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ORIGINAL ARTICLE

Neighborhood-Level Risk Factors for Severe Hyperglycemia among Emergency Department Patients without a Prior Diabetes Diagnosis

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Abstract A person's place of residence is a strong risk factor for important diagnosed chronic diseases such as diabetes. It is unclear whether neighborhood-level risk factors also predict the probability of undiagnosed disease. The objective of this study was to identify neighborhood-level variables associated with severe hyperglycemia among emergency department (ED) patients without a history of diabetes. We analyzed patients without previously diagnosed diabetes for whom a random serum glucose value was obtained in the ED. We defined random glucose values ≥ 200 mg/dL as severe hyperglycemia, indicating probable undiagnosed diabetes. Patient addresses were geocoded and matched with neighborhood-level socioeconomic measures from the American Community Survey and claims-based surveillance estimates of diabetes prevalence. Neighborhood-level exposure variables were standardized based on z-scores, and a series of logistic regression models were used to assess the association of selected exposures and hyperglycemia adjusting for biological and social individual-level risk factors for diabetes. Of 77,882 ED patients without a history of diabetes presenting in 2021, 1,715 (2.2%) had severe hyperglycemia. Many geospatial exposures were associated with uncontrolled hyperglycemia, even after controlling for individual-level risk factors. The most strongly associated neighborhood-level variables included lower markers of educational attainment, higher percentage of households where limited English is spoken, lower rates of white-collar employment, and higher rates of Medicaid insurance. Including these geospatial factors in risk assessment models may help identify important subgroups of patients with undiagnosed disease.

Keywords Public health surveillance · Diabetes screening · Emergency department · Geographic information systems

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Introduction

According to the Center for Disease Control 2020 National Diabetes Statistics Report, an estimated 7.3 million Americans are living today with undiagnosed diabetes [1]. Chronic diseases, such as type 2 diabetes mellitus, are commonly multifactorial in etiology. Genetics, behavioral factors, socioeconomic, geographic, and the local built environment can all contribute to an individual person's and a population's risk of diabetes [1–4]. While heritable familial traits also confer elevated risk [5, 6], lifestyle and dietary elements are important predisposing factors [7, 8]. Local, neighborhood-level variables can also play a part in determining diabetes risk [2, 9–12]. Correctly identifying and understanding these neighborhood specific risk factors, especially those more specific to undiagnosed diabetic patients, is critical to addressing shortfalls in the diagnosis of diabetes [13].

Millions of Americans visit emergency departments (EDs) each year to seek healthcare, and many of these patients face socioeconomic burdens and difficulty accessing primary care [14, 15]. Visiting an ED represents a healthcare touch-point for patients who otherwise do not have access, or sufficient access, to primary care and may have undiagnosed diabetes [16]. Undiagnosed or late-diagnosed diabetes is particularly harmful, as duration of hyperglycemia and non-treatment is a predictor of adverse outcomes—including heart disease, stroke, vascular, and kidney disease [17, 18]. Patients diagnosed via screening, rather than after the onset of symptoms, are at substantially lower risk of mortality and morbidity [19]. Thus, an ED patient cohort is useful for identifying which local-level neighborhood variables are associated with likely undiagnosed diabetes as identified by severe hyperglycemia on a random serum glucose test in this population. While prior studies have explored neighborhood-level risk variables for undiagnosed diabetes, this study specifically examines ED patients, and helps define populations visiting EDs for interventions like opportune preventative ED screening or other targeted public health efforts.

The objective of this study was to identify neighborhood-level demographic and geospatial variables in New York City associated with severe hyperglycemia among emergency department (ED) patients without a history of diabetes. We used regression models to determine which variables were the strongest predictors of undiagnosed diabetes.

Methods

Study Population and Setting

We conducted a cross-sectional analysis of patients presenting from January 1, 2021, to December 31, 2021 to four EDs throughout the New York City metropolitan area affiliated with our academic medical center. We extracted clinical and demographic data from the electronic health record (EHR) and analyzed patients who had no documented history of diabetes within the EHR and received a basic or complete metabolic panel during their ED visit.

