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Vision Need Profiles for the City of Richmond, Virginia

A Pilot Application of Calibration Methods to Vision Surveillance

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Purpose: People with vision problems (VPs) have different needs based on their age, economic resources, housing type, neighborhood, and other disabilities. We used calibration methods to create synthetic data to estimate census tract-level community need profiles (CNPs) for the city of Richmond, Virginia.

Design: Cross-sectional secondary data analysis.

Subjects: Anonymized respondents to the 2015 to 2019 American Community Survey (ACS).

Methods: We used calibration methods to transform the ACS 5-year tabular (2015–2019) and Public Use Microdata estimates into a synthetic data set of person-level records in each census tract, and subset the data to persons who answered yes to the question "Are you blind or do you have serious difficulty seeing even when wearing glasses?" To identify individual need profiles (INPs), we applied divisive clustering to 17 variables measuring individual demographics, nonvision disability status, socioeconomic status (SES), housing, and access and independence. We labeled tracts with CNP names based on their predominant INPs and performed sensitivity analyses. We mapped the CNPs and overlayed information on the number of people with VP, the National Walkability Index, and an uncertainty measure based on our sensitivity analysis.

Main Outcome Measures: Individual need profiles and CNPs.

Results: Compared with people without VP, people with VP exhibited higher rates of disabilities, having low incomes, living alone, and lacking access to the internet or private home vehicles. Among people with VP, we identified 7 INP clusters which we mapped into 6 CNPs: (1) seniors ($\geq$ age 65); (2) low SES younger; (3) low SES older; (4) mixed SES; (5) higher SES; and (6) adults and children in group quarters. Three CNPs had lower-than-average walkability. Community need profile assignments were somewhat sensitive to calibration variables, with 18 tracts changing assignments in 1 sensitivity analysis, and 4 tracts changing assignments in $\geq$ 2 sensitivity analyses.

Conclusions: This pilot project illustrates the feasibility of using ACS data to better understand the support and service needs of people with VP at the census tract level. However, a subset of categorical CNP assignments were sensitive to variable selection leading to uncertainty in CNP assignment in certain tracts.

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Approximately 7.08 million Americans experienced uncorrectable vision impairment or blindness in 2017, costing the United States economy > $134 billion in economic burden per year.[1,2] A recent evaluation study found that nearly 1 in 4 Americans aged $\geq$ 71 years had presenting vision impairment in 2021.[3] As many as 24.8 million Americans self-report presenting vision problems (VPs), which are either uncorrectable or could be addressed with simple interventions, such as providing eye examinations and refractive eyeglasses or cataract surgery.[4]

Geographic variation in self-reported VP is associated with differences in social and community determinants of health. For example, researchers have observed higher VP prevalence in neighborhoods with historically race-based, discriminatory housing policy (redlining),[5] and worse self-reported and evaluated presenting vision impairment is associated with worse economic stability, educational attainment, health care access and quality, neighborhood and built environment, and social isolation.[6,7] In self-reported data, there is a strong association of VP with community factors even after adjusting for individual-level predictors.[6] At the national level, several studies have found associations between negative social determinants of health and increased risk of VP or lower use of vision

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services, and this topic is widely discussed.[5–14] Type 2 diabetes prevalence, a primary risk factor for VP, has also been found to be associated with negative social determinants of health at the community level.[15]

In this paper, we attempt to understand and characterize the needs of people with VP at the community level, as opposed to the vulnerability of the population to developing VP. Both the concepts of need and community have been broadly defined, and precise definitions agreed on by all are likely impossible.[16,17] For the purposes of this study, we have defined need instrumentally as a general propensity for certain types of vision services over others, and have defined community as a census tract because a census tract provides a unit of geography small enough to capture differences and large enough to support planning and intervention. This is different from vulnerability, which refers to the potential to suffer loss or harm.[18] In our paper, the focus is on people in whom VP have already occurred, and developing better information to serve them.

Such information is potentially useful for improving vision health because people with VP have different needs for services and support depending on their age, socioeconomic conditions, and the causes of their impairment. Children may have problems with learning, social adaptation, and participating in school activities[19]; working-age adults experience lower rates of labor force participation, social isolation, and exercise less than adults without VP[20–22]; and seniors experience declines in physical and functional abilities and social isolation.[2,23,24]

Importantly, > 80% of people with evaluated visual impairment could improve their vision to 20/40 or better with proper refraction. In the National Health and Nutrition Examination Survey data collected during 2005 to 2008, higher rates of uncorrected refractive errors (UREs) were associated with Hispanic and non-Hispanic Black race and ethnicity, lower household income, lower levels of educational attainment, and lack of health insurance.[25] Proyecto Ver, a population-based study of blindness and visual impairment in Mexican Americans in Arizona, found that URE was associated with older age, less than high school education, low index of acculturation, lack of health insurance, and not seeing an eye-care provider in the last year.[26] The Los Angeles Latino Eye Study found similar results.[27] Recent research in 2 low-income communities in Michigan found URE associated with lower household income and education, but not age, race and ethnicity, sex, employment, and health insurance.[28]

Identifying geographic areas with potentially high levels of URE and untreated cataracts could help benefit local outreach and intervention efforts to improve population vision health.[29] A review of studies of URE in the United States and globally found that numerous social and financial barriers are associated with a higher prevalence of URE, and argued for novel approaches to meet community eye care needs in low-resource settings.[30] From a surveillance perspective, more specific information about where people with VP live could help tailor better vision interventions and support services for URE and other conditions.

