PREVENTING CHRONIC DISEASE

PUBLIC HEALTH RESEARCH, PRACTICE, AND POLICY

U.S. Department of Health and Human Services
Centers for Disease Control and Prevention

About the Journal

Preventing Chronic Disease (PCD) is a peer-reviewed public health journal sponsored by the Centers for Disease Control and Prevention and authored by experts worldwide. PCD was established in 2004 by the National Center for Chronic Disease Prevention and Health Promotion with a mission to promote dialogue among researchers, practitioners, and policy makers worldwide on the integration and application of research findings and practical experience to improve population health.

PCD's vision is to serve as an influential journal in the dissemination of prove and promising public health findings, innovations, and practices with editorial content respected for its intgrity and relevance to chronic disease prevention.

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Table of Contents

01. **PCD 2021 Student Research Collection: Building Public Health Research Capacity in Real-World Settings and the 2022 Call for Papers**
Jack L Jr. PCD

02. **Geographic Clustering of Fast-Food Restaurants Around Secondary Schools in Hong Kong**
Jason Tsz Him Cheung, BA; Ka Chung Tang, MS; Keumseok Koh, PhD

03. **Association Between Food Insecurity and Diet Quality Among Early Care and Education Providers in the Pennsylvania Head Start Program**
Dania Mofleh, MBBCh, MPH; Nalini Ranjit, PhD; Ru-Jye Chuang, MS, DrPH; Jill N. Cox, MS, RD; Christine Anthony, PhD; Shreela V. Sharma, PhD, RDN, LD

04. **New SNAP Eligibility in California Associated With Improved Food Security and Health**
Melinda Wang, BA; Ronli Levi, MPH, RD; Hilary Seligman, MD, MAS

05. **Interest in Receiving Nutrition Information Through Social Media Among Food-Security Program Participants in Washington, DC**
Adrian Bertrand, MS; Melissa Hawkins, PhD; Elizabeth W. Cotter, PhD; Donna Banzon, MPH; Anastasia Snelling, PhD

06. **Effect of Inadequate Sleep on Frequent Mental Distress**
Amanda Blackwelder, MPH; Mikhail Hoskins, MPH; Larissa Huber, PhD

07. **Association of the Neighborhood Built Environment With Incident and Prevalent Depression in the Rural South**
Christopher E. Anderson, PhD, MSPH; Stephanie T. Broyles, PhD; Maeve E. Wallace, PhD, MPH; Lydia A. Bazzano, MD, PhD; Jeanette Gustat, PhD, MPH

08. **Colorectal Cancer Risk Factors and Screening Among the Uninsured of Tampa Bay: A Free Clinic Study**
Ethan Y. Song; Justin Swanson, MPH; Artish Patel; Madeline MacDonald, MS; Alexandra Aponte; Noura Ayoubi, MD; Lucy Guerra, MD; Eduardo Gonzalez, MD; Rahul Mhaskar, PhD; Abu-Sayeef Mirza, MD

09. **Visualizing Potential Effects of Dentist Retirements on Accessibility to Dental Care Among Children in Alabama, 2019**
Steven Samsel, MS; Ryan Tramp, MBA; Irem Sengul Orgut, PhD; Nickolas Freeman, PhD; Jason Parton, PhD; Matthew Hudnall, PhD; Dwight Lewis, PhD

10. **Needs of Individuals Living With Hepatitis Delta Virus and Their Caregivers, 2016–2019**
Priyanka Kumar, MD, MPH; Catherine Freeland, MPH; Sierra Bodor; Sean Farrell; Chari Cohen, DrPH, MPH; Rosemary Frasso, PhD, MSc

11. **A Comparison of Community Resources for Chinese Immigrants Across Philadelphia Neighborhoods**
Ava Wagner; Vikram Bellamkonda; Russell White, MS; Emily Walton, PhD; Carolyn Y. Fang, PhD; Marilyn Tseng, PhD

PREVENTING CHRONIC DISEASE
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EDITORIAL

PCD 2021 Student Research Collection: Building Public Health Research Capacity in Real-World Settings and the 2022 Call for Papers

Leonard Jack Jr, PhD, MSc[1]

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NON–PEER REVIEWED

With this student collection, PCD celebrates the 10-year anniversary of our efforts to build scientific publishing skills and abilities among students. The primary aims of PCD's student manuscripts have evolved over the years. Specifically, we aim to 1) provide an opportunity to become familiar with a journal's manuscript submission requirements and peer review process; 2) foster connections among student knowledge and training, the conduct of quality research, and a journal's publication expectations; 3) develop research and scientific writing skills to become producers of knowledge, rather than just consumers of knowledge; 4) provide an opportunity to become a first author on a peer-reviewed article; and 5) promote supportive, respectful, and mutually beneficial mentee relationships that strengthen students' ability to generate and submit scholarly manuscripts throughout their professional careers (1). We believe that committing time, attention, and resources to providing student authors with valuable feedback (whether or not manuscripts are accepted) serves as a key capacity-building resource. Providing this feedback not only benefits PCD in the future but other peer-reviewed journals as well.

PCD published articles of winning student manuscripts from 2011 through 2015 and in 2017 and 2018. From 2011 through 2015, manuscripts were screened and reviewed by a panel of peer reviewers who identified an overall winner whose manuscript was ultimately published (2–11). Because of the tremendous response from students, we expanded submission screening, peer reviewing, and publishing to 5 student levels in 2017 and 2018, and winners were identified at the high school, undergraduate, graduate, doctoral, and postdoctoral levels (1,12). In addition to publishing student articles in each of the 5 levels, articles that successfully completed the peer-review process were also published. In this 2021 collection, we have continued to publish articles that successfully completed our rigorous peer-review process; however, we chose not to select a winner in each level. The COVID-19 pandemic rendered PCD unable to obtain the human resources necessary for facilitating a timely selection process. PCD will return to its usual selection process of identifying winners at all levels in future student competitions.

Over the years, PCD has refined eligibility requirements for students interested in submitting research manuscripts to the journal. Students must be a high school graduate, an undergraduate or graduate student, a medical resident, or a postdoctoral fellow. Authors must meet the journal's criteria to be recognized as first author; that is, they must have prepared the first draft and conducted research on or practiced in the topic addressed in the manuscript. In addition, their work must have been completed within the previous 12 months. Manuscripts submitted for PCD consideration cannot be under consideration by another journal. PCD only considers Original Research or GIS Snapshots for student submissions. Most importantly, the author must serve in the combined roles of the manuscript's first author and the corresponding author, which allows direct communication with the editor in chief and journal staff members. Students in this role receive critical instruction at every stage of scholarly publication, from submission, to peer review, to editorial revision, to production, and finally, to publication (Box).

Box. Samuel F. Posner, PhD: Student Contest Visionary

The PCD 2021 Student Research Collection is dedicated to Samuel Posner, PhD, the person who envisioned and led the journal's student competition in 2011. Dr Posner provided 9 years of service to PCD as editor in chief, from 2008 through 2016. Dr Posner's legacy is one of scientific excellence, technical innovation, and service.

Dr Posner is now the Acting Director of the National Center for Immunization and Respiratory Diseases (NCIRD) and the center's deputy director for science. In this role, he oversees the center's surveillance, epidemiology, laboratory, and data science programs to expand and refine CDC's capacity to detect, prevent, and respond to vaccine-preventable and respiratory infectious disease threats.

Dr Posner came to CDC in 1998 from the University of California, San Francisco after completing doctoral work in quantitative psychology at the University of Southern California in 1996. He joined NCIRD in January of 2016 as the associate director for epidemiological science and director of the Office of Science and Integrated Programs. In this role, Dr Posner led the scientific review of several NCIRD programs, including the review and reframing of the Legionella program. Under his guidance, the Legionella program has grown in scope and reach and now funds 23 jurisdictions for both prevention and outbreak response.

In the COVID-19 response, Dr Posner co-led the development of a scientific agenda to guide implementation of scientific activities for better understanding of COVID-19 transmission dynamics, risk factors for mortality, and prevention strategies. He also worked closely on the data and informatics architecture for the COVID-19 national vaccine program.

Dr Posner is the author of more than 100 articles published in peer reviewed journals and has written more than 15 book chapters. He is an internationally recognized expert in the fields of preconception care and multiple chronic conditions, and he is an adjunct associate professor at both Emory University's Rollins School of Public Health, Department of International Health, and the University of Alabama, Birmingham's School of Public Health, Department of Health Behavior.

Early in his career, Dr Posner recognized the value of mentoring students in the value of publication, and his student research competition brought a new generation of public health researchers and practitioners to PCD. Since the inception of the competition, the journal has received nearly 500 student manuscripts for consideration. Dr Posner's vision to promote academic research excellence for students around the world lives on today.

PCD's student articles released to date address topics relevant to the prevention, screening, and surveillance of population-based interventions for chronic diseases, including but not limited to arthritis, cancer, diabetes, depression, obesity, and cardiovascular disease. Of the 38 manuscripts submitted for the PCD 2021 Student Research Collection, 10 successfully completed our rigorous internal and external peer-review process and multiple revisions. PCD sincerely appreciates our associate editors, the editorial board, members of the statistics review committee, and the many peer reviewers who provided detailed comments and suggestions to student authors. We congratulate each student author who developed and submitted a manuscript for consideration, whether it was accepted or not.

The current collection addresses a broad range of topics, including childhood obesity in secondary schools in Hong Kong (13); nutrition and physical activity among adults (14–16); the impact of inadequate sleep on mental health (17); the association between neighborhood built environments and depression in the rural South (18); colorectal cancer risk factors and screening among uninsured adults living in Tampa Bay, Florida (19); spatial accessibility to dental care among Alabama youth (20); identifying challenges to care for people living with hepatitis delta virus and their caretakers (21); and community resources to promote health among Chinese immigrants living in Philadelphia (22).

PCD is pleased to announce the Call for Student Papers: 2022 Publishing Opportunity for Students. Information about submission requirements are available on the PCD Announcements page at https://www.cdc.gov/pcd/announcements.htm. The deadline for submissions is Monday, March 28, 2022. PCD looks forward to continuing its commitment to the development of scientific writing and publishing skills among students. For more information about the journal and previous collections of student articles, please visit the PCD website at https://www.cdc.gov/pcd/index.htm.

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ORIGINAL RESEARCH

Geographic Clustering of Fast-Food Restaurants Around Secondary Schools in Hong Kong

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Summary

What is already known on this topic?

Previous literature confirmed a positive association between clusters of fast-food restaurants around schools and obesity rates of school children. Few studies about fast-food clustering around schools have been conducted in a high-density urban setting such as Hong Kong.

What is added by this report?

Fast-food restaurants around secondary schools were substantially clustered in Hong Kong. The school food environment in Hong Kong showed unique heterogeneities compared with the school food environment in a Western setting.

What are the implications for public health practice?

Students in some areas may have a disproportionate share of health problems caused by an obesogenic environment. Observed clusters of fast-food restaurants in Hong Kong can alert policy makers to design effective interventions targeting the secondary schools located in such environments.

Abstract

Introduction

Clustering of fast-food restaurants around schools facilitates fast-food consumption among students, which may cause obesity. We examined the prevalence of fast-food restaurants and identified the clusters of fast-food restaurants near secondary schools in Hong Kong.

Methods

We collected data of Western fast-food chain restaurants and 490 secondary schools in Hong Kong. Descriptive statistics and buffer analysis identified the prevalence of fast-food restaurants around the secondary schools within 400-m and 800-m buffers. Additional analyses compared schools stratified by the 3 main regions in Hong Kong, district-level population density, and median monthly household income. We used Getis-Ord GI* hot spot analysis to measure spatial clusters of fast-food restaurants around schools and Global Moran's *I* to measure the spatial autocorrelation based on each school and the number of fast-food restaurants within the 400-m buffer.

Results

The average number of fast-food restaurants within 400 m and 800 m of a school was 2.0 and 6.3, respectively. Seven in 10 secondary schools had at least 1 fast-food restaurant within 400 m. The number of schools with no fast-food restaurants was higher in Hong Kong Island, considered the "rich region" in Hong Kong. Hot spots of clusters were significantly located in the high-density downtown areas. We observed significant spatial autocorrelation between fast-food restaurants and secondary schools in the areas with high density, low income, and high income ($P < .001$, $z > 2.58$).

Conclusion

Fast-food restaurants were substantially clustered around secondary schools in Hong Kong. Territory-wide studies about the health effect of fast-food clusters around schools on children and adolescents are warranted in Hong Kong.

Introduction

Childhood obesity is a major public health problem in both developed and developing countries (1). In 2015, a total of 107.7 million children were obese across the world, and the rate of increase among children exceeded that among adults (2). The long-term physiological and psychological consequences of obesity include an increased risk of type 2 diabetes, high blood pressure, high cholesterol, fatty liver disease, adverse cardiovascular outcomes, low self-esteem, anxiety, depression, bullying, and stigma, which are likely to persist into adulthood (3–6).

The World Health Organization warned that excessive consumption of a high-fat diet is associated with childhood obesity (7). Fast food is one of the dominant food types constituting a high-fat diet. The consequences of fast-food consumption on children's dietary intake are serious. Compared with nonconsumers of fast food, children who consume fast food were found to have higher intakes of total energy, total fat, saturated fat, and sugar and lower intakes of fiber, fruit, vegetables, and milk (8). In the long run, frequent fast-food consumption among children was associated with a higher body mass index (BMI), higher body fat percentage, and increased odds of being obese (9).

The school food environment is an important factor in shaping children's food choices, along with other factors, such as levels of physical activity, caregivers' income, and social and cultural knowledge and attitudes (10). The rapid expansion of Western fast-food restaurants in urban environments in high-income countries and their increased availability, accessibility, and affordability are associated with the emergence of childhood obesity (11). One study found that children with more fast-food restaurants in their school neighborhoods ate more fast-food meals per week (12). Public health and nutrition professionals recommend various school-based dietary interventions (eg, school lunch programs and nutrition education) to mitigate childhood obesity; such interventions can reduce BMI and the prevalence of childhood obesity (13).

School-based dietary intervention programs are not always effective. In Hong Kong, although most primary schools have dietary intervention programs, secondary school students (particularly seniors) often enjoy having lunch at nearby restaurants. The food choices of secondary school students are often driven by accessibility, availability, affordability, acceptability (eg, perception of their school's food), and attitudes concerning food (14). In Hong Kong, Western fast-food is perceived as "cool" by young people, who also praise its taste, appeal, affordability, and quickness (14–16). In addition, Hong Kong's hyper-dense urban nature gives students an additional benefit — proximity — to fast-food restaurants. The proximity of fast-food restaurants to secondary schools is a crucial factor in determining the daily food choices of students. The overall overweight and obesity rate among secondary school students in Hong Kong increased from 18.2% in school year 2009–2010 to 19.9% in 2018–2019 (17). Nearly 1 in 5 secondary students is overweight or has obesity (17).

To the best of our knowledge, only a few studies have examined the prevalence of fast-food restaurants near secondary schools in Hong Kong (18). Also, few government policies have solely addressed the problem of fast-food restaurants near secondary schools and its health effect on children (18). Therefore, this study aimed to describe the prevalence of fast-food restaurants near secondary schools and identify the vulnerable hot spots of fast-food restaurant clusters near secondary schools.

Methods

We performed a cross-sectional analysis in July 2020 using up-to-date, publicly available data on fast-food restaurants and secondary schools in Hong Kong.

Hong Kong base map data. Hong Kong comprises 3 regions and 18 districts, namely, Hong Kong Island (4 districts), Kowloon (5 districts), and New Territories (9 districts) (Figure 1). We used district-level data to examine the overall prevalence of fast-food restaurants around each secondary school.

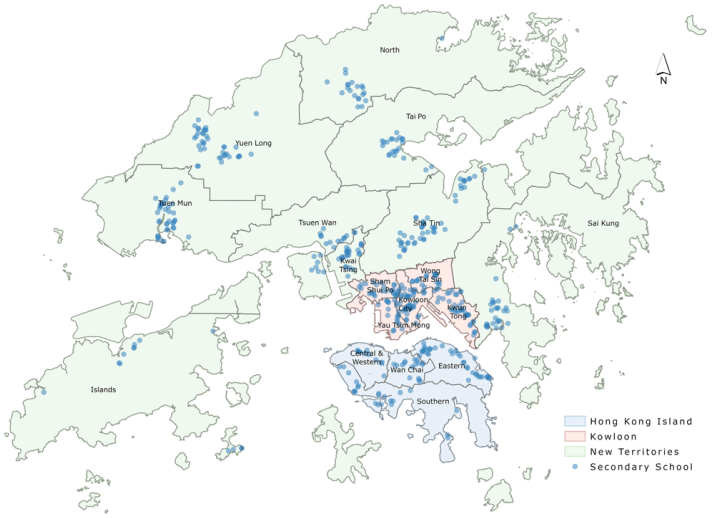

Figure 1. The location of 490 secondary schools in 3 regions and 18 districts in Hong Kong.

Fast-food restaurant data. We compiled the latest list of fast-food restaurants in Hong Kong in July 2020 from a popular and comprehensive website for food and restaurant reviews in Hong Kong, OpenRice (www.openrice.com). We searched the OpenRice fast-food category for the names of major, if not all, Western fast-food chain restaurants (ie, restaurants that quickly serve food such as hamburgers, French fries, fried chicken, submarine sandwiches, and pizza). The 15 fast-food chain restaurants included in the analysis were Burger Circus, Burger Home, Burger King, Burgerman, BurgerRoom, Five Guys, Jollibee, KFC, McDonald's, Moo-Moo, Mos Burger, Popeyes, Subway, Texas Burger, and The Big Bite. We excluded Hong Kong–style fast-food restaurants (eg, Café de Coral, Maxim's MX) because they offer many different styles of cuisines (18). We collected up-to-date street addresses from the of-

ficial website of each fast-food restaurant. We ensured that the restaurants were in business during the time of our analysis (July 2020) and geocoded the street addresses using Google Maps Geocoding Application Programming Interface (API). All records were successfully geocoded. After geocoding, we conducted reverse geocoding to ensure addresses were accurate.

EatSmart restaurant data. In Hong Kong, to advocate for a healthy food environment, the government initiated the EatSmart Restaurant Star campaign in 2008 (19). The campaign uses a label system to indicate the level of fruits and vegetables served to customers. Only 972 of 16,323 restaurants in Hong Kong, and none of the fast-food restaurants analyzed in our study, joined this campaign as of December 2020. To allow the comparison of the spatial variations of fast-food restaurants and the EatSmart restaurants around secondary schools, we collected the addresses of the EatSmart restaurants from the EatSmart Restaurant Star campaign official website in December 2020 (19). We geocoded the street addresses using Google Maps Geocoding API. All records were successfully geocoded. After geocoding, we conducted reverse geocoding to ensure addresses were accurate.

Secondary school data. We obtained secondary school data in 2020 from the Hong Kong GeoData Store, a free geospatial information service run by the Hong Kong government, by using the location search API (20). We included all secondary schools in Hong Kong: aided secondary schools, Caput secondary schools, direct subsidy scheme secondary schools, English Schools Foundation (secondary), government secondary schools, international schools (secondary), and private secondary schools (day/evening). After retrieving the addresses, we compiled a database with 490 listings geocoded by Google Maps Geocoding API. We conducted reverse geocoding to ensure addresses were accurate.

Census data. We collected data on population density and median monthly household income at the district level from the most recent (2016) Hong Kong government census (21,22).

Statistical analyses

First, we calculated the mean and median distance from each secondary school to the closest fast-food restaurant. Second, we conducted 400-m and 800-m Euclidean buffer analyses around each school and identified the number of fast-food restaurants within the buffers. The 400-m Euclidean buffer reflects the reality of students walking to nearby restaurants (23). The 800-m Euclidean buffer was used to characterize a larger school food environment, targeting students who exert extra effort and intention to visit fast-food restaurants (24). Third, we conducted the Getis-Ord GI* hot spot analysis to identify the significant spatial clusters of fast-food restaurants. We adopted the inverse distance-weighted interpolation to visualize the hot spots according to *z* scores, which indicate the significance of the hot spot. A low negative *z* score generally implies a cold spot, a high positive *z* score implies a hot spot, and a *z* score near zero indicates no apparent spatial clustering. Finally, to quantify the degree of clustering, we used the spatial autocorrelation (Global Moran's *I*) tool to measure the spatial autocorrelation based on each school and the number of fast-food restaurants within the 400-m buffer. To allow for the comparison of the geographic clustering of fast-food restaurants and EatSmart restaurants around secondary schools, we also performed the same spatial autocorrelation (Global Moran's *I*) analysis based on each school and the number of EatSmart restaurants within the 400-m buffer. This tool evaluates whether the pattern is clustered, dispersed, or random, where a Moran's *I* value near +1 indicates clustering and a Moran's *I* value near −1 indicates dispersion. The Moran's *I* statistic for spatial autocorrelation is given as

$$I = \frac{N}{S_0}\sum_i\sum_j w_{ij}\frac{(x_i - \mu)(x_j - \mu)}{\sum_i (x_i - \mu)^2}$$

where N is the number of schools; w_{ij} is the element in the spatial-weight matrix corresponding to the samples *i* and *j*; w_{ij} is defined using an inverse distance method; and x_i and x_j are samples for areas *i* and *j* with the mean μ; and

$$S_0 = \sum_i\sum_j w_{ij}$$

All analyses were carried out by using ArcGIS Pro version 2.4.0 (Esri).

We analyzed the data from Hong Kong as a whole and then conducted 3 additional stratified analyses. First, we examined the spatial characteristics of the 3 regions. Second, we classified the 18 districts into 3 strata of population density (high, medium, and low) and analyzed the spatial characteristics of the 3 strata. The 3 strata were classified according to the relative rankings of population density in the 18 districts. We then assigned each school to 1 of the 3 strata of population density, according to their district. Third, we classified the 18 districts into 3 strata of median monthly household income (high, medium, and low) and analyzed the spatial characteristics of the 3 strata. The 3 strata were classified based on the relative rankings of median monthly household income in the 18 districts. We then assigned each school to 1 of the 3 strata of median monthly household income, according to their district.

Results

We found 425 Western fast-food chain restaurants in Hong Kong: Burger Circus (n = 1; 0.2%), Burger Home (n = 1; 0.2%), Burger

King (n = 2; 0.5%), Burgerman (n = 2; 0.5%), BurgerRoom (n = 2; 0.5%), Five Guys (n = 4; 0.9%), Jollibee (n = 10; 2.4%), KFC (n = 87; 20.5%), McDonald's (n = 247; 58.1%), Moo Moo (n = 1; 0.2%), Mos Burger (n = 33; 7.8%), Popeyes (n = 1; 0.2%), Subway (n = 31; 7.3%), Texas Burger (n = 1; 0.2%), and The Big Bite (n = 2; 0.5%).

Overall, in Hong Kong, the mean and median distance between each school and the most proximate fast-food restaurant were 377.0 m and 278.7 m, both within the 400-m walkable distance (Table 1). The average number of fast-food restaurants within 400 m and 800 m of a school was 2.0 and 6.3, respectively (Table 2). Approximately 7 in 10 secondary schools (72.0%) had at least 1 fast-food restaurant within 400 m, and half (52.0%) had more than one. Across the 3 regions, Kowloon had the highest average number of fast-food restaurants within 400 m and 800 m of a secondary school. More than 7 in 10 secondary schools had at least 1 fast-food restaurant within 400 m in Kowloon (76.4%) and New Territories (72.0%). In contrast, Hong Kong Island, which has the highest median monthly household income across the 3 regions, had fewer fast-food restaurants near secondary schools, yet 64.8% had at least 1 fast-food restaurant and 51.1% had more than 1 fast-food restaurant within 400 m. The number of schools with no fast-food restaurants within 400 m was higher in Hong Kong Island (35.2%) than in Kowloon (23.6%) or New Territories (28.0%).

For secondary schools within the districts stratified by population density, secondary schools in high-density districts had a higher percentage of having at least 1 fast-food restaurant and more than 1 fast-food restaurant compared with secondary schools in middle-density and low-density districts (table 2). Three-quarters of secondary schools (75.3%) in high-density districts had at least 1 fast-food restaurant within 400 m. For secondary schools stratified by median monthly household income, secondary schools in low-income (72.9%) and middle-income (73.2%) districts generally had a higher percentage of having at least 1 fast-food restaurant within 400 m. Secondary schools in high-income districts had a higher percentage of having more than 1 fast-food restaurant within 400 m (54.6%).

In the hot spot analysis, we observed that significant clusters were in the high-density downtown areas of Hong Kong (Figure 2). Most hot spots were in Kowloon. The secondary schools in Eastern and Wan Chai districts in Hong Kong Island also were exposed to a significantly high number of clusters of fast-food restaurants. In New Territories, we found fewer clusters of fast-food restaurants around the secondary schools; Tuen Mun district was an exception. In the spatial autocorrelation analysis, we found that clusters of fast-food restaurants around each school were significant in most districts. In sum, fast-food restaurants and secondary schools in high-density urban areas in both low-income and high-income districts had significant spatial autocorrelations ($z > 2.58$; $P < .001$). The only exception for significant clustering of fast-food restaurants was the low-density districts (Table 3). In contrast, the degree of clustering of EatSmart restaurants was significantly lower in most regions and districts compared with that of fast-food restaurants. Although we observed significant clustering of EatSmart restaurants in high-density urban areas in both low-income and high-income districts ($z > 2.58$; $P < .001$), we observed no significant clustering of EatSmart restaurants in middle-income or middle-density districts (Table 3). This result suggests that students in middle-income and middle-density districts may be exposed to clusters of fast-food restaurants with no clusters of EatSmart restaurants to balance the food options.

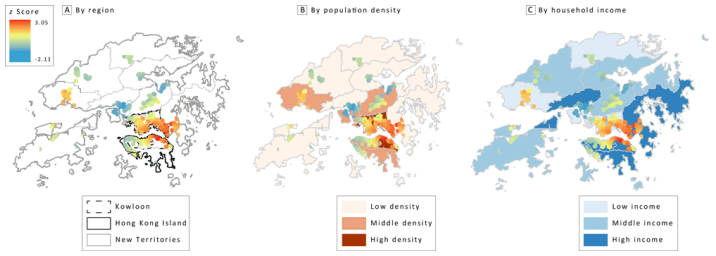

Figure 2. Hot spot analysis of fast-food restaurants near secondary schools in Hong Kong, by A, region, B, population density, and C, income.

Discussion

To the best of our knowledge, our study is one of the first to examine the fast-food environment around secondary schools in Hong Kong. The main objective of this study was to describe the prevalence of fast-food restaurants near secondary schools and identify the hot spots of fast-food restaurants by using publicly available geospatial data. Our results suggest that fast-food restaurants around secondary schools were clustered in Hong Kong as a whole and almost all districts stratified by 3 main regions in Hong Kong, population density, and median monthly household income. The overall prevalence of overweight and obesity among secondary school students increased from school year 2009–2010 to school year 2018–2019 (17), consistent with the pattern observed in previous studies (25). Our study adds to the data on obesogenic school food environments in Hong Kong and complements the existing evidence by suggesting the uniqueness of the school food environment in highly compact cities in an East Asian context compared with Western settings, which are characterized generally by relatively low-density food environments (26).

Obesity rates are associated with fast-food restaurant clusters around schools; high school students with easy access to fast-food restaurants from schools have a higher probability of becoming obese (26). Our findings show that Hong Kong secondary school

students are potentially exposed to substantial amounts of fast-food restaurants, particularly students who study in high-density urban areas in both low-income and high-income districts. On average, around each secondary school, we found 2.0 fast-food restaurants within 400 m and 6.3 fast-food restaurants within 800 m; students could easily walk to these fast-food restaurants. Policy makers may need to develop policies to improve the food environment near secondary schools, considering teenagers may be easily lured to consume unhealthy food in fast-food restaurants through peer influence (27). Most secondary school students, regardless of their financial resources, may find fast food more appealing because of its affordability, "coolness," taste, and convenience (14,15). This appeal may explain why fast-food restaurants were strategically located near secondary schools in both low-income and high-income districts (28), although we also found a moderate cluster among secondary schools in the middle-income districts.

Furthermore, the number of fast-food restaurants around each secondary school in Hong Kong was higher than the number in Western settings (for example, the US) (26). This phenomenon could be attributable to the density of Hong Kong and its gentrification and redevelopment process in some of the older districts such as Kwun Tong and Kowloon City. We found many fast-food restaurant clusters in those redeveloped districts; thus, appraising accessibility to fast-food is crucial in redevelopment initiatives. The government may need to intensively formulate urban policies (eg, incorporating the concept of healthy eating into redevelopment plans) to mitigate potential health inequalities caused by geographic disparity. In Canada, urban planning policies such as zoning bylaws have been proliferated to ban fast-food restaurants (29). These full or partial bans emerged recently in North America to encourage healthier food options. Hong Kong has lacked zoning regulations or restrictions limiting the placement of fast-food restaurants (18). However, instead of a one-way tough-policy approach, the government could consider adopting the concept of zoning by providing incentives (eg, lower rents for places with more population flow) to reward fast-food restaurants that place their restaurants in a nonschool zone. In the long run, the Hong Kong government should initiate the discussion of zoning regulations for fast-food establishments around schools for long-term sociospatial sustainability, especially targeting the districts undergoing redevelopment.

In the autocorrelation analysis of EatSmart restaurants, our results (ie, no significant clustering of EatSmart restaurants in low-density and middle-density districts) may have been due to the strategic placement of restaurants in downtown areas with more population flow. To combat the pervasive clustering of fast-food restaurants, more EatSmart healthy restaurants located near secondary schools are warranted, especially in nondowntown areas. The EatSmart campaign should be further strengthened by fostering collaborations between the government and the food industry by increasing advertisement of this program and implementing attractive reward mechanisms for participating restaurants.

The government in Hong Kong has also attempted to address the problem of childhood obesity and obesogenic school food environments by launching EatSmart@school.hk, which consists of 3 main components: EatSmart School Accreditation Scheme, Salt Reduction Scheme for School Lunches, and Joyful Fruit Month (30). However, this program focuses only on primary school students. Secondary school students in Hong Kong have received limited support for nutrition intake interventions from the government, and Hong Kong's public health community has expressed concerns about fast-food exposure among children and adolescents. Our study serves to raise awareness among authorities about food environments around secondary schools in Hong Kong. In the US, the National School Lunch Program was implemented in 1946 to enhance students' nutritional intake by offering school meals which meet US Department of Agriculture standards: currently, these standards include increasing the number and variety of fruits, vegetables, and whole grains and reducing the intake of trans-fat content and calories (31). This school meal program reduced weight status among school lunch participants, especially among students eligible for subsidies (31). The Hong Kong government could consider formulating a school lunch program with high nutrition standards and subsidizing secondary school students to buy healthy school lunches. Apart from incorporating incentives to encourage students to eat nutritious food for lunch, the government could also initiate policies to lower the appeal of fast food by restricting fast-food advertising in major media channels and holding frequent educational sessions on the consequences of fast-food intake (32,33).

Our study has several limitations. We used Euclidean distance to assess distance between secondary schools and fast-food restaurants. In Hong Kong, which has many hills and short cuts, the distance used in the analysis may not reflect the real network distance between secondary schools and fast-food restaurants. However, given the generally high number of fast-food restaurants around secondary schools, the problem of Euclidean distance is not a major flaw in the interpretation of the severity of fast-food restaurant clusters in Hong Kong. Also, Euclidean buffers may allow a snapshot comparison of fast-food restaurant clustering around schools between Hong Kong and Western settings, because the use of network distance of Hong Kong may not provide a consistent basis for comparison because of the hilly, compact,

and crowded nature of the streets. In addition, we only included the major Western fast-food chain restaurants and excluded the Hong Kong–style fast-food restaurants in our analysis; however, Hong Kong–style fast-food is also criticized because of its poor nutritional value.

The strengths of our study are twofold. It is one of the pioneering studies to examine the prevalence of fast-food restaurants near secondary schools in Hong Kong. Our findings can be used by the public health community and government officials to formulate strategic plans and interventions to improve the unhealthy school food environment in problematic areas. Also, our study provides a new approach to interpreting the school food environment in a compact urban setting, which potentially shows differences when compared with the Western setting, where the density of the food environment is generally lower (26). Our findings highlight the need for further developing theories and models for the school food environment in high-density cities or countries.

Secondary school students are constantly exposed to substantial amounts of fast-food restaurants in Hong Kong. The geographic clustering of fast-food restaurants around secondary schools should be addressed, and policy makers should pay attention to the consequences of this health problem as they unfold. In the near future, evidence from territory-wide cross-sectional and longitudinal studies about the health effects of fast-food restaurant clusters on school children are warranted.

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Tables

Table 1. Number of Secondary Schools and Fast-Food Restaurants and Distance Between Each School and Nearest Fast-Food Restaurant, by Region and District Characteristics, Hong Kong, 2020

Region and Characteristic	No. of Schools	No. of Fast-Food Restaurants	Distance, m			
			Mean	Median	SD	Range
Hong Kong overall	490	531	377.0	278.7	484.4	32.4–7955.2
By region						
Hong Kong Island	88	119	416.0	274.8	402.8	32.4–2502.6
Kowloon	148	183	302.0	275.3	165.9	57.1–848.0
New Territories	254	229	409.2	279.0	614.6	56.3–7955.2
By population density[a]						
Low	137	126	502.7	270.1	869.7	56.3–7955.2
Middle	171	183	383.9	287.2	323.2	32.4–2502.6
High	182	222	307.3	277.4	171.0	40.2–859.3
By household income[b]						
Low	177	172	387.0	305.7	213.7	57.1–1517.3
Middle	183	187	384.1	279.2	429.5	56.3–3749.3
High	130	172	380.4	245.8	370.2	32.4–2502.6

[a] The 3 strata of population density were classified based on the relative rankings of population density in the 18 districts of Hong Kong.
[b] The 3 strata of household income were classified based on the relative rankings of median monthly household income in the 18 districts of Hong Kong.

Table 2. Number of Fast-Food Restaurants Within 400-m and 800-m Buffer of Each Secondary School (N = 490), by Region and District Characteristics, Hong Kong, 2020

Region and Characteristic	400-m Buffer				800-m Buffer			
	Mean No. of Restaurants	Schools With 0 Restaurants, No. (%)	Schools With at Least 1 Restaurant, No. (%)	Schools With >1 Restaurant, No. (%)	Mean No. of Restaurants	Schools With 0 Restaurants, No. (%)	Schools With at Least 1 Restaurant, No. (%)	Schools With >1 Restaurant, No. (%)
Hong Kong overall	2.0	137 (28.0)	353 (72.0)	255 (52.0)	6.3	29 (5.9)	461 (94.1)	435 (88.8)
By region								
Hong Kong Island	2.0	31 (35.2)	57 (64.8)	45 (51.1)	6.2	9 (10.2)	79 (89.8)	76 (86.4)
Kowloon	2.2	35 (23.6)	113 (76.4)	80 (54.1)	8.5	1 (0.7)	147 (99.3)	141 (95.3)
New Territories	2.0	71 (28.0)	183 (72.0)	130 (51.2)	5.2	19 (7.5)	235 (92.5)	218 (85.8)
By population density[a]								
Low	2.0	41 (29.9)	96 (70.1)	70 (51.1)	5.1	17 (12.4)	120 (87.6)	111 (81.0)
Middle	1.9	51 (29.8)	120 (70.2)	85 (49.7)	5.5	11 (6.4)	160 (93.6)	149 (87.1)
High	2.2	45 (24.7)	137 (75.3)	100 (54.9)	8.1	1 (0.5)	181 (99.5)	175 (96.2)
By household income[b]								
Low	1.9	48 (27.1)	129 (72.9)	86 (48.6)	6.4	6 (3.4)	171 (96.6)	163 (92.1)
Middle	2.0	49 (26.8)	134 (73.2)	98 (53.6)	6.4	11 (6.0)	172 (94.0)	159 (86.9)
High	2.3	40 (30.8)	90 (69.2)	71 (54.6)	6.2	12 (9.2)	118 (90.8)	113 (86.9)

[a] The 3 strata of population density were classified based on the relative rankings of population density in the 18 districts of Hong Kong.
[b] The 3 strata of household income were classified based on the relative rankings of median monthly household income in the 18 districts of Hong Kong.

Table 3. Spatial Autocorrelation (Global Moran's Index) Based on Each School and the Number of Fast-Food Restaurants and EatSmart Restaurants[a] Within a 400-m Buffer, By Region and District Characteristics, Hong Kong, 2020

Region and Characteristic	Fast-Food Restaurants			EatSmart Restaurants		
	Global Moran's Index	*z* Score	*P* Value	Global Moran's Index	*z* Score	*P* Value
Hong Kong overall	0.26	3.30	<.001	0.19	2.41	.02
By region						
Hong Kong Island	0.58	8.21	<.001	0.08	1.24	.21
Kowloon	0.32	6.24	<.001	0.39	7.73	<.001
New Territories	0.53	2.51	.01	0.32	1.58	.11
By population density[b]						
Low	0.57	1.66	.10	0.34	1.05	.30
Middle	0.67	2.29	.02	0.41	1.41	.16
High	0.28	6.87	<.001	0.34	8.32	<.001
By household income[c]						
Low	0.14	4.97	<.001	0.18	6.31	<.001
Middle	0.52	2.30	.02	0.37	1.68	.09
High	0.48	8.34	<.001	0.23	4.31	<.001

[a] Restaurants that adopted a labeling system indicating the level of fruits and vegetables served to customers.
[b] The 3 strata of population density were classified based on the relative rankings of population density in the 18 districts of Hong Kong.
[c] The 3 strata of household income were classified based on the relative rankings of median monthly household income in the 18 districts of Hong Kong.

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ORIGINAL RESEARCH

Association Between Food Insecurity and Diet Quality Among Early Care and Education Providers in the Pennsylvania Head Start Program

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PEER REVIEWED

Summary

What is already known about this topic?

High rates of food insecurity were reported among early care and education (ECE) providers. Little research has examined the association between food insecurity and diet quality behaviors among ECE providers.

What is added by this report?

Our study confirmed the high prevalence of food insecurity among ECE providers. Food insecure ECE providers were less likely to use nutrition labels and more likely to report cost as a perceived barrier to eating fruits and vegetables.

What are the implications for public health practice?

Our results can help inform intervention strategies to mitigate food insecurity and improve diet quality among ECE providers.

Abstract

Introduction

Food insecurity affects dietary behaviors and diet quality in adults. This relationship is not widely studied among early care and education (ECE) providers, a unique population with important influences on children's dietary habits. Our study's objective was to explore how food insecurity affected diet quality and dietary behaviors among ECE providers.

Methods

We used baseline data from a cluster-randomized controlled trial (January 2019−December 2020) on 216 ECE providers under the Pennsylvania Head Start Association. We used radar plots to graph scores for the Healthy Eating Index 2015 and the Alternative Healthy Eating Index (AHEI) 2010 and fitted a multivariate regression model for diet quality measures, adjusting for covariates.

Results

Among the 216 participants, 31.5% were food insecure. ECE providers who were food insecure had a lower AHEI-2010 mean score (mean difference for food insecure vs food secure = −4.8; 95% CI, −7.8 to −1.7; $P = .002$). After adjusting for covariates, associations remained significant (mean difference = −3.9; 95% CI, −7.5 to −0.4; $P = .03$). Food insecure ECE providers were less likely to use nutrition labels (22.8% vs 39.1%; $P = .046$) and more likely to report cost as a perceived barrier to eating fruits and vegetables.

Conclusion

We found a significant inverse association between food insecurity and the AHEI-2010 diet quality score among ECE providers after adjusting for covariates. More studies are needed to examine the effects of food insecurity on dietary behaviors of ECE providers and their response to nutrition education programs targeting their health.

Introduction

More than 2 million early care and education (ECE) providers, mostly women, provide care to over 10 million preschool-age children in the US (1). As adults who take care of children for a substantial part of the day, they model and cultivate healthy eating behaviors essential to children's long-term health and behavior outcomes (2,3). Therefore, the health and well-being of ECE providers are essential to a child's early learning and development

success (2). However, ECE providers are susceptible to poor diet quality, sedentary lifestyle, stress, and economic worry (4) because they are more likely to live in poverty than, for example, K-12 teachers (5), earn low wages (national median wage = $24,230) (6), are often uninsured, and lack support and flexibility in their work environment (1).

Recent studies confirmed high rates of food insecurity among ECE providers (2,7). Food insecurity is defined as household-level economic hardship that limits a person's ability to access an adequate amount of food (8). Although 10.5% of US households are food insecure (9), the prevalence is triple that among ECE providers, with estimates ranging from 34.5% to 42% (2,7). Moreover, studies showed that ECE providers, like other food insecure populations, have low nutrition knowledge (10,11), low fruit and vegetable consumption, and high intake of unhealthy foods (11,12), all of which increase their risk of chronic conditions, such as diabetes, hypertension, and hyperlipidemia (13,14). Food insecurity is linked to low diet quality in the general US population (15); however, little research has examined the association between ECE providers' food insecurity and their diet quality and dietary behaviors.

Methods

We used baseline data from the Create Healthy Futures study (16) to conduct a cross-sectional analysis to estimate the prevalence of food insecurity and examine the association between food insecurity and diet quality among ECE providers employed at Head Start programs in Pennsylvania. The Create Healthy Futures study is a cluster-randomized controlled trial evaluating a web-based intervention developed by Penn State Extension Better Kid Care (https://extension.psu.edu/programs/betterkidcare). Our sampling frame consisted of Center-based ECE programs in Pennsylvania, operating under the Pennsylvania Head Start Association, that offered year-round education to children aged 0 to 5 years. We estimated that 182 providers were needed from a minimum of 16 Head Start sites to detect significant differences of at least 0.5 standard deviation units in dietary outcomes, with 80% power. Eligibility criteria for ECE providers were 1) being employed at a participating ECE site at the time of recruitment, 2) the ability to read and speak English, 3) having a working email address, and 4) providing care for children aged 0 to 5 years in a classroom setting. We recruited a total of 12 ECE programs that comprised 39 sites to participate in our study. We invited 428 ECE providers working at these sites via email to participate in the study. Of these, a convenience sample of 256 providers agreed to participate (60% recruitment rate); 216 ECE providers completed the baseline survey for the Create Healthy Futures clinical trial from October 2019 through January 2020. We obtained informed consent electronically by email prior to accessing the surveys. The University of Texas Health Committee for Protection of Human Subjects institutional review board approved the study protocol and data collection.

We administered all surveys through Research Electronic Data Capture (RedCap) and Qualtrics (Qualtrics XM), both of which are HIPAA compliant web-based software. The baseline survey took approximately 30 to 45 minutes to complete. ECE providers who completed the baseline survey received a $25 gift card for a retail store.

Measures

Food insecurity was self-reported by using a previously validated 2-item questionnaire, the Hunger Vital Sign (17), with response options of "never true," "sometimes true," or "often true" to the following statements: "Within the past 2 months I worried whether our food would run out before we got money to buy more" and "Within the past 2 months the food I bought just didn't last and I didn't have the money to get more" (17).

Sociodemographic measures collected were self-reported sex, race/ethnicity, age, educational level, work history, and income. By using self-reported height and weight, we computed participants' body mass index (BMI) (weight in kg/height in m^2) (18).

We assessed perceived concern about life necessities with the following questions (19): "In the past month, how much concern about life necessities like having a place to live, having enough to eat, or feeling like you are safe bothered you?" with 7-point response options ranging from 1, "never," to 7, "always" (19). We assessed capacity to deal with problems with the following question: "How sure are you that you can deal with problems that come up in your life?" The 7-point Likert scale response options ranged from 1, "very unsure" to 7, "very sure" (19). These 2 questions were summed after collapsing each item's responses into 3 categories and reverse coding the question measuring capacity to deal with life problems. The resultant measure, "coping ability with life problems," was used as a proxy for participants' socioeconomic status (range, 0-4), with a higher score indicating a lesser ability to cope with life problems (19). We used 1 question to measure perceived stress: "In the last month, how often have you felt nervous and stressed?" A 5-point scale of response options ranged from 1, "never," to 5, "very often" (19).

Diet quality measures

The primary dependent variables were 2 measures of diet quality, the Healthy Eating Index (HEI) 2015 (20), and the Alternative Healthy Eating Index (AHEI) 2010 (21), as assessed from the 2014 Block Food Frequency Questionnaire (22), a self-reported

tool measuring food frequency intake from a list of 127 food and beverage items. Scoring methods for HEI-2015 and AHEI-2010 were previously validated (21,23,24). HEI-2015 consists of 13 components, each representing a major food group. Collectively, the components yield a maximum score of 100, and a higher score indicates a better alignment with the Dietary Guidelines for Americans (23). Nine components represent adequacy (foods needed for overall good health): total fruit, whole fruit, total vegetables, greens and beans, whole grains, dairy, total protein foods, seafood and plant proteins, and fatty acids. Four components represent moderation (foods that should be limited in a diet): refined grains, sodium, added sugars, and saturated fats (20). AHEI-2010 was developed by using evidence-based recommendations to incorporate additional components focusing on food group nutrients that predict risk for chronic diseases (21,25). AHEI-2010 consists of 11 components that produce a maximum score of 110. Although there are no distinct adequacy and moderation subgroups, 6 components are considered adequacy components: total vegetables, total fruit, whole grain, nuts and legumes, fish fatty acids, and polyunsaturated fatty acids. One component; alcohol, can be considered a moderation component, and 4 components are not favorable: sugary beverages (any beverage with sugar, natural or added), fruit juices, red and processed meat, and trans fat (26).

Dietary habits

We used various previously validated items to measure dietary habits (22). We used a 2-item questionnaire to measure the frequency of fruit and vegetable consumption (22) (eg, "How many fruits eaten per day or week") with response options on a 9-point scale ranging from 1, "rarely," to 9, "4 or more per day." We used a 2-item questionnaire to measure frequency of meals and snacks consumption (22) (ie, "How many meals per day?") with response options ranging from 1 to 5 times per day. We measured perceived barriers to eating fruits and vegetables by using 4 items from the Family Life, Activity, Sun, Health, and Eating Study (27). For example, "I don't eat fruits and vegetables as much as I like to because they cost too much." The research team members added a fifth item, "I don't know how to cook vegetables," to this study. Responses were scored on a 5-point Likert scale, from 0 ("strongly disagree") to 4 ("strongly agree"). We computed a summative scale for the perceived barrier to eating fruits and vegetables ranging from 0 to 20 (Cronbach's $\alpha = 0.73$).

We used 5 items to measure nutrition knowledge (16) (eg, "About how much of your plate should be fruits and vegetables?") with response options of "one-quarter," "one half," "three-quarters," or "all of it"). Each question consisted of 4 answer choices, with only 1 correct response recoded as 1 for correct and 0 for incorrect answers. The final knowledge index score ranged from 0 to 5. We used a single item to assess the use of nutrition labels to evaluate a provider's ability to navigate the food environment (16): "How often do you use the nutrition facts label on foods and beverages to make your grocery purchasing decisions," with answer choices of "never," "rarely," "sometimes," "often," and "always."

Statistical analysis

We used the Student *t* test for continuous variables, and the Pearson χ^2 or Fisher exact test for categorical variables to examine distributional differences in the dependent variables and covariates across food insecure and food secure groups by using a 2-tailed *P* value of $< .05$ as a threshold for significance. We compared diet quality among food secure and food insecure ECE providers for HEI-2015 and AHEI-2010 component scores.

Of the 216 ECE providers, 16 (7.4%) refused to provide income information, and 1 (0.5%) had missing information for meal patterns. We used a multivariable linear regression analysis as our main method to assess the association between diet quality and food insecurity status and to assess the association between food insecurity and dietary behaviors and diet-related psychosocial factors, including nutrition knowledge and perceived barriers to consumption of fruits and vegetables. Our final adjusted model included the following covariates: age, BMI, income, employment status (full-time vs part-time), coping ability with life problems, and work duration at the facility. All models relied on listwise deletion to handle missing data. Finally, we used a multivariable logistic regression analysis to assess the predicted probability of using nutrition labels to make grocery purchasing decisions by food insecurity status and Poisson regression to assess predicted counts for the frequency of fruit and vegetable consumption and the number of meals and snacks consumed per day. Significance was established at $P < .05$.

Because data were collected as part of a cluster-randomized clinical trial, we calculated the intraclass correlation coefficient (ICC) for ECE programs (ICC = 0.0075) and sites (ICC = 0). These small values suggested that observations were independent and that multilevel models were not required. We formally tested linearity assumptions of the 2 primary dependent variables, HEI-2015 and AHEI-2010. We also tested the homogeneity of variance. We conducted all analyses using STATA 15.0 statistical software (StataCorp LLC).

Results

A total of 216 ECE providers completed the baseline survey (50.5% response rate). The prevalence of food insecurity was 31.5% among our sample of ECE providers in fall 2019 (Table 1). Participating ECE providers were predominantly women (97.7%),

White (78.2%), and had a mean age of 41.1 (standard deviation [SD], 11.9 y). About 44% had some college education or less, 33% had a household income from all sources of less than or equal to $25,000, and about 28% had concerns about life necessities.

Several socioeconomic measures differed significantly by food security status among ECE providers. Food insecure providers were younger (mean age, 37.8 y for food insecure vs mean 42.5 y for food secure, $P = .01$), had higher self-reported BMI (mean = 32.4 kg/m^2 for food insecure vs 29.0 kg/m2 for food secure, $P = .046$), were less likely to have worked for more than 10 years at the ECE facility (14.7% for food insecure vs 28.4% for food secure, $P = .04$), and less likely to earn higher wages, defined as an annual income of $35,000 to $50,000 (6.1% for food insecure vs 20.7% for food secure, $P = .004$) (Table 1). A higher proportion of food insecure ECE providers reported having occasional or constant concerns about life necessities, such as having a place to live, feeling safe, and having enough to eat, compared with their food secure counterparts (64.7% vs 11.5%, $P < .001$).

We constructed radar plots to visualize the unadjusted differences in intakes of foods from multiple component food groups across food insecure and food secure ECE providers for diet quality measures of both HEI-2015 and AHEI-2010 (Figure). Overall, the median HEI-2015 score for ECE providers was less than for fatty acid ratio, sodium, and saturated fatty acids (Figure A). When stratified by food security status, compared with food secure ECE providers, food insecure ECE providers reported a median score of approximately 30% lower for seafood and plant proteins ($P = .02$), a 15% lower median score for whole fruits ($P = .38$), a 14% lower median score for total vegetables ($P = .09$), 13% lower scores for added sugars ($P = .11$), a 5% higher score for sodium ($P = .35$), and 14% higher scores for dairy ($P = .29$). The AHEI-2010 showed 50% or lower scores for total vegetables, total fruits, whole grain, fish fatty acids, sodium, and sugary beverages among all ECE providers (Figure B). The median score for fish fatty acid and sugary beverages was lower among food insecure ECE providers than among those who were food secure; (9%, $P = .04$) and (11%, $P = .06$), respectively. Overall, the AHEI-2010 scores were lower among those who are food insecure than among food secure ECE providers (mean, 49.1 [SD, 9.6] vs mean, 53.9 [SD, 1.0]; $P = .002$).

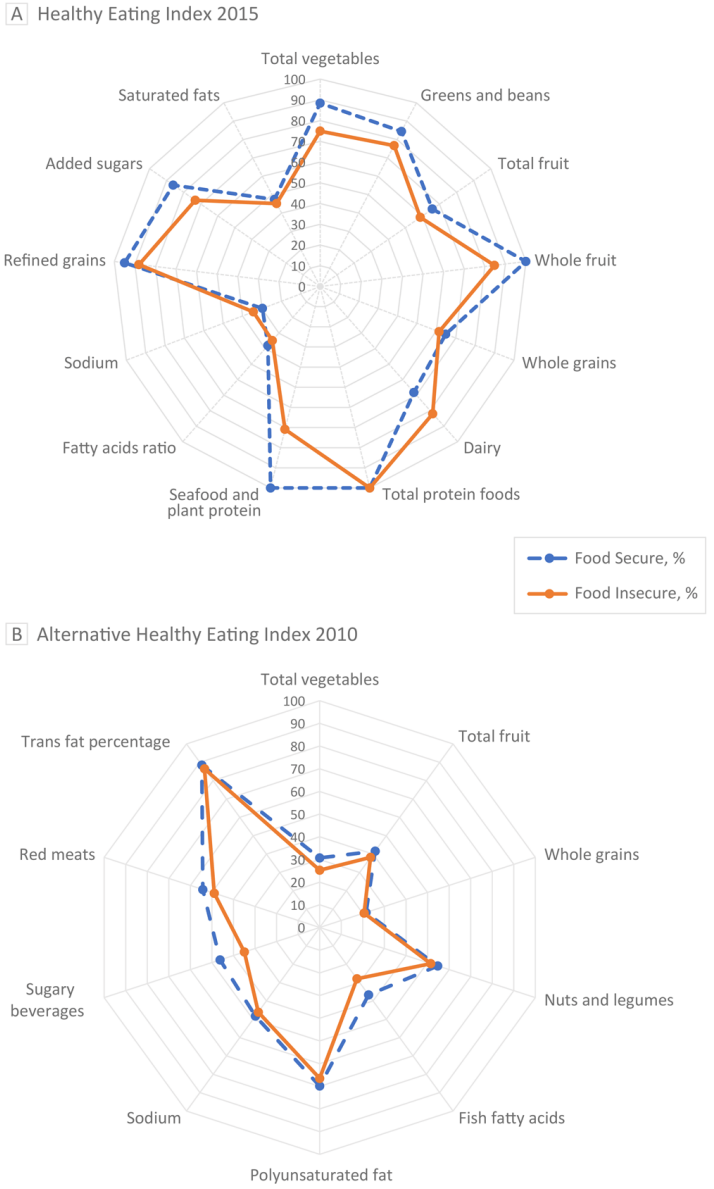

Figure. Radar plots of Healthy Eating Index (HEI) 2015 and Alternative Healthy Eating Index (AHEI) 2010 food components for both food secure and food insecure early childhood education providers. The radial axes represent median scores for food components graphed as percentages of each component's total maximum score. The radar plots' outer edges represent a maximum score of 100%, while the centers represent a minimum score of 0%. Plot A illustrates trends from HEI-2015. Total fruit represents all forms of fruit, including fruit juice; whole fruit represents all forms of fruit except fruit juice. Plot B illustrates trends from AHEI-2010. The median score for food secure was 53.1. For food insecure, the median score was 49.4. A higher score indicates a higher diet quality. Sugary beverages are any beverage with natural or added sugar.

For AHEI-2010 diet quality measures, regression analysis results examining the association between food insecurity and diet qual-

ity measures showed a significant inverse association with food insecurity (Table 2). The unadjusted model showed that ECEs who were food insecure had significantly lower AHEI-2010 scores than those who were food secure (mean difference, −4.8; 95% CI, −7.8 to −1.7; $P = .002$). These associations remained significant after controlling for covariates (mean difference, −3.9; 95% CI, −7.5 to −0.4; $P = .03$). We also saw an inverse association between food insecurity and HEI-2015, but it was not significant.

Food insecure ECE providers reported consuming fewer meals per day than their food secure counterparts (adjusted predicted counts, 2.6 vs 2.9 meals per day; $P = .03$) (Table 3). Furthermore, the frequency of use of nutrition labels to make grocery purchasing decisions was significantly lower among those who were food insecure than among their food secure counterparts (22.8% vs 39.1%; $P = .046$). We also assessed the relationship between food insecurity and perceived barriers to eating fruits and vegetables. We found that food insecure providers were more likely to report cost of food as being a perceived barrier to eating fruits and vegetables than their food secure counterparts (37.2% vs 23.3%; $P = .03$) after adjusting for age, BMI, income, employment status, coping ability with life problems, and work duration at the Head Start facility.

Discussion

Our study demonstrated that food insecure ECE providers had lower diet quality and were consuming significantly fewer meals per day than their food secure counterparts. The prevalence of food insecurity in our sample, 31.5%, was high and higher than the national average, although it was consistent with the prevalence of food insecurity among low-income households (9). These rates of food insecurity are comparable with a recent study examining 307 ECE providers, which found that 34.5% were food insecure (7). The low national median wages for ECE providers of $24,230 (6) coupled with the high prevalence of food insecurity and poor diet quality seen in our population warrants immediate attention to the ECE environment and increased support to ECE providers in order to address their basic needs.

Overall HEI-2015 diet quality scores for ECE providers in our study were comparable to the national average of 58.4; however, the overall AHEI-2010 scores in our study population were higher than the national average of 41.8 (28), possibly because of differences in sex, socioeconomic status, and age distribution. In our study, food insecure ECE providers had HEI-2015 scores comparable to food secure providers; however, for AHEI-2010, the scores were significantly lower among those who were food insecure. These results align with those from a study that used National Health and Nutrition Examination Survey data that reported significantly lower overall scores in AHEI-2010 and a previous version of HEI-2015 dietary measures among food insecure adults compared with food secure adults in the US (15). Furthermore, food insecure ECE providers reported lower scores for fish fatty acids and sugary beverages per AHEI-2010. AHEI-2010 is designed to capture additional nutrition information on diet quality affecting preventable chronic diseases (24). Literature shows an association between low AHEI-2010 scores and increased risk for type 2 diabetes (25) and increased mortality rates for cardiovascular disease and cancer (29). These findings, along with those from our study, suggest that food insecurity among ECE providers could potentially predispose them to higher risks of chronic diseases in later life because of low diet quality (21,24,30); these relationships could be explored in future research. Our results can help inform intervention strategies to mitigate food insecurity and improve diet quality among ECE providers (15).

Our study also showed that food insecure ECE providers were less likely to read food labels often or always than food secure providers. This finding could be due to purchases being driven primarily by cost rather than the nutrition content of the foods. These results are consistent with those of previous studies of low-income households that report lower use of nutrition labels to navigate the food environment (31). Furthermore, our results showed that food insecure ECE providers were more likely to perceive barriers to eating fruits and vegetables than food secure providers, specifically barriers related to cost. Nutrition knowledge did not differ between the 2 groups. Programs targeting ECE providers' healthy eating need to address environmental factors to reduce perceived barriers to eating fruits and vegetables (eg, enrollment of those eligible in the Supplemental Nutrition Assistance Program and the Special Supplemental Nutrition Program for Women, Infants, and Children) and provide skill-based nutrition education to improve food preparation, food budgeting, and use of nutrition labels to guide grocery shopping.

Head Start programs outline several domains that emphasize child health outcomes, including healthy nutrition. ECE providers, such as those in our study, are in a unique position to implement nutrition education and act as role models for healthy eating for children in their care (3); they can play critical roles in the success of interventions targeting childhood obesity (11). Our study's results underscore the need to provide support to the Head Start ECE providers community to improve their own dietary behaviors so that they can effectively implement health education programs for children in their care. Furthermore, given the recent COVID-19 pandemic and its related financial crisis, which have increased food insecurity nationwide, our results demonstrate a call for further research to assess the pandemic's impact on ECE providers who are among frontline workers (32).

Our study's strengths include the provisional insight it provides in assessing ECE providers' nutrition needs. We calculated food insecurity by using validated measures and a coding scheme with high specificity (17). We used reliable measures to estimate dietary intake (22) and assessed a variety of dietary behavior indicators. Our study also had limitations. It may not adequately represent ECE providers across the US because the study sample was conducted in Pennsylvania only, limiting the study's generalizability. Moreover, a selection bias may have been introduced because we used a convenience sample, and participation was voluntary; no information was available on the 40% of ECE providers who chose not to respond to the survey. We did not collect information about whether ECE providers were their household's primary shopper and thus could not apply such information to our analysis. Potential issues also existed with the measures. Self-reported dietary intake measures are subject to social desirability bias; however, we used the validated Block Food Frequency Questionnaire. Coping ability with life problems, knowledge index, and navigating the food environment measures were not previously validated, although they demonstrated face validity. Finally, although the difference in AHEI-2010 mean scores across food secure and food insecure populations were significant, those differences were small and likely not meaningful in relation to risk for chronic disease. Nevertheless, the persistence of significance after adjustment suggests that this finding is robust.

Our study confirms a high prevalence of food insecurity among ECE providers and demonstrates that food insecurity is associated with lower diet quality, less frequent use of nutrition labels, and higher perceived barriers to consuming fruits and vegetables related to cost among food insecure providers than their food secure counterparts. These results warrant further investigation to inform the development of strategies mitigating food insecurity and promoting healthy eating behaviors in this ECE provider population.

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Tables

Table 1. Sociodemographic Characteristics, by Food Security Status, Early Care and Education Providers (N = 216), Pennsylvania Head Start Association, January 2019–December 2020[a]

Characteristic	Total, N = 216	Food Secure, n = 148 (68.5%)	Food Insecure, n = 68 (31.5%)	*P* Value[b]
Age, mean (SD)	41.1 (11.9)	42.5 (12.5)	37.8 (9.7)	.01
Sex				
Male	5 (2.3)	5 (3.4)	0	.33
Female	211 (97.7)	143 (96.6)	68 (100)	
Race/ethnicity				
White	169 (78.2)	120 (81.1)	49 (72.1)	.14
Non-White	46 (21.8)	28 (18.9)	19 (27.9)	
Body mass index (weight in kg/height in m^2) , mean (SD)	30.1 (8.0)	29.0 (6.6)	32.4 (10.1)	.046
Education				
Some college education or less	95 (44.0)	60 (40.5)	35 (51.5)	.13
College degree	121 (56.0)	88 (59.5)	33 (48.5)	
Current position				
Teacher	115 (53.2)	82 (55.4)	33 (48.5)	.52
Assistant teacher	74 (34.3)	47 (31.8)	27 (39.7)	
Other	27 (12.5)	19 (12.8)	8 (11.8)	
Program type[c]				
Center-based Head Start	173 (80.1)	118 (79.7)	55 (80.9)	.84
Home-based Head Start	11 (5.1)	7 (4.7)	4 (5.9)	.74[d]
Preschool or public school Pre-K	37 (17.1)	24 (16.2)	13 (19.1)	.60
Duration of work at the ECE facility, y				
1–5	128 (59.2)	86 (58.1)	42 (61.8)	.04
6–10	36 (16.7)	20 (13.5)	16 (23.5)	
>10	52 (24.1)	42 (28.4)	10 (14.7)	
Annual income from all sources[e]				
≤25,000	66 (33.0)	37 (27.4)	29 (44.6)	.004
25,000–35,000	56 (28.0)	34 (25.2)	22 (33.9)	
35,000–50,000	32 (16.0)	28 (20.7)	4 (6.1)	
>50,000	46 (23.0)	36 (26.7)	10 (15.4)	
Has concerns about life necessities				
Never or rarely	155 (71.8)	131 (88.5)	24 (35.3)	<.001
Occasionally	35 (16.2)	12 (8.1)	23 (33.8)	
Frequently or always	26 (12.0)	5 (3.4)	21 (30.9)	

Abbreviation: ECE, early childhood education.
[a] Values are number (percentage) unless otherwise indicated.
[b] *P* value calculated by using χ^2 for categorical variables unless specified otherwise. Significant at $P < .05$.
[c] Category totals do not equal total sample size because of multiple value selections.
[d] Fisher Exact Test used to calculate *P* value.
[e] Data missing for 16 people who refused to answer.

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Table 1. Sociodemographic Characteristics, by Food Security Status, Early Care and Education Providers (N = 216), Pennsylvania Head Start Association, January 2019–December 2020[a]

Characteristic	Total, N = 216	Food Secure, n = 148 (68.5%)	Food Insecure, n = 68 (31.5%)	*P* Value[b]
Ability to deal with problems that come up in their life				
Very unsure/a little unsure	28 (13.0)	17 (11.5)	11 (16.2)	.57
Neutral	23 (10.6)	17 (11.5)	6 (8.8)	
A little sure/very sure	165 (76.4)	114 (77.0)	51 (75.0)	
In the last month, how often have you felt nervous and stressed				
Never or almost never	16 (7.4)	12 (8.1)	4 (5.9)	.79
Sometimes or fairly often	144 (66.7)	99 (66.9)	45 (66.2)	
Very often	56 (25.9)	37 (25.0)	19 (27.9)	

Abbreviation: ECE, early childhood education.
[a] Values are number (percentage) unless otherwise indicated.
[b] *P* value calculated by using χ^2 for categorical variables unless specified otherwise. Significant at $P < .05$.
[c] Category totals do not equal total sample size because of multiple value selections.
[d] Fisher Exact Test used to calculate *P* value.
[e] Data missing for 16 people who refused to answer.

Table 2. Mean Difference in Diet Quality Scores, by Food Security Status, Using Unadjusted and Adjusted Models, Early Care and Education Providers (N = 216), Pennsylvania Head Start Association, January 2019–December 2020

	Unadjusted Model				Adjusted Model[a]			
	Food Secure	Food Insecure	Difference Across Groups		Food Secure	Food Insecure	Difference Across Groups	
Model	Mean (SE)	Mean (SE)	Mean Difference[b] (95% CI)	*P* Value[c]	Mean[d] (SE)	Mean[d] (SE)	Mean Difference[b] (95% CI)	*P* Value[c]
Healthy Eating Index 2015	62.2 (0.8)	60.2 (1.1)	−2.0 (−4.7 to 0.7)	.152	62.2 (0.8)	60.4 (1.3)	−1.8 (−4.9 to 1.4)	.27
Alternative Healthy Eating Index 2010	53.9 (0.9)	49.1 (1.3)	−4.8 (−7.8 to −1.7)	.002	53.6 (0.9)	49.7 (1.4)	−3.9 (−7.5 to −0.4)	.03

Abbreviations: SE, Standard Error.
[a] Adjusted models controlled for age, body mass index (weight in kg/height in m^2), income, employment status, duration of work at facility, and ability to cope with life problems.
[b] Mean difference represents the difference in means between food secure and food insecure ECE providers.
[c] Significant at $P < .05$.
[d] The predicted adjusted mean represents the average mean for Alternative Healthy Eating Index 2015 or Alternative Healthy Eating Index 2010 for each group (food secure vs food insecure) obtained from the adjusted models after controlling for age, body mass index (weight in kg/height in m^2), income, employment status, duration of work at facility, and ability to cope with life problems.

Table 3. Differences in Dietary Behaviors and Perceptions Across Food-Secure and Food-Insecure Early Care and Education Providers (N = 216), Pennsylvania Head Start Association, January 2019–December 2020[a]

Modifiable Risk Factors	Unadjusted			Adjusted[b]		
	Food Secure, Mean (SE)	Food Insecure, Mean (SE)	*P* Value[c]	Food Secure, Mean (SE)	Food Insecure, Mean (SE)	*P* Value[c]
Meal patterns[d,e]						
Vegetables eaten per day, no. of servings	1.2 (0.1)	1.0 (0.1)	.12	1.2 (0.1)	1.1 (0.1)	.61
Fruits eaten per day, no, of servings	1.0 (0.1)	0.9 (0.1)	.33	1.0 (0.1)	0.9 (0.1)	.46
Number of meals per day	2.9 (0.1)	2.7 (0.1)	.02	2.9 (0.1)	2.6 (0.1)	.03
Number of snacks per day	1.9 (0.1)	2.1 (0.1)	.12	1.9 (0.1)	2.0 (0.1)	.78
Perceived barriers to eating fruits and vegetables[f]	6.1 (0.3)	7.3 (0.5)	.04	6.2 (0.4)	6.8 (0.6)	.37
Nutrition knowledge index[g]	3.2 (0.1)	3.1 (0.1)	.58	3.2 (0.1)	3.2 (0.1)	.96
Use nutrition labels[h], % (SE)						
Never to sometimes	60.2 (0.0)	78.0 (0.1)	.01	60.9 (0)	77.2 (0.1)	.046
Often to always	39.8 (0.04)	22.0 (0.1)		39.1 (0)	22.8 (0.1)	

Abbreviations: SE, standard error.
[a] Multivariable linear regression analysis reported means unless specified otherwise.
[b] Adjusted means were controlled for age, body mass index (weight in kg/height in m^2), income, employment status, duration of work at facility, and coping abilities with life problems.
[c] Significant at $P < .05$.
[d] Predicted counts, obtained from a Poisson regression analysis.
[e] Data missing for 1 observation.
[f] Scale is a 5-point Likert scale (strongly disagree = 0 and strongly agree = 4.) Scores were converted to a 20-point scale for analysis. A higher score indicated a higher perceived barrier of healthy eating.
[g] The Nutrition Knowledge Index is a 5-item subscale. Each item is scored from 0 (least knowledge) to 1 (greatest knowledge); the sum was used for analysis.
[h] Predicted probabilities, reported as percentages obtained from a logistic multivariable regression analysis.

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ORIGINAL RESEARCH

New SNAP Eligibility in California Associated With Improved Food Security and Health

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Accessible Version: www.cdc.gov/pcd/issues/2021/20_0587.htm

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Summary

What is already known on this topic?

Federally funded food assistance programs such as the Supplemental Nutrition Assistance Program (SNAP) reduce food insecurity and improve health in the general population.

What is added by this report?

Little is known about how new eligibility for SNAP affects food insecurity and health, especially among older adults and adults with disabilities. We demonstrated that expansion of SNAP eligibility to recipients of Supplemental Security Income (SSI) in California was associated with improvements in food security and general health.

What are the implications for public health practice?

Older adults and adults with disabilities are likely to derive substantial benefit from SNAP enrollment. Policies that streamline the receipt and maintenance of benefits may improve the health of older adults and adults with disabilities.

Abstract

Introduction

In California, Supplemental Security Income beneficiaries were ineligible to receive Supplemental Nutrition Assistance Program (SNAP) benefits until a June 2019 policy change. The objective of this study was to determine whether SNAP eligibility was associated with changes in food insecurity and health among older adults and adults with disabilities.

Methods

We administered a survey to SSI recipients (N = 213) before (May–August 2019) and after (September 2019–January 2020) the policy change. We examined changes in food insecurity (primary outcome), health status, stress, medication adherence, and dietary intake from baseline to follow-up. Multivariable analyses adjusted for age, sex/gender, race/ethnicity, and education.

Results

Of 213 participants at baseline, 56.8% were male, 43.7% were Black/African American, 88.7% had an annual income of less than $15,000, and 89.7% were currently housed. Of 157 participants at follow-up, 114 (72.6%) were newly enrolled in SNAP. At follow-up, compared with baseline, participants were less likely to report food insecurity (83.1% vs 67.5%, $P < .001$), required less additional money for food ($73.33 vs $47.72 weekly, $P < .001$), were more likely to report excellent/very good health (26.8% vs 27.6%, $P < .001$), and were less likely to report cost-related medication nonadherence (24.1% vs 17.7%, $P < .001$) or use free food programs (82.6% vs 74.5%, $P < .001$). We found no changes in dietary intake.

Conclusion

SNAP uptake rates were high after the policy change. Policies that support older adults and adults with disabilities to enroll in or maintain SNAP benefits may improve health outcomes.

Introduction

The Supplemental Nutrition Assistance Program (SNAP) is the largest federally funded food assistance program operated by the US Department of Agriculture (1). SNAP improves food access, reduces food insecurity, and decreases poverty among eligible low-income households (2,3).

About 11% of US households were food insecure in 2018, with 4.3% of US households experiencing the most severe form of food insecurity ("very low food security") (4,5). SNAP benefits decreased rates of food insecurity by about 30% in 2018 (4). From 2016 through 2018, as a result of SNAP benefits, more than 3.5 million people, about 1% of Americans, rose above the federal poverty threshold (4,5).

A robust body of literature demonstrates that SNAP also improves health outcomes (6). These studies showed that SNAP enrollment was associated with decreases in risk of chronic disease, risk of cost-related medication nonadherence among adults with diabetes, hospitalizations and nursing home placements among older adults, and visits to the emergency department for pregnancy-related diagnoses, hypertension, hypoglycemia, and childhood asthma (7–14).

However, SNAP's capacity to drive these positive outcomes is limited in some populations. Many food-insecure people in the United States, such as people with incomes above the eligibility threshold and undocumented immigrants, are not eligible for SNAP benefits (7). The minimum SNAP benefit level is generally $16 per month in California, but some exceptions allow even lower benefit amounts. In California, beneficiaries of Supplemental Security Income (SSI) — low-income older adults and adults with disabilities — have not been eligible to receive SNAP benefits. Instead, these populations have been able to use a cash benefit provided by SSI to cover food expenses. However, the value of this cash benefit has not increased over time. Thus, many SSI recipients who were otherwise eligible for SNAP benefits because of low household income were excluded in California.

California Assembly Bill 1811 reversed this eligibility policy, allowing California's SSI recipients to be newly eligible for SNAP (known as CalFresh in California) effective June 1, 2019. Given the positive effect of SNAP in other populations, we sought to determine whether this policy change was associated with changes in food insecurity and health among people receiving SSI in California.

Methods

We conducted a pre/post study among SSI recipients living in the San Francisco Bay Area. We recruited participants from a network of low-income and supportive housing sites, congregate meal sites, and SNAP outreach events. Participants were also recruited by direct outreach via newsletters, flyers, and referrals. Inclusion criteria were 1) being aged 18 years or older, 2) receiving SSI, 3) not receiving SNAP benefits at baseline, 4) being able to complete the survey in English, and 5) having access to a telephone to complete dietary recalls. Participants who met all criteria but were cognitively impaired (defined as dementia, mental illness, or active substance abuse severe enough to render the person incapable of providing informed consent) were excluded from study participation. Of 236 SSI recipients recruited, we excluded 23 because they received SNAP at baseline (n = 15) or declined to participate (n = 8).

After eligibility was confirmed, we invited potential participants to an in-person orientation to review study details. People who provided informed consent then completed a baseline survey that included questions about demographic characteristics, food insecurity, health status, stress, medication adherence, and knowledge of the new policy. All participants were asked to complete three 24-hour dietary recalls, the gold-standard for assessing dietary intake, over the telephone after the baseline survey. Baseline study participation occurred from May 2019 through August 2019.

Follow-up occurred after the policy change and 4 to 6 months after completion of the baseline survey (September 2019–January 2020). The follow-up survey was administered either by study staff members via telephone or self-administered in person at various outreach sites. We attempted 3 follow-up dietary recalls for each participant.

Participants received a $10 gift card for completion of each survey and, depending on the number completed, $10 to $20 for dietary recalls. The study was approved by the University of California San Francisco Institutional Review Board.

Measures

Sociodemographic measures. Participants were asked to self-report age, sex/gender (male, female, or other), race/ethnicity (American Indian/Alaska Native, Asian, Black/African American, Hispanic/Latino, Native Hawaiian/Pacific Islander, White, or other), highest level of education (<high school, high school graduate/GED, some college/vocational degree, or ≥college graduate), veteran status (yes/no), employment status (yes/no), annual household income (≥$15,000 or <$15,000), and housing status (currently housed or unstably housed). We defined "currently housed" as renting, owning, or living in a single room occupancy unit/motel/hotel, low-income housing, or subsidized housing. We included residents of single room occupancy units/motels/hotels in the "currently housed" category because these types of housing are often used as a permanent housing strategy in San Francisco, where the cost of living is high. We considered participants who identified as homeless or were living in a shelter or "staying for free at someone else's house" to be unstably housed.

Outcomes. Our primary outcome was food security. We scored the 6-item version of the US Department of Agriculture's US Household Food Security Survey Module: Six-Item Short Form as a dichotomous variable: food secure (0 or 1 item answered affirmatively) or food insecure (2–6 items answered affirmatively) (15). Among participants who were food insecure at baseline, we defined those who became food secure at follow-up as "newly food secure" and those who remained food insecure at follow-up as "persistently food insecure." To increase the statistical power of

our study, we also scored the food security module as a continuous variable (with values ranging from 2.86 to 8.48 and higher values indicating greater food insecurity) by using the US Department of Agriculture's published weights derived from a Rasch model (15).

Secondary outcomes were stress (measured by the Perceived Stress Scale, which has 10 items scaled 0–40: low, 0–13; moderate, 14–26; high, 27–40) (16), general health status (excellent/very good or good/fair/poor) (17), health-related quality of life reported as number of unhealthy days (4-item CDC Healthy Days Measure, scaled 0–30 unhealthy days of the month) (17), cost-related medication nonadherence (3-item scale for skipping medications to save money, taking less medicine to save money, or delaying filling a prescription to save money: yes, 3, no, 0; not scored, 1 or 2) (18), food trade-offs (4 items assessing trade-offs between food and medical care, utilities, housing, and transportation) (19), use of free community food resources in the past 30 days (including free food program, free groceries, free dining room/soup kitchen, or free home-delivered meals), and average weekly food budget shortfall (1 item) (20). All variables were measured at baseline and at follow-up.

We calculated scores for the Healthy Eating Index–2015 and the alternative Healthy Eating Index–2010 from dietary recalls. The Healthy Eating Index–2015 was calculated as described previously; components were weighted equally across food groups for a maximum score of 100 (21). The alternative Healthy Eating Index–2010, which more strongly predicts chronic disease risk, was also calculated by using a previously described scoring algorithm (22).

In addition, at baseline we asked participants about their familiarity with the upcoming SNAP policy change, familiarity with SNAP, and confidence in enrolling in SNAP (none/somewhat vs moderate/very). At follow-up, we asked participants about their familiarity with the SNAP policy change, their familiarity with SNAP, and their satisfaction with SNAP benefit levels.

Statistical analysis

We examined changes in variables of interest from baseline to follow-up among all participants and conducted sensitivity analyses among only participants who enrolled in SNAP. We stratified results according to whether participants remained persistently food insecure or became food secure and whether food security scores improved from baseline to follow-up among persistently food-insecure participants.

To accommodate nonnormally distributed data, we analyzed data by using nonparametric statistical tests and SPSS version 24 (IBM Corporation). We used means and ranges to describe continuous variables. Baseline and follow-up data were analyzed by using Mann–Whitney *U* tests for continuous variables and Fisher exact tests for categorical variables. Analyses were conducted to detect differences at baseline and follow-up among all participants, at baseline between newly secure and persistently insecure participants, and at follow-up after adjusting for baseline differences. We conducted the last analysis by using a difference-in-differences strategy that compared newly food-secure and persistently food-insecure participants. We adjusted all multivariable analyses for age, sex/gender, race/ethnicity, and education. A P value $\leq .05$ was considered significant.

Results

Of the 213 SSI recipients who completed the baseline survey, 157 (73.7%) completed a follow-up survey; the mean time to follow-up was 4.7 months (range, 3.7–7.5 mo). We found no significant differences in any variables (age, sex/gender, race/ethnicity, education, employment, veteran status, food insecurity, health status, and food trade-offs) between participants who did and did not complete a follow-up survey. Overall, 153 of 213 (71.8%) participants completed at least 1 dietary recall at baseline. Participants who completed at least 1 dietary recall completed an average of 2.8 baseline recalls. Almost all (152 of 157) participants at follow-up completed at least 1 recall at follow-up, with an average of 2.7 follow-up recalls per participant. We found no significant differences in variables between participants who did and did not complete at least 1 dietary recall.

Participants at baseline were 56.8% male, 43.7% Black/African American, 11.3% American Indian/Alaska Native, and 8.0% Hispanic/Latino; 11.3% were living in a household with annual household income of $15,000 or more (Table 1). Most participants were food insecure at baseline (83.1%) and currently housed (89.7%); 10.3% were unstably housed.

The percentage of food-secure participants increased from 16.9% at baseline to 32.5% at follow-up ($P < .001$) (Table 2). The average amount of additional money per participant needed to cover all household food needs for the week decreased from $73.33 at baseline to $47.72 at follow-up ($P < .001$). From baseline to follow-up, the percentage of participants who reported excellent or very good health increased (26.8% vs 27.6%; $P < .001$), and the percentage of participants who reported cost-related medication nonadherence decreased (24.1% vs 17.7%; $P < .001$). A smaller percentage of participants at follow-up also used free community food resources (82.6% vs 74.5%; $P < .001$).

At the time of the follow-up survey, 43 (27.4%) participants had not received benefits (including 8.9% who had unsuccessfully attempted to enroll and 18.5% who had not attempted to enroll in

SNAP), 50 (31.8%) had received SNAP benefits for 0 to 2 months, 59 (37.6%) had received SNAP benefits for more than 3 months, and 5 (3.2%) had received SNAP benefits for an unknown period of time. The mean self-reported SNAP benefit among those successfully enrolled was $73.50 per month (range, $6.00–$345.00). Among the 114 participants who answered a question about satisfaction with SNAP benefit levels, 24 participants (21.1%) reported the amount of SNAP benefit they received each month was "about right" and others reported receiving benefits at a level that was "a little too low" (n = 38; 33.3%) or "way too low" (n = 49; 43.0%); no participants reported benefit levels that were "a little high" or "way too high." Among participants who received SNAP, greater monthly SNAP benefits correlated with a smaller weekly food budget shortfall ($P < .001$) (Figure).

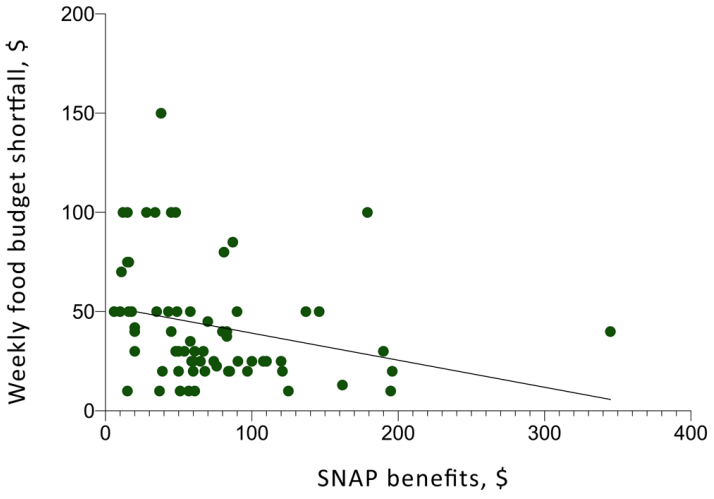

Figure. Correlation between SNAP benefits and weekly budget shortfall at follow-up. All units are US dollars. A line of best fit has a negative slope and an r^2 of 0.066. Abbreviation: SNAP, Supplemental Nutrition Assistance Program.

Of the 128 participants who were food insecure at baseline, 28 (21.9%) participants became newly food secure and 98 (76.6%) participants remained persistently food insecure. We found no significant differences in demographic characteristics or SNAP benefit factors (amount of money received in SNAP benefits or length of time receiving SNAP benefits) between participants who became newly food secure and participants who remained persistently food insecure. However, participants who became newly food secure had reported less severe food insecurity at baseline than participants who were persistently food insecure (6.7 vs 7.2; $P = .003$). At follow up, compared with persistently food-insecure participants, newly food-secure participants reported having less stress ($P = .02$) in the difference-in-differences analysis (Table 3). Newly food-secure participants also reported more familiarity with changes to SNAP policy than persistently food-insecure participants (78.6% vs 52.6%; $P = .02$) but were not more likely to receive SNAP (75.0% vs 72.4%; $P > .99$). Receipt of SNAP did not predict becoming newly food secure at follow-up either in bivariate analysis ($P = .83$) or after adjusting for sex/gender, education, age, and race/ethnicity ($P = .11$).

Among the 98 participants who remained persistently food insecure at follow-up, regardless of SNAP status, food-insecurity scores improved (paired sample mean range, from 7.4 to 7.2; $P < .001$). Receipt of SNAP did not predict improvement in food-security scores at follow-up either in bivariate analysis ($P = .83$) or after adjusting for sex/gender, education, age, and race/ethnicity ($P = .55$).

With the exception of employment, baseline demographic characteristics were not significantly different between participants who received SNAP benefits and participants who did not receive SNAP benefits. