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Patterns of Chronic Conditions in Older Adults:

Exploratory Spatial Findings from the Eldersmile Program

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Abstract

Background—The increasing prevalence of primary care sensitive conditions, notably diabetes and hypertension, among older adults presents a challenge to the public health community. Systems science conceptualizations of health, along with considerations of the social and environmental context in which older adults live, are needed before effective interventions can be designed and implemented.

Purpose—To examine whether spatial patterns exist in hemoglobin A1c and blood pressure measurements among participants in ElderSmile, a community-based oral health and primary care screening program.

Methods—Two spatial statistical methods, global Moran's *I* and Cuzick-Edwards tests, were used to determine if there were significant spatial patterns among ElderSmile participants residing in northern Manhattan during 2010–2012. The analyses were conducted in 2013.

Results—Significant spatial patterns of hemoglobin A1c values and potential diabetes cases, and possibly blood pressure measurements, were found among ElderSmile participants residing in northern Manhattan.

Conclusions—The presence of spatial patterns allows for the identification of subpopulations in need of additional resources, and can assist in informing advanced spatial and statistical analyses. Screening data collected from an ongoing community-based program can be used to understand broader patterns of urban health.

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Introduction

The onset and high prevalence of chronic conditions in rapidly aging populations worldwide raise challenges for protecting their quality of life.¹ U.S. black and Hispanic older adults often have limited access to healthcare, and those living in underserved communities may not receive early diagnosis and effective treatment for preventable and manageable diseases such as hypertension and diabetes.² Hypertension is established as a significant risk factor for cardiovascular disease morbidity and mortality in older adults, but diagnosis, awareness, and control, particularly among racial/ethnic minorities, continue to be problematic.^{3,4} Similarly, given the microvascular and cardiovascular complications associated with diabetes, along with significant lack of awareness among many older adults of their diabetes status, enhanced initiatives for education and screening are needed.^{5,6}

ElderSmile is a community-based program established to provide oral health education and prevention services to older adults in northern Manhattan and adjacent communities.^{7,8} As oral health and general health are closely linked, ElderSmile now includes education and screening for diabetes and hypertension, providing referrals to primary care providers when warranted.^{9–12} Because home addresses of ElderSmile participants are recorded upon entry, the opportunity exists to examine how the health of this population manifests geographically.

This study is an exploratory investigation into whether there are spatial patterns of hemoglobin A1c (HbA1c), systolic blood pressure (SBP), and diastolic blood pressure (DBP) among ElderSmile participants. A previous study of the ElderSmile population reported high levels of undiagnosed diabetes and hypertension.¹² Geographic differences in disease rates in urban areas are commonly linked to social and economic deprivation.¹³ Understanding whether spatial patterns exist is a first step in addressing differences in contextual factors that impact participants' health. These patterns can inform future investigations of influences on the health of older adults and more effective design of health services.

Methods

This research conducted in 2013 used demographic information, self-reported health information (e.g., diabetes and hypertension diagnoses by a primary care provider), HbA1c levels, BP measurements (SBP and DBP), and home addresses for a representative sample of ElderSmile participants.¹⁴ Of the 776 ElderSmile participants enrolled from 2010–2012, 751 provided full addresses, and 615 lived in northern Manhattan (Figure 1). The study area was limited to northern Manhattan for increased neighborhood sample size and improved interpretability of findings.

To determine if significant spatial patterns exist among ElderSmile participants in the study area, two spatial statistical tests, global Moran's *I* and Cuzick-Edwards tests, were employed on the georeferenced participant information. Both tests are global tests that determine if observed spatial patterns deviate from complete spatial randomness (CSR). CSR implies no spatial pattern because the phenomenon is equally likely to occur at any location. Global

tests describe the pattern of an entire study area, and thus indicate if the phenomenon clusters anywhere in the study area.¹⁵ Expressions for these test statistics are provided in the Appendix (Online Supplement).

The global Moran's I test for spatial autocorrelation is used to assess the degree to which a phenomenon is correlated with itself in space (e.g., whether neighbors have similar attribute values). The I statistic indicates whether the spatial arrangement is: clustered, as indicated by a positive I value (high values near high and low values near low); dispersed, as indicated by a negative I value (high values near low); or random, as indicated by a zero I value.^{15,16} To explore whether spatial autocorrelation among participants' self-reported diagnosed disease status (hypertension and diabetes) varied with different sociodemographic characteristics, the I statistic was calculated (Esri ArcGIS, version 10.1) for several analysis groups stratified by race/ethnicity (black, white, or Hispanic), gender (female or male), and education (with or without a high school diploma). The sum of participants did not equal the number of georeferenced participants (615) because not all participants completed screenings. For race/ethnicity, participants were asked to identify both a race **and** an ethnicity, and their responses were used to derive the racial/ethnic categories (e.g., all participants self-identified as Hispanic were categorized as Hispanic). A direct approach to the false discovery rate (FDR) in the context of multiple testing was used, and adjusted p -values (q -values) are presented.^{17,18} These computations were conducted using statistical software (R, version 3.0.2).

The Cuzick-Edwards test was used to determine if there were more cases of diabetes or hypertension near other cases with the same condition than would be expected if the data were distributed randomly across the study area. This test was performed using spatial analysis software (BioMedware ClusterSeer, version 2.5) to indicate whether cases were clustered relative to controls. The Cuzick-Edwards test statistic is the count of k -nearest neighbors of a case that are also cases, where k determines the spatial scale.¹⁹ A first test assumes that an ElderSmile participant with a valid HbA1c score is a potential diabetes case when HbA1c is $\geq 6.5\%$, and a control otherwise.²⁰ A second test assumes a participant with valid SBP and DBP measurements is a potential hypertension case when the SBP is ≥ 140 mmHg or DBP is ≥ 90 mmHg.²¹ The parameter k (the number of nearest neighbors) is varied from 1–20 to evaluate the sensitivity to k .

Results

Significance at the 0.05 level was used to assess all conducted tests (adjusted p -values for the global Moran's I and standard p -values for the Cuzick-Edwards statistics).

The global Moran's I results for HbA1c levels and BP measurements are presented in Table 1 and Table 2, respectively. No significant spatial clustering of HbA1c was detected when using adjusted p -values. For DBP, there was significant spatial clustering for the following groups: all participants, all participants with diagnosed hypertension, and all male participants. For SBP, there was no significant spatial clustering or dispersion.

The Cuzick-Edwards results are presented in Table 3. For HbA1c levels, 14 of 20 k parameter values indicate that there were significantly more cases near cases than expected by chance. For BP measurements, no significant spatial clustering was found across k parameter values. These results indicate that among ElderSmile participants, there may be spatial clustering of participants with diabetes, but not for participants with hypertension.

Discussion

This paper presents two methods—global Moran's I and Cuzick-Edwards—for identifying spatial patterns. The results confirm spatial clustering of potential diabetes cases, and possibly BP measurements, among certain subgroups of ElderSmile participants in northern Manhattan. Within the limits of conducting analyses on self-reported health status and chairside screening data from a population that is representative of northern Manhattan adults attending senior centers, the findings of this exploratory investigation suggest that social and environmental factors have an effect on the health outcomes of this population.

Spatial methods can be used to identify communities that may require additional resources for better health services, particularly chronic disease treatment for older adults, but also enhanced health education and promotion of disease prevention and management activities.²² This study will inform future ElderSmile program analyses, which aim to identify the locations of specific clusters and account for spatial autocorrelation and the dense multiresidential urban environment. The existence of spatial structure of the data violates distributional assumptions of classical statistics, which can bias results.^{23,24} This study demonstrates how spatial analyses with data from community-based health programs, like ElderSmile, can provide insights regarding primary care-sensitive conditions that extend beyond their original scope.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

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Figure 1.
The residences of ElderSmile participants in northern Manhattan

Table 1Moran's *I* values for HbA1c analysis, stratified by the 24 analysis groups

	Moran's <i>I</i>	Adjusted <i>p</i> -value	<i>n</i>
All participants	0.018	0.53	460
Participants with diabetes diagnosis	−0.002	0.58	251
Participants without diabetes diagnosis	0.064	0.47	334
White participants	0.058	0.53	141
White with diabetes diagnosis	0.184	0.53	56
White without diabetes diagnosis	0.736	0.08	81
Black Participants	0.044	0.47	172
Black with diabetes diagnosis	0.188	0.26	72
Black without diabetes diagnosis	−0.059	0.53	96
Hispanic participants	0.018	0.53	295
Hispanic with diabetes diagnosis	0.072	0.53	137
Hispanic without diabetes diagnosis	0.141	0.47	152
Participants with high school education	−0.019	0.53	214
High school with diabetes diagnosis	−0.065	0.53	90
High school without diabetes diagnosis	0.063	0.53	116
Participants without high school education	0.029	0.53	166
No high school with diabetes diagnosis	−0.089	0.53	73
No high school without diabetes diagnosis	−0.370	0.10	93
Female participants	0.097	0.26	346
Woman with diabetes diagnosis	0.090	0.47	153
Woman without diabetes diagnosis	0.110	0.47	187
Male participants	−0.043	0.53	107
Man with diabetes diagnosis	−0.115	0.53	42
Male without diabetes diagnosis	0.081	0.53	63
Participants with hypertension diagnosis	0.045	0.47	274
Hypertension with diabetes diagnosis	0.095	0.47	133
Hypertension without diabetes diagnosis	0.108	0.47	138

Note: boldface indicates $p < 0.05$.

HbA1c, hemoglobin A1c

Table 2

Moran's *I* values for diastolic/systolic blood pressure, separately, stratified by the 24 analysis groups

	Diastolic blood pressure		Systolic blood pressure	
	Moran's <i>I</i>	Adjusted <i>p</i> -value	Moran's <i>I</i>	Adjusted <i>p</i> -value
All participants				
Participants with hypertension diagnosis	0.096	0.01	0.049	0.45
Participants without hypertension diagnosis	0.096	0.03	0.064	0.45
White participants				
White with hypertension diagnosis	0.083	0.10	-0.013	0.93
White without hypertension diagnosis	0.157	0.10	-0.109	0.84
Black participants				
Black with hypertension diagnosis	0.048	0.10	0.093	0.45
Black without hypertension diagnosis	-0.118	0.10	-0.391	0.45
Hispanic participants				
Hispanic with hypertension diagnosis	0.008	0.14	0.068	0.84
Hispanic without hypertension diagnosis	0.008	0.14	0.068	0.84
Participants with high school education				
High school with hypertension diagnosis	0.055	0.10	0.113	0.45
High school without hypertension diagnosis	-0.074	0.12	-0.270	0.47
Participants without high school education				
No high school with hypertension diagnosis	0.055	0.10	-0.004	0.93
No high school without hypertension diagnosis	0.135	0.10	-0.043	0.84
Female participants				
Woman with hypertension diagnosis	0.052	0.10	0.080	0.45
Woman without hypertension diagnosis	0.111	0.10	0.159	0.72
Male participants				
Man with hypertension diagnosis	0.270	0.08	0.025	0.84
Male without hypertension diagnosis	0.216	0.10	-0.149	0.84

Note: boldface indicates $p < 0.05$.

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Table 3

Results from the two Cuzick-Edwards statistic pseudo-experiments^a

<i>k</i>	Diabetes case-control pseudo-experiment			Hypertension case-control pseudo-experiment		
	<i>T_k</i>	<i>E</i> [<i>T_k</i>]	<i>p</i> -value	<i>T_k</i>	<i>E</i> [<i>T_k</i>]	<i>p</i> -value
1	35	25.6515	0.072	50	57.8697	0.795
2	68	51.3029	0.033	94	115.739	0.946
3	90	76.9544	0.121	151	173.609	0.915
4	133	102.606	0.009	209	231.479	0.880
5	168	128.257	0.003	279	289.349	0.686
6	200	153.909	0.002	347	347.218	0.504
7	216	179.56	0.016	400	405.088	0.580
8	257	205.212	0.002	467	462.958	0.440
9	285	230.863	0.002	541	520.827	0.237
10	304	256.515	0.010	604	578.697	0.196
11	330	282.166	0.012	650	636.567	0.332
12	353	307.818	0.020	691	694.436	0.543
13	376	333.469	0.031	734	752.306	0.710
14	400	359.121	0.042	802	810.176	0.594
15	423	384.772	0.059	881	868.046	0.357
16	450	410.423	0.059	932	925.915	0.434
17	478	436.075	0.054	975	983.785	0.592
18	513	461.726	0.028	1030	1041.65	0.618
19	533	487.378	0.049	1057	1099.52	0.857
20	552	513.029	0.084	1123	1157.39	0.799
	Combined <i>p</i> -value Bonferroni <i>p</i> -value: 0.036 Simes <i>p</i> -value: 0.027			Combined <i>p</i> -value Bonferroni <i>p</i> -value: 1.000 Simes <i>p</i> -value: 0.799		

Note: boldface indicates *p*<0.05. Combined *p*-values account for multiple testing.

^a*T_k* is the sum of cases near cases, with a given *k* parameter; *E*[*T_k*] is the value *T_k* is expected to take under complete randomness; and the *p*-value is the upper-tail *p*-value, which indicates whether there are significantly more cases near other cases than would be expected by chance.