Methods developed by geographers to understand community-level vulnerability to disaster events can be adapted to help describe geographically distributed needs for vision services. Such measures can reflect the multidimensionality of public health problems, reduce complexity, and help programmatic planning.[31] Earlier social vulnerability models created a quantitative index score which summarized vulnerability in a geographic area into a numeric score value.[32] Rufat[33] first developed vulnerability profiles, which although driven by quantitative data, provided qualitative vulnerability assessments based on a summary of convergence of characteristics or processes rather than a quantitative numeric measure of vulnerability. Burton et al[18] argued that numeric index values are less useful to policy planners than categorical community vulnerability profiles that summarize the different types of factors that contribute to vulnerability across geographic areas. Further extensions of this work developed profiles based on the estimated individual-level attributes of people in each community created using synthetic data, and provide a methodology to estimate these.[34]

Building on this work, we used synthetic data methods to categorize individual needs for vision services geographically at the census tract level in Richmond, Virginia, and evaluated the sensitivity of these categorizations to the variables used to construct the data.[34] Our goal was to categorize Richmond census tracts based on the need characteristics of people with VP in each tract to inform the development of programmatic interventions. We selected Richmond based on its size and diversity as well as future opportunities to implement vision services interventions based on data-driven results. We consider these findings to be a pilot study that takes advantage of the unique attributes of the American Community Survey (ACS) with the awareness that the expansion of these methods nationally will require extensive input from experts for the needs of people with VP.

Methods

Strategy

We used ACS data to measure VP and individual attributes related to the need for public health services. American Community Survey is the only data source that includes a measure of VP and has a design and sample size able to produce estimates at the census tract level. Because the detail offered at the census tract level in ACS data is often limited to univariate control totals, we used calibration methods to estimate a synthetic data set of multivariable individual-level information for each tract. We used a clustering algorithm to identify common typologies of individual-level responses called individual need profiles (INPs). We imposed decision rules to classify census tracts based on their most common combinations of INPs to create a set of community need profiles (CNPs) that described the tracts. We assessed the heterogeneity of INPs within each CNP category and within each census tract. To support planning, we mapped CNPs and overlayed the number of VP persons in each tract, and the tract-level walk score, a measure of how easy it is for a person to perform daily activities without a car, which we hypothesize is related to the needs of people with VP for support services, and the results of our sensitivity analyses. This study used only publicly available secondary data sources, complies with the Declaration of Helsinki, and was deemed exempt by NORC's Institutional Review Board.

Data

We analyzed census Public Use Microdata Sample (PUMS) 2015 to 2019 5-year data for the city of Richmond Public Use Microdata Area (PUMA) containing approximately 226 000 people, and publicly available ACS tabular estimates (accessed via the census application programming interface using the tidycensus package in the R software [The R Project for Statistical Computing, The R Foundation, Vienna, Austria]).[35] Richmond has 66 census tracts and a racially and ethnically diverse population, of whom, > 21% were living below 100% of the federal poverty line. In 2019, the estimated prevalence of VP in Richmond was 3.0%, compared with the national average of 2.2%.[36] Public Use Microdata Sample is an individual-level ACS data set that supports multivariable evaluation at the individual or PUMA level of geography. American Community Survey tabular estimates provide estimated counts of people with each variable response within each census tract but do not support the estimation of combinations of variables. We used the ACS question "Are you blind, or do you have serious difficulty seeing even when wearing glasses?" to measure VP. This question has low sensitivity for detecting measured best-corrected vision acuity (BCVA) problems but high specificity (sensitivity and specificity of 0.43 and 0.93, respectively of detecting BCVA of ≥ 20/40 to < 20/200, and 0.70 and 0.88, respectively of detecting a BCVA of 20/200 or worse).[37] Other studies have assumed that responses to this question are correlated with the overall amount of BCVA at the state and county level.[1,36]

We used ACS variables or combinations of variables to measure demographics (age category [children 0−17, adults 18−64, seniors ≥ 65 years], race and ethnicity other than non-Hispanic White); nonvision related disabilities (self-care, independent living, or ambulatory difficulty; hearing difficulty; and cognitive difficulty); socioeconomic conditions (receiving food stamps, unemployed, and income < 200% poverty-to-income ratio [PIR]); housing and living situation (house built before 1990, living in group quarters, living alone, and child in a 1-parent family); and access and independence (no internet access at home, no vehicle access, no health insurance, limited English proficiency, or noncitizen).

For this pilot study, we selected a parsimonious list of variables from the ACS that are related to differing needs for vision services. For example, the ACS can support estimates of VP by age group. Vision problem among people < 65 years may be more likely to be caused by URE and may be amenable to simple interventions, such as glasses, whereas older people are more likely to have uncorrectable problems and may have a higher need for low-vision services.[38] People with other disabilities may face greater difficulties managing their VP and might potentially be a target for additional support. Likewise, for other variables measured by ACS, people with VP with low incomes or who qualify for federal assistance may be a higher public health priority than those with more resources. Housing conditions may also be related to needs for vision services. For example, people who live in homes built before 1990 when the Americans with Disabilities Act was passed may live in housing with fewer accommodations for disabilities, and parents of children with VP face greater care burdens which are likely magnified when the child lives with only 1 parent. People who live alone may face greater social isolation because of their VP, especially compared with people with VP in group quarters such as nursing homes, or adult group homes. Future studies after this pilot should engage experts in vision treatment and rehabilitation services to refine this list of input variables.

Creating Synthetic Individual Records

We sought to estimate cross-stratified individual need characteristics at the census tract level which are not provided by ACS. Publicly available ACS tabular estimates provide univariate census tract totals, and PUMS data provide the ability to create cross-stratified information at the PUMA level (for Richmond, the PUMA boundaries are the same as the city boundaries). To create cross-stratified estimates at the tract level, we used calibration methods (generalized exponential tilting) to create a synthetic data set based on the constraints of the census tract univariate cross-stratified totals.[39] The calibration method adjusted the individual PUMS survey weights subject to the constraints of the ACS tabular totals in each tract for the variables used to benchmark the calibration. To the degree that the benchmark characteristics are related to VP and correlated to other characteristics for individuals with VP, this method results in a tract-level microdata set that provides granular insight into the entire population represented in PUMS and ACS.

We used ACS variables measuring VP, gender, age, employment status, race and ethnicity, individual income, hearing impairment, health insurance status, English proficiency, educational attainment, marital status, the year the housing unit was built, and type of housing unit (rent, own, group quarters, or vacant) to benchmark the calibrated estimates. The resulting synthetic data set contained individual-level records with responses for all ACS variables for individuals in Richmond, and an estimated weight for each observation indicating the number of individuals represented by the synthetic record in the census tract. Public Use Microdata Sample provides variables related to a wide range of personal and household characteristics. From these estimates, we defined more specific characteristics based on combinations of variables. One tract (51760040900) did not contain any visually impaired residents and was excluded from subsequent analyses.

INP

We identified groups of people with VP with shared characteristics and labeled the groups INPs.[34] To identify INPs, we subset the synthetic data to synthetic respondents who answered "Yes" to the VP question. We used combinations of ACS variables to create 17 dichotomous variables measuring individual demographics, disability status, socioeconomic conditions, housing and living situation, and access and independence. We next used divisive clustering[40] using the divclust R package[41] (R Foundation) to categorize observations into 10 clusters based on distance- and variance-minimization algorithms. To increase interpretability and usability of the results, we further aggregated 4 similar subgroups with other clusters in the same cluster branch. This resulted in 7 INPs that were based on unique combinations of variables identified by the divisive clustering as relevant in categorizing individuals (Fig 1): (1) adults and children in group quarters; (2) seniors with no car; (3) children in 1-parent households; (4) community-dwelling seniors; (5) seniors in group quarters; (6) adults and children in households with incomes > 200% PIR; and (7) adults and children with incomes < 200% PIR or who had no health insurance. Individuals in each INP had other attributes not listed above but were not selected by the clustering algorithm for dividing people into unique groups because the attributes were shared across individuals in different INPs.

CNP

A mixture of different INPs is contained within each census tract. To summarize the type of vulnerability need most commonly seen in each tract, we used a heuristic approach to create the CNPs[34] based on tract distributions of INP characteristics of age group, SES, and group quarters status. We assigned each census tract to 1 of 6 CNPs based on the following decision rules: (1) seniors, if > 50% of the estimated tract's VP residents were aged ≥ 65