Geospatial Variables and Primary Outcome

Patient addresses were geocoded by Census tract. These geocodes were used to obtain neighborhood-level estimates of demographics and socioeconomics from the 2015–2019 American Community Survey ('Census') [20] and diabetes prevalence based on ED claims data using previously published methods that leverage claims data to estimate neighborhood-level disease prevalence [21]. Because certain geospatial datasets were only available for New York City, only patients residing within city boundaries were analyzed. For our primary outcome, a serum glucose value greater than or equal to 200 mg/dL was considered uncontrolled hyperglycemia, representing probable undiagnosed diabetes. Eligible patients were stratified according to this outcome, and compared across demographic, clinical, and geospatial attributes.

Statistical Analyses

A series of logistic regression models were used to assess the relationship between each geospatial variable independently and the outcome of interest, serum glucose $\geq$ 200 mg/dL. Geospatial variables were standardized to z-scores to increase interpretability of the odds ratios obtained from these models. First, unadjusted odds ratios were calculated for each geospatial predictor and the outcome. In a second set of models, adjustment was made for patient age and sex. The third set of models additionally adjusted for the individual-level socioeconomic variables of race, ethnicity, health insurance status, and prior outpatient and emergency department utilization within our health system. Lastly, individual-level health variables, body mass index (BMI), history of hypertension and dyslipidemia, and prescriptions for antihypertensive and statin medications were added to the last set of models. Controlling for different sets of individual-level variables allows for alternative interpretations of the associations between the geospatial variables and the outcome.

A series of lasso-regularized logistic regression models were used to determine which geospatial measures were most strongly associated with the outcome when the entire set of variables was considered simultaneously. Using regularization was necessary because many of the geospatial exposures were highly colinear, and thus could not be included simultaneous in an unpenalized logistic regression model. Lasso regularization applies an L1 penalty (proportional to the sum of the absolute values of the coefficients) for non-zero coefficients in a regression model, which effectively performs feature selection during model fitting by shrinking the coefficients of unimportant predictor variables to zero. This allows for consideration of high-correlated predictor variables within the same model. Four such models were built, controlling for the same sets of individual-level variables as in the logistic regression models above: the first model included only geospatial variables, the second model added patient age and sex, the third model added patient race, ethnicity, health insurance status, and prior care utilization, and the fourth model added BMI, history of hypertension and hyperlipidemia, and antihypertensive and statin medications. Standardized coefficients for all such models are reported.

Statistical analyses were performed using R 4.1.2 (R Foundation; Vienna, Austria, 2021). Geographic analysis was performed using ArcGIS Pro 2.8.3 (ESRI; Redlands, CA, 2021). This study was approved by the Institutional Review Board at the New York University School of Medicine.

Results

The sample included 77,882 unique individual ED patients, of which 1,715 (2.2%) were found to have uncontrolled hyperglycemia on serum random glucose tests despite having no documented history of diabetes. Patients with uncontrolled hyperglycemia were older, more likely to be male, had higher BMIs, were more likely to be taking antihypertensive and statin medications, had higher triage blood pressures, and were less likely to have received prior care within our medical system, particularly in the outpatient setting. They more often identified as Asian or Hispanic or Latino, and were more often insured through Medicare or Medicaid or were uninsured.

The Census tracts in which patients with uncontrolled hyperglycemia resided contained higher percentages of Asian and Hispanic residents, had lower median incomes, higher poverty and unemployment rates, lower educational attainment, more residents without United States citizenship, more households where limited English is spoken, and higher estimated diabetes prevalence (Table 1).

Several geospatial variables were associated with uncontrolled hyperglycemia in logistic regression models, and in most cases these associations remained significant even when corrections were made for important individual-level variables (Table 2). The rates of high school non-completion and households where limited English is spoken were among the most strongly associated variables across all sets of models. The strength of this relationship decreased after correction for individual-level socioeconomic variables. Local rates of Medicaid insurance and college graduation were also strongly associated with uncontrolled hyperglycemia.

The lasso-regularized logistic regression models identified the strongest predictors from the set of geospatial variables (Table 3). Regardless of which individual-level variables were included in the models, at least one measure of educational attainment, either the high school noncompletion rate or the college graduation rate, was identified as predictive in all models. In three of the four models, the percentage of households where limited English is spoken was also identified as an important predictor. The coefficients for the geospatial variables were smaller in magnitude than the coefficients for individual level variables such as patient age and sex. However, these models indicate which of the geospatial variables are most informative.

Discussion

We identified a cohort of ED patients in the New York City area who did not have a previous diagnosis

Table 1 Descriptive Characteristics of Emergency Department Patients without a History of Diabetes with and without Hyperglycemia (Serum Glucose ≥ 200)

	Glucose ≥ 200	Glucose < 200	*P*-value
Count	1715	76167	–
Age (mean)	60.2	51.5	< 0.001
Male	59.4%	42.5%	< 0.001
BMI (mean)	33.2	28.2	0.03
History of Hypertension	30.0%	29.2%	0.53
History of Dyslipidemia	20.2%	21.6%	0.17
Hypertension Medications	18.6%	11.6%	< 0.001
Statin Medications	27.6%	18.3%	< 0.001
Systolic Blood Pressure (mean)	141.1	136.6	< 0.001
Diastolic Blood Pressure (mean)	82.2	80	< 0.001
Office Visit Past 1 Year	29.9%	41.9%	< 0.001
ED Visit Past 1 Year	17.4%	19.6%	0.03
Race and Ethnicity			
Asian	10.6%	6.5%	< 0.001
Hispanic or Latino	26.5%	21.9%	–
Non-Hispanic Black	13.2%	14.6%	–
Non-Hispanic White	39.7%	47.5%	–
Multiple/Other	10.0%	9.5%	–
Insurance Status			
Blue Cross	9.6%	12.9%	< 0.001
Commercial	8.3%	7.2%	–
Managed Care	30.1%	42.3%	–
Medicaid	8.6%	5.5%	–
Medicare	33.8%	27.2%	–
Insurance Other/Unknown	1.3%	1.0%	–
Self-Pay	8.2%	3.8%	–
Smoking Status			
Never Smoker	32.0%	50.3%	< 0.001
Quit Smoking	11.7%	15.7%	–
Unknown Smoking Status	49.2%	25.5%	–
Current Smoker	7.1%	8.5%	–
Census-Tract-Level Variables (Means)			
Residents Older than 65	15.6%	15.3%	0.14
Female Residents	51.6%	51.6%	0.59
Non-Hispanic White Residents	43.6%	47.4%	< 0.001
Non-Hispanic Black Residents	13.6%	14.6%	0.07
Black Residents	14.7%	15.8%	0.07
Asian Residents	16.4%	13.8%	< 0.001
Hispanic Residents	23.8%	21.7%	< 0.001
Poverty Rate	15.7%	13.7%	< 0.001
High School Non-Completion Rate	18.5%	15.1%	< 0.001
College Graduation Rate	45.4%	50.1%	< 0.001
Unemployment Rate	5.5%	5.3%	0.06
Median Household Income	175673	191661	< 0.001
Rent > 50% Income	27.0%	26.0%	< 0.001

Table 1 (continued)

	Glucose ≥ 200	Glucose < 200	*P*-value
Medicaid Rate, Age 19 to 64	26.0%	21.6%	< 0.001
Employer Insurance Rate, Age 19 to 64	63.6%	67.5%	< 0.001
Uninsured Rate, Age 19 to 64	10.9%	9.4%	< 0.001
Gini Index	45.6%	45.6%	0.85
Non-US Citizen Residents	15.1%	13.4%	< 0.001
Disability Rate	6.8%	6.5%	0.01
White Collar Employment Rate	62.6%	66.4%	< 0.001
Limited English in Household	16.7%	12.8%	< 0.001
Supplemental Security Income	7.1%	6.2%	< 0.001
Public Assistance Rate, including SNAP Benefits	17.5%	14.8%	< 0.001
Poor Glycemic Control Among Individuals with Diabetes	16.0%	16.0%	0.61
Estimated Diabetes Prevalence	10.3%	9.9%	< 0.001

T-tests were used to compare continuous variables, and Chi-squared tests were used to compare categorical variables

Table 2 Odds ratios for standardized geospatial exposures considered independently

	Set 1	Set 2	Set 3	Set 4
Residents Older than 65	1.04	0.94*	1.01	1.01
Female Residents	0.99	0.99	1.01	1.00
Non-Hispanic White Residents	0.88***	0.80***	0.91**	0.91**
Non-Hispanic Black Residents	0.96	1.03	0.97	0.97
Black Residents	0.95	1.03	0.97	0.97
Asian Residents	1.17***	1.15***	1.08***	1.08**
Hispanic Residents	1.12***	1.20***	1.07**	1.08**
Poverty Rate	1.16***	1.23***	1.13***	1.13***
High School Non-Completion Rate	**1.26*** **	**1.33*** **	**1.19*** **	**1.19*** **
College Graduation Rate	0.80***	0.74***	**0.82*** **	**0.82*** **
Unemployment Rate	1.04	1.09***	1.02	1.02
Median Household Income	0.85***	0.83***	0.87***	0.87***
Rent > 50% Income	1.09***	1.10***	1.07**	1.07**
Medicaid Rate, Age 19 to 64	**1.23*** **	**1.30*** **	1.18***	1.18***
Employer Insurance Rate, Age 19 to 64	0.82***	0.78***	0.86***	0.86***
Uninsured Rate, Age 19 to 64	1.19***	1.26***	1.12***	1.12***
Gini Index	1.00	1.00	0.99	0.99
Non-US Citizen Residents	1.17***	1.23***	1.08**	1.09***
Disability Rate	1.06*	1.08***	1.04	1.04
White Collar Employment Rate	0.81***	0.75***	0.84***	0.84***
Limited English in Household	**1.27*** **	**1.28*** **	**1.17*** **	**1.17*** **
Supplemental Security Income	1.14***	1.18***	1.11***	1.11***
Public Assistance Rate, including SNAP Benefits	1.18***	1.25***	1.15***	1.15***
Poor Glycemic Control Among Individuals with Diabetes	0.98	1.10**	1.02	1.02
Estimated Diabetes Prevalence	1.16***	1.28***	1.16***	1.17***

The models in set 1 are unadjusted. The models in set 2 include age and sex, those in set 3 also include race, ethnicity, insurance status, and prior outpatient and ED care utilization, and those in set 4 additionally include BMI, history of hypertension, hyperlipidemia, and prescriptions for antihypertensives and statins. All geospatial variables were standardized to mean 0 and standard deviation 1. The three exposures with the smallest p-values in each set of models are bolded. $p<0.05$ *. $p<0.01$ **. $p<0.001$ ***

Table 3 Standardized Coefficients from Lasso-Regularized Logistic Regression Models Including All Geospatial Exposures

alpha = 0.003	Model 1	Model 2	Model 3	Model 4
Age	–	0.44	0.62	0.64
Patient Sex	–	0.30	0.55	0.54
Asian	–	–	0	0
Hispanic or Latino	–	–	0.02	0
Multiple/Other Race	–	–	0	0
Non-Hispanic Black	–	–	0	0
Non-Hispanic White	–	–	–0.14	–0.15
Blue Cross	–	–	0	0
Commercial	–	–	0	0
Managed Care	–	–	0	0
Medicaid	–	–	0	0
Medicare	–	–	–0.10	–0.10
Other/Unknown Insurance	–	–	0	0
Self-Pay			0	0
Office Visit Past 1 Year	–	–	–0.32	–0.29
Office Visit Past 5 Years	–	–	0	0
ED Visit Past 1 Year	–	–	0	0
ED Visit Past 5 Years	–	–	0	0
BMI	–	–	–	0.22
History of Hypertension	–	–	–	–0.09
History of Dyslipidemia	–	–	–	–0.06
Hypertension Medications	–	–	–	0.11
Statin Medications	–	–	–	0.07
Residents Older than 65	0.10	0	0	0
Female Residents	0	0	0	0
Non-Hispanic White Residents	0	0	0	0
Non-Hispanic Black Residents	0	0	0	0
Black Residents	0	0	–0.07	0
Asian Residents	0.06	0	0	0
Hispanic Residents	0	0	0	0
Poverty Rate	0	0	0	0
High School Non-Completion Rate	0.10	0.15	0.10	0
College Graduation Rate	0	0	–0.11	–0.12
Unemployment Rate	0	0	0	0
Median Household Income	0	0	0	0
Rent > 50% Income	0	0	0	0
Medicaid Rate, Age 19 to 64	0	0	0	0
Employer Insurance Rate, Age 19 to 64	0	0	0	0
Uninsured Rate, Age 19 to 64	0	0	0	0
Gini Index	0	0	0	0
Non-US Citizen Residents	0	0	0	0
Disability Rate	0	0	0	0
White Collar Employment Rate	0	0	0	0
Limited English in Household	0.17	0.18	0	0.12
SSI	0	0	0	0
Public Assistance Rate, including SNAP Benefits	0	0	0.04	0

Table 3 (continued)

alpha = 0.003	Model 1	Model 2	Model 3	Model 4
Poor Glycemic Control Among Individuals with Diabetes	0	0	0	0
Estimated Diabetes Prevalence	0	0	0	0

