sample	Latinx	Non-Latinx	F-stat (p-value)
Observations	N = 257,763	N = 39,934	N = 217,829	
Diabetes	9.6%	10.4%	9.5%	16.94 (<0.001)
Latinx	12.7%	100.0%	0.0%	– –
Age (Mean)	49.05 (18.48)	42.88 (16.65)	49.95 (18.56)	1611 (<0.001)
Female	53.4%	52.9%	53.5%	2.42 (0.120)
Race				357.7 (<0.001)
White	80.8%	90.8%	79.4%	
African American	12.8%	4.2%	14.0%	
Asian	4.9%	1.8%	5.4%	
Native American	1.0%	2.4%	0.8%	
Other	0.5%	0.8%	0.4%	
Education				2178 (<0.001)
Less Than High School	12.2%	30.4%	9.6%	
HS Diploma or GED	24.7%	25.5%	24.6%	
More than High School	62.8%	43.4%	65.6%	
Unknown	0.3%	0.7%	0.3%	
Income (Federal Poverty Level)				1065 (<0.001)
<1 FPL	14.8%	24.4%	13.4%	
1.00–1.99 FPL	18.9%	27.6%	17.6%	
2.00–3.99 FPL	29.2%	28.1%	29.3%	
≥4 FPL	37.2%	19.9%	39.7%	
Household Size (Mean)	2.38 (1.41)	3.07 (1.73)	2.28 (1.33)	2508 (<0.001)
Married	44.4%	45.9%	44.2%	16.96 (<0.001)
Census Region				242.0 (<0.001)
Northeast	17.4%	14.3%	17.9%	
North Central/Midwest	23.6%	9.4%	25.6%	
South	36.7%	38.1%	36.5%	
West	22.3%	38.2%	20.0%	
BMI (Mean)	27.45 (5.41)	28.04 (5.19)	27.37 (5.43)	251.1 (<0.001)
Smoking Status				593.7 (<0.001)
Smokes	17.1%	12.0%	17.9%	
Quit	23.5%	15.8%	24.6%	
Never Smoked	59.3%	72.0%	57.4%	
Unknown	0.1%	0.1%	0.1%	
Health Insurance				1943 (<0.001)
No Coverage	12.3%	27.7%	10.0%	
Coverage	87.4%	71.9%	89.6%	
Unknown	0.3%	0.4%	0.3%	
Nativity				8163 (<0.001)
Born in U.S.	84.2%	44.0%	90.0%	
Not Born in U.S.	15.8%	55.8%	9.9%	
Birthplace Unknown	0.1%	0.2%	0.1%	
Interview Language English Only	95.3%	67.5%	99.4%	15,200 (<0.001)
Latinx Origin				– –
Non-Latinx	87.3%	0.0%	100.0%	
Mexican	7.4%	58.0%	–	
Puerto Rican	1.5%	11.5%	–	
Cuban	0.6%	5.0%	–	
Dominican	0.5%	3.7%	–	
Central or South American	2.2%	16.9%	–	
Other Latinx	0.6%	4.9%	–	
Year of Survey				3.383 (0.028)
2010	10.3%	9.4%	10.5%	
2011	11.1%	10.3%	11.2%	
2012	10.8%	10.6%	10.8%	
2013	11.2%	11.2%	11.2%	
2014	11.0%	11.2%	11.0%	

(*continued on next page*)

Table 1 (*continued*)

Characteristics	Whole Sample	Latinx	Non-Latinx	F-stat (p-value)
2015	11.0%	11.1%	11.0%	
2016	11.3%	11.6%	11.3%	
2017	11.5%	11.9%	11.4%	
2018	11.9%	12.8%	11.7%	

Differences between Latinx and Non-Latinx sample characteristics were tested using the adjusted Wald test for continuous and binary variables and the design-based Pearson test for categorical variables. The F-statistic and p-value are reported in Column 4.

lowest high school completion rates in the U.S. Correspondingly, Latinx people report earning lower incomes—over 24% have incomes below the federal poverty level and another 28% have incomes less than double the federal poverty level, contrasted to approximately 13% and 17% of non-Latinx populations. Latinx people report higher BMI scores than non-Latinx people. Finally, more Latinx people are immigrants (over half of the Latinx people in this sample are foreign-born versus less than 10% of the non-Latinx population). This corresponds with the measure of English proficiency: where almost all (over 99%) of the non-Latinx population reports taking this survey in English, close to 1 out of 3 Latinx people opt to take the survey in a language other than English or a combination of English and another language. Other descriptive statistics can be seen in greater detail in Table 1.

Logistic regression results. Table 2 shows the logistic regression results. Column 1 shows the simple regression of how being Latinx is linked to diabetes. Columns 2 through 4 report results for full models (with all controls) for the whole sample and the Latinx and non-Latinx subgroups. The first model mirrors the results from the descriptive statistics and shows that in this sample Latinx people are 10.8% (OR 1.082, [95% CI, 1.057–1.162]) more likely to report diabetes than non-Latinx people. In the full model, as the descriptive statistics suggest, this gap widens to 64.5% (OR 1.645, [95% CI, 1.536–1.760]). This model also shows how the different variables are associated with diabetes. For example, as people age, they are more likely to develop diabetes. People with more education are less likely to report diabetes than people with less than high school levels of education. People with higher levels of income are less likely to report diabetes than people who have income levels below the federal poverty line. As BMI scores increase, the likelihood of reporting diabetes also increases.

Being an immigrant seems to function a bit differently for Latinx and non-Latinx populations. Where the trend suggests that being an immigrant (non-U.S. born) may be protective against diabetes for Latinx people (although this finding is only moderately significant at the $p < 0.10$ level), in the non-Latinx population being an immigrant is statistically significantly associated with an 8.6% (OR 1.086, [95% CI, 1.009–1.169]) greater risk of reporting diabetes. People who chose to take the survey in another language or a combination of another language and English are *not* statistically significantly different in their reported diabetes compared to people who speak English only. Finally, it is worth noting that among the Latinx population, the origin of Latinx ethnicity predicts diabetes as well. While people with Mexican and Puerto Rican heritage are more likely than non-Latinx groups to report diabetes, people from Cuban, Dominican, and other Central and South American countries are less likely to report diabetes than non-Latinx groups (See Column 3). Other details about key variables are available in Table 2.

The most important takeaways from the logistic regression models are (1) by controlling for key social determinants of health, the diabetes disparity is revealed to be much greater than the initial gap indicates and (2) the social determinants of health included in the model have strong independent associations with diabetes. These patterns provide strong justification to use the Oaxaca-Blinder decomposition technique to better understand which factors help explain the Latinx diabetes disparity.

Oaxaca-Blinder decomposition results. Table 3 presents the findings of the Oaxaca-Blinder decomposition analysis of the diabetes disparity comparing the Latinx group to the non-Latinx group for the whole sample. The age group decomposition analyses are shown in Table 4. The coefficients in each row represent the average contribution of each variable to the *explained* difference. In other words, it depicts the difference between the observed coefficient for diabetes in the Latinx sample compared to the counterfactual coefficient if the Latinx group had the same value of any given characteristic (such as education) as the non-Latinx group. This analysis shows that age is such an important suppressor of the disparity that age group analysis is needed to improve the understanding of what informs the disparity in specific populations.

In the full sample decomposition (see Table 3), age is the greatest suppressor of the diabetes disparity. The decomposition based on the full sample shows that if Latinx people were on average the same age as the non-Latinx sample, the proportion of Latinx people with diabetes would increase by a statistically significant 2.55 percentage points. This is because on average the Latinx group is younger than the non-Latinx group and risk of diabetes increases with age. As age is such a powerful suppressor, the results related to other variables are harder to interpret in the decomposition of the full model—in fact, age is the primary variable that leads to the result where more is left unexplained than explained in the decomposition of the differences between these groups.

To gain better insights into how key variables affect the diabetes disparity, three additional models by age group (18–39, 40–64, and older than 65 years) are presented (Table 4). In the youngest age group, age 18–39 years old, the diabetes disparity appears to be small (about 2% of young Latinx people report diabetes and 1.7% of non-Latinx people). However, this does represent a 13.9% difference, and significant and meaningful differences in education, income, and BMI are already present. The diabetes disparity increases in the age group of those 40–64 years old, where approximately 13.7% of Latinx people report diabetes versus about 10% of non-Latinx people (a 36.9% difference) and is at the widest for the group older than 65 years, where 32.3% of Latinx people and 19.2% of non-Latinx people report diabetes (a 68.5% difference). By breaking the samples into age groups, the contribution of age within each group to the explained difference diminishes, and by the decomposition of the disparity in the age group of 65 and older, if Latinx people were on average the same age as non-Latinx people, the explained gap (0.0663) would only increase by 0.0015, which is an increase of about 2.3% The younger mean age of the Latinx population matters greatly in relation to the reported diabetes disparity. By adding age group analyses, the nuances of how the other social determinants contribute to the diabetes disparity emerge.

The findings for the middle age group (40–64 years) and the oldest age group (65 years and older) decomposition models show that differences in the included observable characteristics explain over 42% and 50.5% respectively of the reported difference in diabetes outcomes between the Latinx and non-Latinx groups. After controlling for age, measurable differences in education, income, and BMI are the largest contributors to the diabetes disparity. Even though there are significant differences between the Latinx and non-Latinx groups related to immigration and acculturation, these factors do not emerge as statistically significant key predictors of the diabetes disparity. These results help identify some priority areas for intervention.

Education. If Latinx people had the same levels of education as non-Latinx people, the proportion of Latinx people with diabetes would decrease across all models. The portion of the explained difference that is related to education is statistically significant and an important contributor across the models: education contributes approximately 88% to the total gap in the decomposition of the whole sample (Table 3), 57% to the gap of the youngest age group, about 61% to the middle age group, and 16.1% to the oldest age groups (Table 4). Latinx people without a high school level of education comprise over a third, by far the largest segment, of the Latinx population. This analysis suggests that

Table 2
Logistic regression of Latinx ethnicity and diabetes and subgroup analysis. Odds Ratios.

	Whole Sample		Latinx	Non-Latinx
	(1)	(2)	(3)	(4)
Variables (reference group)	Diabetes	Diabetes	Diabetes	Diabetes
Observations	N = 257,763	N = 257,763	N = 39,934	N = 217,813
Latinx	1.1082***	1.6445***		
	(1.057–1.162)	(1.536–1.760)		
Age		1.0559***	1.0712***	1.0538***
		(1.055–1.057)	(1.068–1.074)	(1.053–1.055)
Female		0.7661***	0.8695**	0.7521***
		(0.742–0.791)	(0.795–0.951)	(0.727–0.778)
Race (White)				
Black		1.5005***	0.9499	1.5078***
		(1.437–1.567)	(0.765–1.180)	(1.441–1.577)
Asian		1.8044***	1.1443	1.8267***
		(1.654–1.969)	(0.821–1.594)	(1.655–2.016)
Native American		1.9315***	1.0462	2.3659***
		(1.601–2.330)	(0.814–1.344)	(1.928–2.903)
Other		1.4281**	1.4340[b]	1.4201**
		(1.155–1.766)	(0.952–2.161)	(1.111–1.815)
Education (<High School)				
HS Diploma or GED		0.8848***	0.8609*	0.8980***
		(0.839–0.933)	(0.760–0.975)	(0.847–0.952)
> High School		0.8192***	0.8132***	0.8258***
		(0.778–0.863)	(0.721–0.917)	(0.779–0.875)
Unknown		0.7716*	0.6787	0.7958
		(0.606–0.982)	(0.411–1.122)	(0.601–1.053)
Income (<1.00 FPL)				
1.00–1.99 FPL		0.8157***	0.7896***	0.8366***
		(0.774–0.860)	(0.701–0.890)	(0.789–0.887)
2.00–3.99 FPL		0.6730***	0.6752***	0.6849***
		(0.639–0.709)	(0.594–0.768)	(0.645–0.727)
≥4 FPL		0.5526***	0.5496***	0.5607***
		(0.523–0.584)	(0.478–0.631)	(0.528–0.595)
Household Size		1.0032	1.0168	1.0049
		(0.988–1.019)	(0.989–1.046)	(0.987–1.023)
Married (Not Married)		1.0922***	1.0845	1.0918***
		(1.050–1.136)	(0.982–1.198)	(1.045–1.141)
Census Region (Northeast)				
North Central/Midwest		1.1269***	0.9918	1.1381***
		(1.070–1.186)	(0.815–1.207)	(1.078–1.201)
South		1.2050***	0.9776	1.2229***
		(1.151–1.262)	(0.837–1.141)	(1.163–1.285)
West		1.0125	0.9350	0.9957
		(0.959–1.068)	(0.789–1.108)	(0.940–1.055)
BMI		1.1263***	1.1070***	1.1286***
		(1.123–1.130)	(1.098–1.116)	(1.125–1.132)
Smoking Status (Smokes)				
Quit		0.9058***	1.0535	0.9029***
		(0.860–0.954)	(0.918–1.210)	(0.853–0.955)
Never Smoked		0.7810***	0.8056***	0.7866***
		(0.744–0.820)	(0.715–0.908)	(0.746–0.830)
Unknown		0.8162	0.5363	0.9124
		(0.526–1.266)	(0.184–1.565)	(0.571–1.459)
Health Insurance (No Coverage)				
Coverage		1.4537***	1.4658***	1.3783***
		(1.364–1.550)	(1.290–1.665)	(1.278–1.487)
Unknown		0.9078	0.7266	0.9050
		(0.615–1.340)	(0.293–1.801)	(0.583–1.406)
Nativity (Born in U.S.)				
Not Born in U.S.		1.0529[b]	0.8959[b]	1.0862*
		(0.993–1.117)	(0.801–1.002)	(1.009–1.169)
Birthplace Unknown		1.0656	2.6765[b]	0.4381[b]
		(0.496–2.291)	(0.899–7.965)	(0.169–1.137)
Interview Language English Only		1.0466	1.0412	1.0667
		(0.965–1.135)	(0.934–1.161)	(0.895–1.272)
Latinx Origin (Mexican/Mexican American)				
Puerto Rican		1.0756	1.0126	–
		(0.950–1.218)	(0.872–1.176)	
Cuban		0.5576***	0.5193***	–
		(0.469–0.663)	(0.429–0.629)	
Dominican		0.9494	0.9079	–
		(0.738–1.221)	(0.684–1.205)	
Central or South American		0.6678***	0.6779***	–
		(0.584–0.763)	(0.585–0.786)	
Other Latinx		0.9957	0.8729	–

(*continued on next page*)

Table 2 (*continued*)

	Whole Sample		Latinx	Non-Latinx
	(1)	(2)	(3)	(4)
		(0.832–1.192)	(0.722–1.055)	
Constant	0.1051*** (0.103–0.107)	0.0002*** (0.000–0.000)	0.0003*** (0.000–0.000)	0.0002*** (0.000–0.000)

Also adjusted for year of survey. Standard errors in parentheses.
***p p < 0.001, **p < 0.01, *p < 0.05, [b]p < 0.10.

Table 3
Decomposition results of the "explained" gap of the diabetes disparity between U.S. Latinx and non-Latinx groups.

Variable (reference group)	Whole sample (*N* = 257,763)	
	Coef.	(95% CI)
Age	**−0.0255**	(-0.0269, −0.0241)
Female	0.0001	(0.000, 0.0002)
Race (White)		
Black	**−0.0024**	(-0.0028, −0.0020)
Asian	**−0.0013**	(-0.0015, −0.0011)
Native American	**0.0009**	(0.0005, 0.0012)
Other	**0.0001**	(0.0000, 0.0002)
Education (<High School)		
HS Diploma or GED	**−0.0003**	(-0.0005, −0.0001)
> High School	**0.0081**	(0.0069, 0.0093)
Unknown	**−0.0001**	(-0.0002, 0.0000)
Income (<1.00 FPL)		
1.00–1.99 FPL	**−0.0015**	(-0.0020, −0.0010)
2.00–3.99 FPL	**0.0004**	(0.0002, 0.0007)
≥4.00 FPL	**0.0113**	(0.0103, 0.0122)
Household Size	−0.0004	(-0.0012, 0.0003)
Married (Not Married)	**−0.0001**	(-0.0001, 0.0000)
Census Region (Northeast)		
North Central/Midwest	**−0.0011**	(-0.0018, −0.0005)
South	0.0002	(-0.0001, 0.0005)
West	0.0006	(-0.0001, 0.0013)
BMI	**0.0063**	(0.0055, 0.0071)
Smoking Status (Smokes)		
Quit	**−0.0009**	(-0.0013, −0.0005)
Never Smoked	−0.0003	(-0.0008, 0.0002)
Unknown	0.0000	(0.0000, 0.0000)
Health Insurance (No Coverage)		
Coverage	**−0.0062**	(-0.0068, −0.0055)
Unknown	0.0000	(0.0000, 0.0000)
Nativity (Born in U.S.)		
Not Born in U.S.	0.0017	(-0.0001, 0.0035)
Birthplace Unknown	0.0000	(-0.0001, 0.0001)
Interview Language English Only	**0.0039**	(0.0017, 0.0061)
Latinx Diabetes Mean	0.1043	
Non-Latinx Diabetes Mean	0.0951	
Total Gap	**0.0092**	(0.0049, 0.0135)
Explained Gap	**−0.0064**	(-0.0094, −0.0034)
Unexplained Gap	**0.0156**	(0.0128, 0.0184)
Explained %	−69.57%	
Unexplained %	169.57%	

Also adjusted for year of survey.
Bold coefficients indicate statistical significance ($p \leq 0.05$).

education disparity plays a very meaningful role in the Latinx diabetes disparity.

Income. Similarly, almost double the proportion of Latinx people have a household income lower than the federal poverty line compared to non-Latinx people. This matters. This analysis suggests that if Latinx people had the same levels of income as non-Latinx people, the proportion of Latinx people with diabetes would decrease. The contribution of income to the explained difference is statistically significant in all the decompositions except for the youngest age group. Income makes such a large contribution to the explained difference that if Latinx people had the same income distribution as non-Latinx people, the diabetes gap would decrease by nearly the amount of the explained gap. Also, it is important to note that income contributes much more to the explained gap than BMI.

BMI. The effect of BMI is persistent and statistically significant across all the models. In every model, if Latinx people had the same mean BMI score as non-Latinx people (which would be a lower score), they would report lower levels of diabetes. That noted, it is also important to note that BMI accounts for more of the of the explained difference for the middle age group (46.8%) than the oldest age group (14.6%).

Acculturation. The measures of acculturation are only statistically significant for the oldest age group and represent approximately 23.5% of the explained difference. If the same proportion of Latinx people were born in the U.S. and had the same level of English proficiency, they would report lower levels of diabetes. The coefficients for these variables make a meaningful contribution to the explained diabetes difference.

The analysis of the difference in diabetes outcomes for Latinx people using Oaxaca-Blinder decomposition provides additional support for the logistic regression analysis findings, as well as support for the claim that the disparity between Latinx and non-Latinx groups is largely due to social differences.

Discussion

The analyses in this paper provide evidence that largely supports the hypotheses. Overall, the evidence from the different analyses supports the first hypothesis that structural factors will be primary factors contributing the diabetes disparity. Regarding the second hypothesis, the evidence shows that some factors, such as age and racial composition, if the U.S. Latinx population had the same characteristics as their non-Latinx peers, they would have even higher rates of diabetes. Due to the fact that age is so strongly linked to diabetes and the Latinx population is notably younger than the non-Latinx population, studies investigating diabetes and race and ethnicity should always show the age-adjusted model or the extent of racial and ethnic disparities will be masked. Finally, the third hypothesis is also largely supported, as the evidence demonstrates that if the U.S. Latinx population had the same income and education as their non-Latinx peers, they would have lower rates of diabetes.

The results of this study offer another perspective on the factors that contribute to the Latinx diabetes inequity and supports the theory that diabetes needs to be addressed through social policy as much as health policy (Arcaya et al., 2015; Berwick, 2020; McKinlay & Marceau, 2000). Even though social epidemiology and other medical social sciences have presented strong cases that diabetes is heavily influenced by factors outside of individual health behaviors and genetics, most of the approaches for addressing diabetes rely on individual-level clinical interventions and do not take into consideration the social perspective (Boles, Kandimalla, & Reddy, 2017; Rodriguez-Sanchez, Aranda-Reneo, Oliva-Moreno, & Lopez-Bastida, 2021). Considering that most public health and clinical medicine interventions focus on reducing BMI as a means to prevent and manage diabetes, these findings support other scholarship which argues for priority focus to be addressed at the structural level if the aim is to reduce health disparities (Berwick, 2020; Brown et al., 2019; Harris & Pamukcu, 2020; McKinlay & Marceau, 2000).

The results of this study also point to the urgency of addressing this disparity. As the relatively young mean age of the U.S. Latinx population is identified as a major suppressor of the diabetes disparity, if the U.S.

Table 4
Decomposition results of the "explained" gap of the diabetes disparity between U.S. Latinx and non-Latinx groups by age group.

Variable (Reference Group)	Age 18–39 (N = 89,235)		Age 40–64 (N = 107,020)		Age 65+ (N = 61,508)	
	Coef.	(95% CI)	Coef.	(95% CI)	Coef.	(95% CI)
Age	**0.0003**	(0.0001, 0.0005)	**−0.0129**	(-0.014, −0.0117)	**−0.0015**	(-0.0022, −0.0007)
Female	0.0000	(0.0000, 0.0000)	0.0000	(-0.0001, 0.0001)	−0.0001	(-0.0009, 0.0008)
Race (White)						
Black	−0.0001	(-0.0005, 0.0003)	**−0.0025**	(-0.0032, −0.0018)	**−0.0051**	(-0.0061, −0.0040)
Asian	**−0.0003**	(-0.0005, −0.0001)	**−0.0014**	(-0.0018, −0.0011)	**−0.0014**	(-0.0019, −0.0008)
Native American	**0.0002**	(0.0000, 0.0004)	**0.0011**	(0.0005, 0.0016)	**0.0023**	(0.0012, 0.0035)
Other	0.0000	(0.0000, 0.0001)	0.0001	(0.0000, 0.0002)	0.0004	(0.0000, 0.0007)
Education (<High School)						
HS Diploma or GED	0.0000	(-0.0003, 0.0002)	0.0001	(-0.0002, 0.0004)	**0.0022**	(0.0012, 0.0031)
> High School	**0.0016**	(0.0006, 0.0026)	**0.0096**	(0.0073, 0.0118)	**0.0107**	(0.0079, 0.0135)
Unknown	0.0000	(-0.0001, 0.0001)	−0.0002	(-0.0004, 0.0000)	**−0.0003**	(-0.0007, 0.0000)
Income (<1.00 FPL)						
1.00–1.99 FPL	−0.0003	(-0.0007, 0.0000)	**−0.0030**	(-0.0041, −0.0018)	**−0.0012**	(-0.0023, −0.0001)
2.00–3.99 FPL	**0.0001**	(0.0000, 0.0003)	**−0.0013**	(-0.0019, −0.0008)	**0.0035**	(0.0021, 0.0049)
≥4.00 FPL	**0.0021**	(0.0015, 0.0026)	**0.0198**	(0.0177, 0.0219)	**0.0108**	(0.0081, 0.0134)
Household Size	0.0002	(-0.0003, 0.0008)	**0.0021**	(0.001, 0.0032)	**0.0076**	(0.0052, 0.0099)
Married (Not Married)	−0.0001	(-0.0003, 0.0000)	**−0.0001**	(-0.0003, 0.0000)	0.0000	(-0.0002, 0.0001)
Census Region (Northeast)						
North Central/Midwest	0.0002	(-0.0004, 0.0008)	**−0.0020**	(-0.0029, −0.001)	**−0.0024**	(-0.0045, −0.0003)
South	0.0000	(-0.0001, 0.0000)	0.0002	(-0.0002, 0.0007)	**0.0009**	(0.0000, 0.0017)
West	−0.0003	(-0.0010, 0.0003)	**0.0013**	(0.0002, 0.0024)	0.0008	(-0.0012, 0.0029)
BMI	**0.0024**	(0.0020, 0.0028)	**0.0073**	(0.0059, 0.0087)	**0.0097**	(0.0069, 0.0126)
Smoking Status (Smokes)						
Quit	**0.0002**	(0.0001, 0.0003)	−0.0001	(-0.0005, 0.0003)	**−0.0016**	(-0.0030, −0.0002)
Never Smoked	−0.0003	(-0.0006, 0.0001)	**−0.0011**	(-0.0019, −0.0004)	−0.0002	(-0.0017, 0.0014)
Unknown	0.0000	(0.0000, 0.0000)	0.0000	(-0.0001, 0.0001)	0.0000	(-0.0001, 0.0001)
Health Insurance (No Coverage)						
Coverage	**−0.0012**	(-0.0018, −0.0007)	**−0.0065**	(-0.0076, −0.0055)	**−0.0020**	(-0.0031, −0.0010)
Unknown	0.0000	(0.0000, 0.0000)	−0.0001	(-0.0001, 0.0000)	0.0001	(-0.0001, 0.0002)
Nativity (Born in U.S.)						
Not Born in U.S.	−0.0010	(-0.002, 0.0001)	0.0015	(-0.0020, 0.0050)	**0.0175**	(0.0099, 0.0251)
Birthplace Unknown	**0.0000**	(0.0000, 0.0000)	0.0000	(-0.0001, 0.0001)	−0.0001	(-0.0002, 0.0001)
Interview Language (English Only)	−0.0008	(-0.0021, 0.0005)	0.0038	(-0.0001, 0.0078)	**0.0156**	(0.0060, 0.0252)
Latinx Diabetes Mean	0.0197		0.1373		0.3227	
Non-Latinx Diabetes Mean	0.0173		0.1003		0.1915	
Total Gap	**0.0024**	(0.0000, 0.0048)	**0.0370**	(0.0300, 0.0441)	**0.1312**	(0.1156, 0.1468)
Explained Gap	**0.0028**	(0.0013, 0.0044)	**0.0156**	(0.0108, 0.0203)	**0.0663**	(0.0561, 0.0766)
Unexplained Gap	−0.0004	(-0.0023, 0.0014)	**0.0214**	(0.0166, 0.0263)	**0.0649**	(0.5222, 0.7760)
Explained %	118.34%		42.03%		50.54%	
Unexplained %	−16.67%		57.84%		49.47%	

Also adjusted for year of survey.
Bold coefficients indicate statistical significance ($p \leq 0.05$).

policymakers do not act, this health disparity will worsen as the U.S. population ages (Sáenz, 2015). The older adult population is rapidly diversifying as the more diverse cohorts of Americans age (Sáenz, 2015). So, at the very least, early screening practices should be better integrated into care plans. Latinx people, who are still the most likely to be uninsured in the U.S., need better access to affordable health care (van der Goes & Santos, 2018). As Texas, one of the states with the largest proportion of Latinx people (and Latinx people with Mexican heritage), has still not expanded Medicaid, one policy move that could swiftly provide access to some degree of health care is to further incentivize states to expand Medicaid. However, while this approach will be necessary, it is still mainly focused on secondary and tertiary forms of prevention (early screening of diabetes and working to manage symptoms of diabetes).

Addressing the social inequalities that perpetuate health inequities would be a more powerful form of primary prevention potentially. After acknowledging the role that age plays in Latinx diabetes patterns, through the age group decomposition models, this study shows that inequities in education and income are the major contributors of the diabetes gap between Latinx and non-Latinx populations. Education and income have long been identified as fundamental determinants of health, and studies repeatedly show that Latinx people in the U.S. are the least likely to complete high school or the equivalent (Carnevale & Fasules, 2017). As education and income are so intricately linked, developing policies that encourage and support Latinx people to attain high school degrees (or their equivalents), will also likely increase income. This strategy aligns with the "health in all policies" (HIAP) approach that argues that health care is only one piece of the puzzle in improving population health (De Leeuw & Peters, 2015). HIAP approaches are largely designed to promote population health through prevention more than specific treatments and health equity is a central tenet (De Leeuw & Peters, 2015; Van Vliet-Brown, Shahram, & Oelke, 2018). While diabetes is mentioned as a condition that is well-suited for a HIAP approach, there is very little literature investigating HIAP interventions and diabetes outcomes. This would be a good area for future studies in Latinx diabetes disparity research.

There are limitations to this study. The major limitations are in the design of the survey: it is a cross-sectional design, and it is all self-reported. For more nuance and stronger arguments about causality, a survey with a longitudinal design and clinical measures would be helpful. However, most clinical data does not include the degree of information about social determinants that NHIS includes, so there are trade-offs. Also, with any quantitative study on racial and ethnic inequities, there comes a risk in over-generalizing about priority populations. This can happen at the conceptualization and operationalization phase, which then leads to interpretations of results that run the risk of reifying and pathologizing racial and ethnic groups (Gómez & López, 2013; Montoya, 2011; Zuberi and Bonilla-Silva, 2008).

While this study works to avoid that by including race in the models in addition to ethnicity and includes information about the ethnic origins of individuals' Latinx heritage, any takeaways from this study should be treated as pieces of evidence, but not used to make sweeping generalizations about Latinx people in the U.S.

The U.S. needs to focus on priority populations facing disparities in policy development. A one-size-fits-all approach has not worked, and it will not work in the future. Education policy should prioritize Latinx youth. Labor policy must make work safer and more equitable. Health policy should address inequities in the system. There are opportunities to move the needle in each of these areas. And as this study suggests, improvement in these social factors may decrease the diabetes disparity and have a meaningful impact on holistic health equity.

Funding

Not applicable.

Availability of data and material (data transparency)

The data used for this project are publicly available at IPUMS.org.

Code availability (software application or custom code)

Not applicable.

Authors' contributions

This is a solo-authored work. The author designed the project, conducted the project, and wrote the project.

Declaration of competing interest

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

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