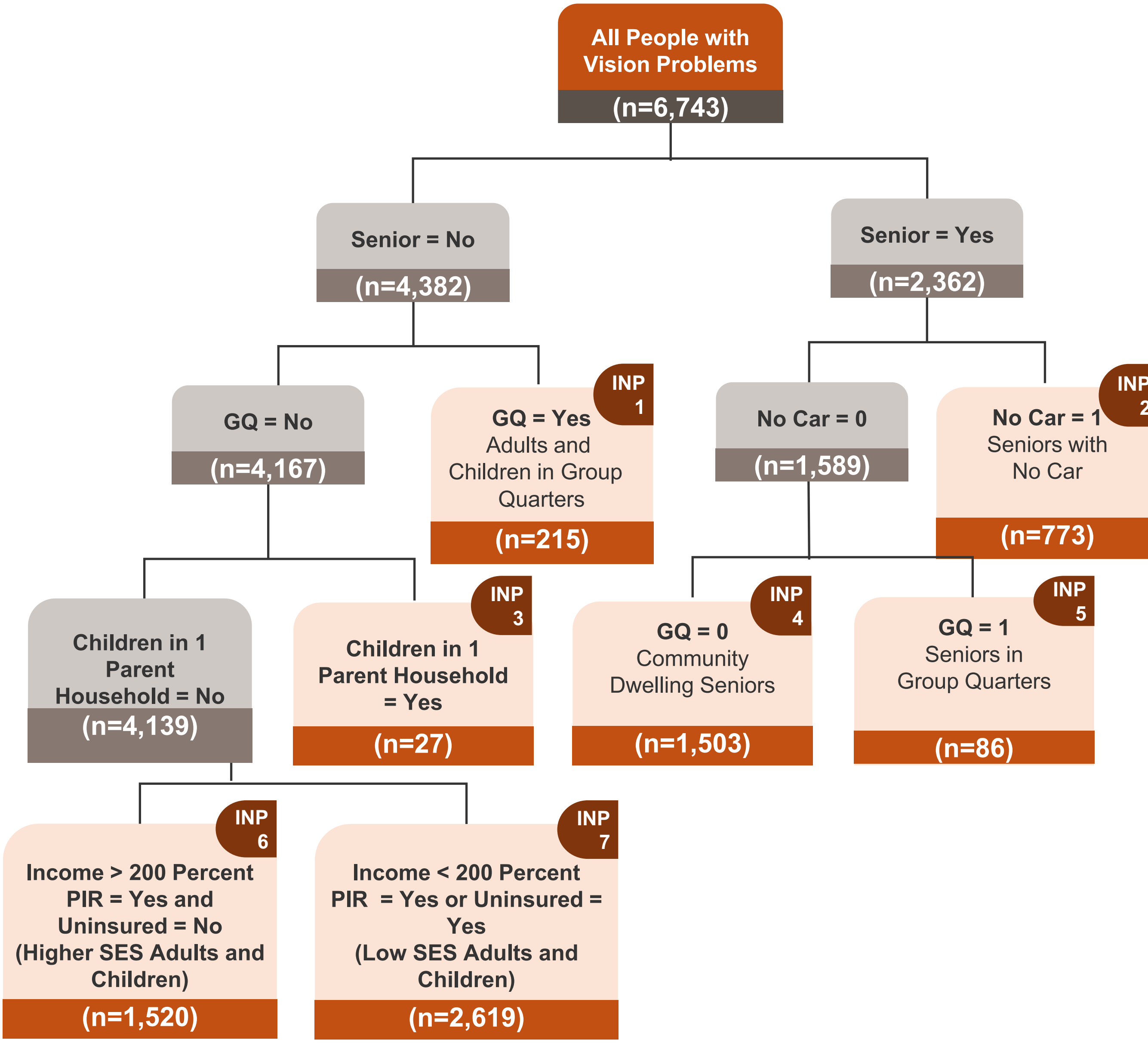

Figure 1. Individual need profile (INP) divisive clustering analysis. Figure 1 depicts the separation of estimated individuals with vision problems into mutually exclusive INPs. Individual attributes that were important in determining unique clusters included senior and group quarter (GQ) status, whether a person had access to a car, whether a person was a child in a 1 parent family, and whether a person had an income below 200% of federal poverty or was uninsured. PIR = poverty-to-income ratio; SES = socioeconomic status.

years across INPs; (2) group quarters adults and children, if > 40% of the tract's VP residents were adults and children in group quarters; (3) low SES younger, if the percent of individuals in INPs 3 and 7 combined were > 10% greater than those in INP 6 and seniors were < 25% of the population; (4) low SES older, if the percent of individuals in INPs 3 and 7 combined were > 10% greater than those in INP 6 and seniors were 25% to < 50% of the population; (5) mixed SES, if INPs 3 and 7 combined was within ± 10% of the percent in INP6 and the percent of seniors was < 50%; and (6) higher SES, if the percentage in INP6 was 10% greater than the combined percentage in INPs 3 and 7 and the percent of seniors was < 50%.

Walkability

We used the Environmental Protection Agency's National Walkability Index[42] to provide information on the ease of walking in each tract without the need for a private automobile. The index is informed by 3 key characteristics: intersection density, proximity to transit stops, and diversity of land uses. The score ranges from 1 to 20 and is categorized into 4 groups from least to most walkable. We calculated a tract-level walk score by estimating the average walkability score of census block groups within each tract weighting for block group population. We hypothesize that better walkability would help people with VP navigate their community independently, and conversely that lower walkability indicates greater need.

Evaluation

We used ACS tabular totals to estimate the frequency and proportion of people with VP in each tract (Table S1, available at www.ophthalmologyscience.org). We used PUMS data to estimate the proportion of people with each need characteristic among people without and with VP at the Richmond PUMA level. We used PUMS replicate weights to estimate standard errors for each proportion using Successive Difference Replication and tested the statistical difference of proportions of those with and without VP using the Rao−Scott chi-square test. For people with VP, we used our synthetic data set to estimate the number and percent of people estimated in each INP, the number of tracts and people in each CNP category, and additionally estimated the distribution of walkability scores within each CNP category. We further estimated the percentage of VP residents in each INP within each tract. Finally, we mapped CNPs to census tracts and overlayed the CNP's walkability score, the number of people with VP living in the tract, and the uncertainty measure described subsequently.

Sensitivity Analysis

Existing synthetic data methodologies do not support the estimation of error associated with these estimates. As an alternative, we compared the percentage of people in Richmond identified in each INP using the synthetic data to the percentage identified using the PUMS data. Substantial differences in these percentages indicate worse performance of the synthetic estimates. Synthetic cross-stratified data at the census tract level may also be sensitive to the variables used in calibration, leading to misclassification of INPs or CNPs. We performed 3 sensitivity analyses to test the sensitivity of our results to different calibrators. In 3 sensitivity analyses (SA) we recreated the synthetic data while sequentially omitting variables measuring hearing loss (SA1), individual income (SA2), and age and gender (SA3). We evaluated the sensitivity of our estimates by comparing the aggregate percentage of people estimated in each INP with the PUMA data benchmark and our baseline estimate and computed the mean squared error of each synthetic data set compared with the PUMA estimates. We then recalculated CNPs for each tract based on each alternative synthetic data set and compared these to our baseline estimates and assigned uncertainty to each tract based on whether their assignment changed 0, 1, 2, or 3 times.

Results

Based on ACS tabular totals out of 226 622 residents, an estimated 6743 or 3.0% (95% confidence interval [CI], 2.9%−3.1%) had VP with rates ranging by tract from 0% (no CI) to 10.1% (CI, 8.1%−12.0%, Table S1). Using PUMS data, Richmond residents with VP were more likely to be seniors when compared with Richmond residents without VP, and more likely to be a person of color (Table 2). Nearly 68.0% (CI, 61.8%−74.1%) of people with VP reported difficulties with self-care, independent living, ambulation, hearing, or cognition, compared with 12.6% (CI, 11.8%−13.5%) of Richmond residents without VP. Similarly, people with VP were more likely to receive food stamps and have a household income < 200% of the poverty level, live alone, and not have home internet access or a private vehicle, than Richmond residents without VP. Residents with VP were less likely to be children in a 1-parent household, be uninsured, and have limited English proficiency or be foreign born than Richmond residents without VP. Residents with VP did not significantly differ from Richmond residents without VP in their unemployment rate, living in a house built before 1990, or rate of living in group quarters.