Model 1 is unadjusted. Model 2 includes age and sex, model 3 also includes race, ethnicity, insurance status, and prior outpatient and ED care utilization, and model 4 additionally includes BMI, history of hypertension, hyperlipidemia, and prescriptions for antihypertensives and statins

of diabetes, who were found to have severe hyperglycemia on random glucose testing to a level that likely represents previously undiagnosed diabetes. We analyzed various geospatial variables to identify those factors that were predictive of undiagnosed diabetes. We also fit penalized and unpenalized logistic regression models which controlled for individual level characteristics or risk factors to remove confounders and better assess geospatial factors that were independently predictive. A patient's geographic location of residence and associated geospatial variables have been previously shown to help predict health outcomes [22, 23]; these results suggest potential risk variables that can be used to fine-tune diabetes screening programs to improve specificity and yield and focus resources to identify those most likely to have undiagnosed disease.

Approximately half of all ED patients receive blood testing for some indication during their evaluation in the ED [24]. Patients who otherwise face obstacles to accessing primary care frequently visit EDs for care; thus the ED is a potential setting for screening and intervention [16, 25–29]. Previous studies have largely attempted non-targeted or loosely targeted screening using ADA or other primary care screening guidelines, which were not specifically designed to screen ED patients. These studies have found a substantial burden of undiagnosed disease, but noted barriers to implementing a screening program in the ED environment [16, 30]. To balance those barriers – including crowding, staffing concerns, laboratory burden, and availability of counseling and follow-up [31] – with the potential for identifying undiagnosed diabetes, specificity in screening criteria can help reduce the number of patients to be screened. Especially in the ED setting, where a large proportion of patients are high-risk, geospatial and demographic risk modelling beyond existing primary care guidelines is needed.

In our study, we found specifically that lower median income, lower educational attainment, and a higher proportion of non-English-speaking households in patients' neighborhoods of residence were independently associated with severe hyperglycemia (Table 3). These findings suggest that these subgroups of ED patients may be most high-risk in screening for diabetes in the ED, especially given that these same groups often face significant barriers to accessing primary care and as a result may be less likely to receive preventive healthcare [32]. Even when these patients are able to access primary care, prior literature suggests that they may still be less likely to receive necessary preventive screening [11, 33]. It is important to note that some predictors (e.g., high BMI, high blood pressure, or statin use) controlled in Model 4 may be along the causal pathway or be comorbid with hyperglycemia. Therefore, it may be more meaningful to look at the results of the other models that did not include these variables that themselves can be considered health outcomes. It is notable however that the predictors of severe hyperglycemia were largely consistent across all models examined.

A major goal for ED-based diabetes screening programs is to limit burden to ED providers, and to determine which patients are at risk (and thus most high-yield to screen). While individual risk factors are critical to determining the risk of developing diabetes, utilizing geospatial variables based on the patient's place of residence can also offer an opportunity to specifically screen those patients with a higher risk of undiagnosed diabetes. In prior research, local public health measures have been targeted towards higher-risk patients on the basis of their geospatial risk, utilizing the results of survey data and other epidemiological studies [34, 35]. The data from this study suggests the possibility for ED diabetes screening targeted to a patient's risk of undiagnosed diabetes based on available geographic data at the time of triage, even though their individual socioeconomic data may not be available or collected by the ED.

This study was subject to some limitations. First, there is a potential for selection bias that might influence the results, as only patients who received blood work in the ED were included; it is possible this introduced systemic bias in the results which would limit generalizability beyond the patient population served by emergency departments. Secondly, while our study used severe random hyperglycemia as a proxy for likely undiagnosed diabetes, this may create some small inaccuracy (e.g., including patients without diabetes with some other condition causing hyperglycemia); not every patient with elevated blood glucose would necessarily have had underlying, previously undiagnosed diabetes. Finally, these results are an analysis of cross-sectional data and any identified associations should not be interpreted as evidence of causality. More complex statistical modelling that evaluates mediation may be needed to interrogate the nature of these associations.

Conclusions

In our study, we found that lower median income, lower educational attainment, and a higher proportion of non-English-speaking households in patients' neighborhoods of residence were independently associated with severe hyperglycemia, which likely reflects undiagnosed diabetes. Including these geospatial factors in risk assessment models may help identify important subgroups of patients with undiagnosed diabetes, especially in the emergency department population, for opportune screening or other public health measures.

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Data Availability Deidentified participant data used in this study will be shared with researchers who provide a methodologically sound proposal upon reasonable request up to two years following article publication.

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