The most common INP (Table 3) was low SES or uninsured adults and children followed by higher SES adults and children, community-dwelling seniors, and seniors without a vehicle. Adults and children in group quarters, seniors in group quarters, and children in 1-parent families comprised lower proportions of the VP population. Analyses using the PUMS data found strong agreement at the PUMA level between aggregated census tract estimates created using synthetic data, and PUMA level estimates for the Richmond PUMS.

Among the 65 census tracts with VP population, we categorized 23 as mixed SES, 18 as low SES older, 12 as low SES younger, 7 as senior, 3 as higher SES, and 2 as adults and children in group quarters (Table S4, Table 5). An approach using PUMS data alone, without the individual-level tract imputation, would assign the entire city of Richmond to the most common INP in the PUMA, either mixed SES adults and children, or a combined category of low SES older and younger.

Community need profiles were concentrated spatially across the city (Fig 2). Low SES CNPs were clustered in the southern, central, downtown areas, and eastern parts of the city. The mixed and higher SES adults and children CNP tracts were primarily in the west and north of the city. The 7 senior tracts were scattered throughout the western and northern areas of the city. The 3 higher SES tracts were to the west. One of the 2 group quarters adults and children tracts was in the same tract as the Virginia Commonwealth University and the other in the same tract as the University of Richmond.

Walkability was generally very high in Richmond with most neighborhood tracts having above-average walkability (compared with national levels). Twenty-one tracts are in the most walkable category. Only 3 tracts have a below-average walkability rating. Of the 3 tracts with lower-than-average walkability, 1 was categorized as senior, 1 as higher SES, and a third as low SES younger.

Sensitivity Analysis

When aggregated to the PUMA level, the INP assignment was insensitive to the calibrators used to create the synthetic data (Table S6). The largest changes observed were in SA3 which had a 1.26 percentage point increase in community-dwelling seniors and a 1.20 percentage point decrease in low SES adults and children compared with our baseline estimate. When compared with the PUMA estimates of INP membership, our baseline mean squared error was 0.059%, SA1 (hearing loss omitted) was 0.051%, SA2 (income omitted) was 0.007%, and SA3 (age and gender omitted) was 3.664%. When comparing CNP assignments, 43 of 65 possible assignments did not change across the 3 sensitivity analyses; 18 assignments changed in 1 of 3 sensitivity

Table 2. Proportion of People with Each Evaluated Vulnerability Characteristic Among People in Richmond City, Virginia Who Answered Yes to the American Community Survey* Question "Are you blind, or do you have serious difficulty seeing even when wearing glasses?" and Rationale for Each Variable's Inclusion in the Analysis

Variable	Persons without VP %, (SE)	Persons with VP %, (SE)	*P* Value	Inclusion Rationale
Demographics				Vision service needs vary by age and demographics
Children (0–17 yrs of age)	18.0 (0.1)	6.8 (1.8)	< 0.01	Unrecognized refractive errors, astigmatism and amblyopia, strabismus, and convergence insufficiency are the most common VP in children
Adult (18–64 yrs of age)	70.0 (0.2)	57.3 (3.3)	< 0.01	Uncorrected refractive errors are the most common cause of presenting VP in working-age adults
Senior (65+ yrs of age)	12.1 (0.2)	35.9 (3.2)	< 0.01	Uncorrectable VP are much more common among older adults
People of color (POC)	54.1 (0.4)	72.4 (3.6)	< 0.01	POC, especially Black people, are at greater risk for glaucoma. POC may also experience systemic racism that impedes their ability to access vision services
Disability status				Other disabilities may increase a person's need for help managing their VP
Self-care	2.2 (0.2)	22.4 (3.3)	< 0.01	Self-care difficulties may indicate a person needs help around the house
Independent living	4.3 (0.3)	36.9 (3.5)	< 0.01	Difficulty performing activities of daily living indicates a need for assistance, for example, help performing errands
Ambulatory	6.4 (0.3)	48.0 (3.6)	< 0.01	Difficulty walking may indicate a greater need for assistance
Hearing difficulty	2.2 (0.2)	21.0 (3.1)	< 0.01	Difficulty hearing when combined with VP may lead to greater isolation and more need for assistance
Cognitive difficulty	6.2 (0.3)	31.2 (3.5)	< 0.01	Difficulty remembering, concentrating, or making decisions may lead to a greater need for assistance
Any of the above disabilities	12.6 (0.4)	68.0 (3.1)	< 0.01	Any form of disability, when combined with VP, likely increases the need for help and assistance
Socioeconomic conditions				Lack of resources increases the need for outside assistance to manage VP
Receiving food stamps	15.3 (0.3)	26.2 (3.7)	< 0.01	Receiving food stamps indicates low income and a need for federal assistance
Unemployed	3.4 (0.3)	2.9 (1.1)	0.15	Lack of employment may be a consequence of VP and may indicate a need for vision correction or rehabilitative training
Income < 200% of the poverty line	44.4 (0.9)	57.8 (4.0)	< 0.01	People with low incomes have fewer resources to devote to vision care such as eye examinations and glasses
Housing and living situation				Living conditions may increase an individual's need for help to manage their VP
House built before 1990	84.5 (0.6)	85.6 (2.6)	0.69	Houses built before 1990 are less likely to have adaptations that make them easier for people with disabilities to live in
Group quarters	5.2 (0.3)	6.6 (1.8)	0.29	People living in group quarters such as seniors in nursing homes, or adults in group homes, have different needs than people living in the community. Interventions to reach them may benefit from the ability to reach multiple people at a single location
Living alone	17.7 (0.4)	27.8 (3.2)	< 0.01	People living alone are at risk for greater social isolation and may have a greater need for assistance with their VP
Children in 1-parent household	5.0 (0.4)	2.1 (1.0)	< 0.05	Caring for children with VP involves challenges that are magnified when only 1 parent is available
Access and independence				Resources such as internet access, vehicles, health insurance, and English proficiency can help a person navigate their daily life. Lack of access to these resources may increase a person's need for assistance
No internet access in home	13.2 (0.6)	21.6 (3.3)	< 0.01	People without the internet lack the ability to easily seek information and services online
No vehicle access in home	10.2 (0.5)	17.7 (3.2)	< 0.01	People living in households without vehicles may have difficulty traveling to eye care and other rehabilitative services
No health insurance	12.0 (0.5)	7.1 (1.7)	< 0.05	People without health insurance face financial and administrative barriers to accessing health care services such as eye care
Limited English proficiency or noncitizen	6.7 (0.3)	3.5 (1.1)	< 0.05	People with limited English language skills or noncitizens may be reluctant to seek out services when they need help

SE = standard error; VP = vision problems.
*As measured in the Public Use Microdata Sample (PUMS).

Table 3. INP, Attributes That Describe Each INP, Number, and Percentage of People with Vision Impairment and Blindness

INP			Synthetic Estimate*		PUMS Estimate†		
INP	*Label*	Attributes	*People*	*Percent*	*People*	*Percent*	Difference
1	Adults and children in group quarters	Ages 0–64 yrs and reside in group quarters	215	3.2%	221	3.2%	−0.1%
2	Seniors with no car	Age ≥ 65 yrs with no vehicle	773	11.4%	789	11.6%	−0.2%
3	Children in 1-parent families	Ages 0–17 yrs and only 1 parent in the household	27	0.2%	22	0.3%	−0.1%
4	Community-dwelling seniors	Ages ≥ 65 yrs and do not reside in group quarters	1503	22.3%	1513	22.2%	0.1%
5	Seniors in group quarters	Ages ≥ 65 yrs and reside in group quarters	86	1.2%	142	2.1%	−0.8%
6	Higher SES‡ adults and children	Ages 0–64 yrs, household income > 200% PIR, and had health insurance	1520	22.7%	1588	23.3%	−0.6%
7	Low SES‡ adults and children	Ages 0–64 and household income < 200% PIR, or had no health insurance	2619	38.9%	2529	37.2%	1.7%

INP = individual need profiles; PIR = poverty-to-income ratio; PUMS = Public Use Microdata Sample; SES = socioeconomic status.
*City-level estimates using the aggregated estimated characteristics of the census tract-level synthetic data set.
†City-level estimates using the PUMS.
‡We used the shorthand term SES to refer to whether a person had an income above or below 200% of the poverty-to-income ratio and/or was or was not uninsured.

analyses, 2 changed in 2 sensitivity analyses, and 2 changed in all 3 sensitivity analyses. Of the 18 tracts that changed assignment 1 time, 14 changed only when age and gender were removed from the calibration, and the remaining 4 changed when income was removed.

Discussion

Our study demonstrated a high level of need among people with VP in Richmond. Compared with people who did not report VP, people with self-reported VP were much more likely to have low incomes and receive food stamps, and were vastly more likely to report other disabilities. They were also more likely to report no internet access at home, and no access to a private vehicle, which may lead to isolation. Our INPs reflect a diversity of characteristics of people with VP, ranging from children in 1-parent households to seniors in group quarters. This study is the first, to our knowledge, to demonstrate the high levels of need among people who self-report VP. However, several previous studies have demonstrated strong associations between negative social determinants of health and the risk of self-reported and evaluated VP.[5–7,11]

Although the prevalence rate of VP was strongly associated with increased age, the greatest number of people with VP were adults aged 18 to 64 years, and many of these people were people with low incomes or socioeconomically disadvantaged. A total of 38.9% of people with VP were < 64 years old with indicators of low SES (INP 7). In contrast, people ≥ 65 years old (INPs 2, 4, and 5) with VP comprised 35.0% of the population. Although the cause of VP among people < 65 years is not known, many of these individuals likely suffer from URE, which could potentially be addressed with an acuity examination and glasses. In 1 study, low-cost readers substantially improved the vision of most participants.[43] Seniors with VP in Richmond may also experience URE but are also more likely to have uncorrectable VP. They may benefit from programs to

Table 5. Distribution of Census Tracts by CNP, Persons with Vision Problems and Blindness in Each CNP Category, and Number of Tracts in Each CNP with Each of 3 Levels of Walkability

Community Census Person Walkability	Census Tracts	Person Count	Walkability Below Average	Walkability Above Average	Most
Senior	7	602	1	2	4
Mixed SES*	23	2013	0	17	6
Higher SES*	3	37	1	1	1
Low SES older*	18	2737	0	14	4
Low SES younger	12	1276	1	5	6
Group quarters adults and children	2	78	0	2	0

CNP = community need profiles; SES = socioeconomic status.
*SES to refers to income above or below 200% of the poverty-to-income ratio and/or if the persons was or was not uninsured.

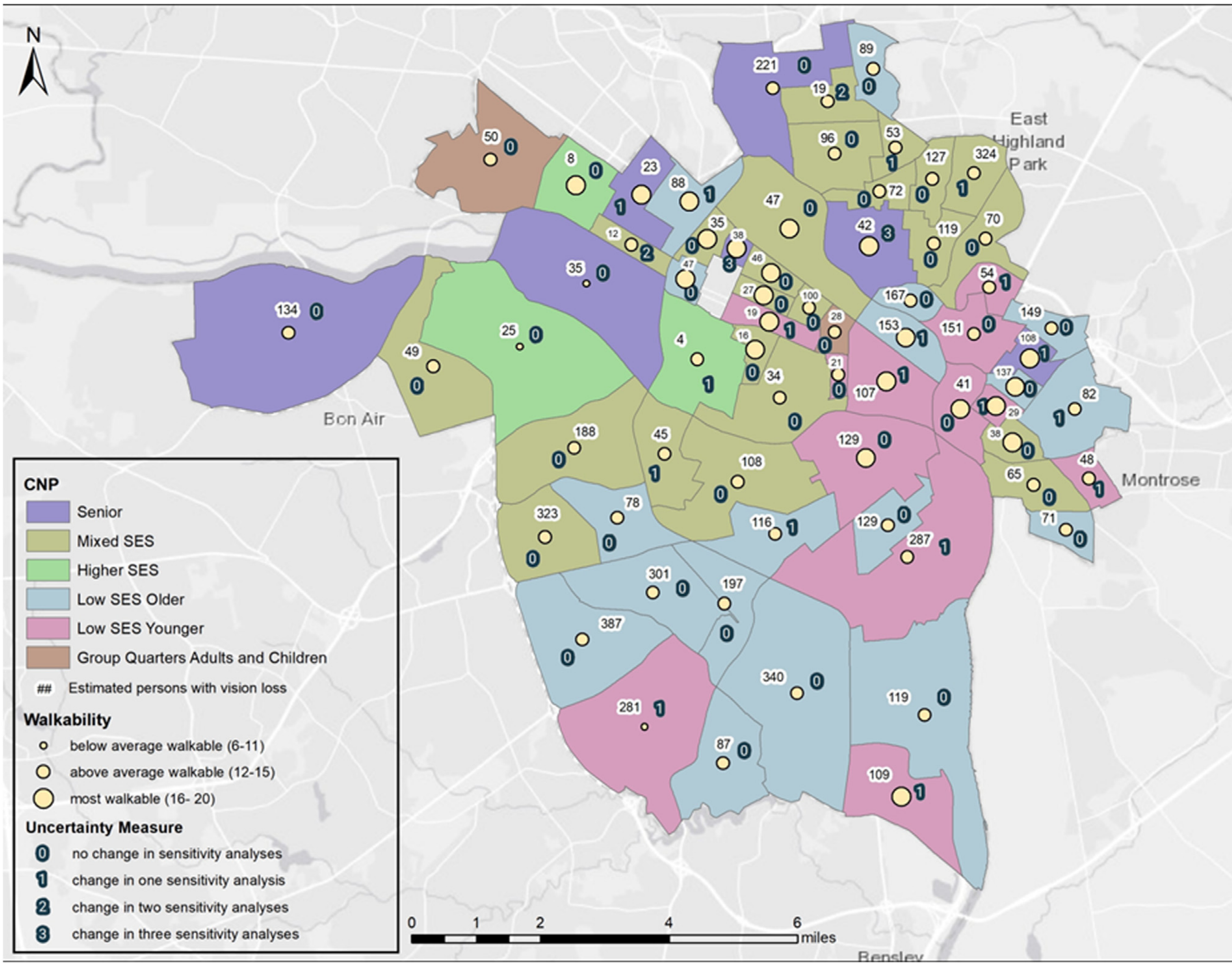

Figure 2. Community need profiles (CNP), people with vision impairment and blindness, and walkability of census tracts in Richmond City, Virginia. Figure 2 depicts a map of Richmond, Virginia with each census tract shading with its corresponding CNP color code. Map overlays display the estimated number of people with vision problems in each tract (numeral with white background), a circular indicator of the census tract's estimated average walkability with larger circles indicating greater walkability, and the number of sensitivity analyses in which the tract assignment changed (numeral with black background). Tract assignments with more changes are more uncertain. SES = socioeconomic status.

deliver low-vision rehabilitation and assistance with daily living. Additionally, many seniors in INPs 2, 4, and 5 also had low SES.

Our CNP information provides guidance on where to target specific vision outreach services to maximize impact. Census tracts in the south of the city have a large number of both older and younger people with VP, are socially disadvantaged, and have relatively worse walkability than other areas of the city. These census tracts seem to be an ideal target for vision service outreach such as mobile vans staffed by technicians able to evaluate vision acuity and provide glasses. Several census tracts with a high number of seniors with VP were in Northern Richmond. These areas may benefit from interventions to correct habitual low vision and to provide low-vision rehabilitation and support services.

We classified 2 census tracts as adults and children in group quarters, and both tracts contained universities. It is tempting to conclude the individuals with VP in these CNPs are students in dormitories; however, more research is required. People with VP in this CNP experienced extremely high rates of poverty and cognitive disabilities (data not shown), which, when considered along with their group quarters residence, suggests that they may potentially be adults residing in group homes or care facilities rather than students in dorms. More investigation is warranted because the group quarters setting of these individuals could serve as an ideal intervention setting.

Our CNP estimates are measured with uncertainty and no gold standard measures of multiattribute characteristics exist at the census tract level for validation. Because calibrated synthetic data estimates depend on the variables used in calibration, we performed sensitivity analyses by omitting certain calibrators and evaluating how these omissions affected our CNP assignments. Overall, 43 of 65 census tracts retained the same CNP assignment as the baseline in each sensitivity analysis, whereas another 22 changed their assignment $\geq$ 1 time. However, of these 22, 14 changed only when age and gender were omitted from the calibration, which is an extreme test because age is a major determinative factor in our CNP assignment which specifies an age group in 4 out of the 6 CNPs. The CNPs themselves are derived from INPs which are at least partially defined by an age group in all 7 instances. There is no programmatic reason to omit these variables from calibration, and the sensitivity analysis that omitted them performed markedly worse at the PUMA level than the baseline or SAs 1 or 2. Of the 65 tracts evaluated, 57 (87.7%) either did not change assignments or changed only when age and gender were removed from calibration. Of the 14 tracts that changed only when age and gender were omitted from the calibration, 7 tracts changed from low SES younger to low SES older, an unsurprising result given the sensitivity of the CNP assignment algorithm to age.

This study is limited by at least the following factors. First, our estimates of the individual attributes of people with VP were created using calibration using methods that are not able to quantify uncertainty beyond the sensitivity analyses provided. To test the accuracy of our estimates, we aggregated our synthetic estimates of INP membership across census tracts and compared these estimates with those obtained using direct estimates from the city-wide PUMS data and reported differences in totals of INP membership, and the estimated standard error for the PUMS estimate using replicate weights. Most notably, our calibrated estimate of low SES adults and children was 1.7 percentage points higher than the estimate from PUMS, which equates to 90 more people predicted in this category when using calibration than when using PUMS. Additionally, using ACS summary files and replicate weights at the tract level, we estimated uncertainty in the proportion of people with VP in each tract, with an average margin of error of $\pm$ 0.75% and a range of 0.04% to 2.37%. The uncertainty for our synthetic composite estimates is at least as high and likely higher because the sample size for any subset of VP when combined with a demographic trait will be less than the sample size of all persons with VP. Additionally, the derivation of synthetic microdata inherently introduces additional errors. Promising research has evaluated variance estimation methods for composite ACS estimates constructed from $\geq$ 2 variables,[44] but additional research is needed on estimating the variances of estimates derived from synthetic data. Additional research should seek to validate the accuracy of the synthetic data used here and in previous papers,[34,45–47] because the uncertainty for these estimates cannot be estimated using current statistical methods.

Second, because of our reliance on ACS data, we used a self-reported indicator of VP which is not equivalent to clinically administered eye evaluation. Recent research from 1 study population suggests that the ACS vision question is highly specific but has low sensitivity in detecting vision acuity problems.[37] Other research has shown that the ACS question approximates the central tendency of multiple forms of self-reported vision questions, but that self-reported vision measurements across surveys are highly variable.[4] Vision acuity measures from examinations would clearly provide a superior measure of VP. Nevertheless, the ACS question was successful in identifying a group of people with self-reported VP and a high degree of need and is the only feasible measure that can be used to measure vision at the census tract level.

Third, due to sample size limitations and the demography of Richmond, we restricted our definition of race and ethnicity to a dichotomous indicator of non-Hispanic White versus people of color and additionally included a variable to measure if a resident had limited English proficiency or was a noncitizen. This vast simplification of race and ethnicity, although unsatisfying, is a data compromise for Richmond where 84% of the population identified as Black or White, 8% identified as Hispanic, and 5% identified as multiracial.[48] Additionally, because of the unfortunate high correlation between low SES and people of color, our cluster analysis found that the PIR $<$ 200% and uninsured variables were stronger predictors of individual clusters than race and ethnicity. Because this pilot was restricted to Richmond, we cannot provide information on additional impacts of race and ethnicity other than to say that people of color were significantly more likely to report VP than non-Hispanic Whites. Differences in the needs of people of color with VP could become apparent in studies that include larger geographic areas.

Fourth, because this was a pilot study, we used a heuristic approach to assign CNP labels based on the intent to help target public health services. Future applications should engage professionals in community vision services and low-vision rehabilitation to help identify variables to inform INPs and to develop optimal CNP designations.[31] Potentially, future CNP designations could incorporate information from sensitivity analyses. Fifth, we hypothesized that including Walkability Index scores would help identify areas of the city where people with VP were at the highest risk of isolation. However, Richmond is a highly walkable city and we only identified 3 census tracts with below-average walkability, and no tracts were in the Environmental Protection Agency's least walkable category.

Using calibration methods to create synthetic ACS data, clustering methods to create INPs from those data, and heuristic decision rules to summarize INPs at the census tract level of granularity is feasible and may clarify the diverse needs of people with VP in a way that supports programmatic intervention. However, CNP designation in a subset of tracts was sensitive to the variables used in calibration, and methods to quantify uncertainty beyond sensitivity analyses have not been developed. The method could be applied to understand the needs of people with VP nationwide with the understanding that CNPs are estimates only, measured with uncertainty, and ideally should be supported by community-level validation.

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Author Contributions:

Conception and design: Rein, Herring-Nathan

Data collection: Rein, Herring-Nathan

Analysis and interpretation: Rein, Herring-Nathan

Obtained funding: Rein

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Abbreviations and Acronyms:
ACS = American Community Survey; **BCVA** = best-corrected vision acuity; **CI** = confidence interval; **CNP** = community need profiles; **INP** = individual need profiles; **PIR** = poverty-to-income ratio; **PUMA** = Public Use Microdata Area; **PUMS** = Public Use Microdata Sample; **SES** = socioeconomic status; **URE** = uncorrected refractive errors; **VP** = vision problems.

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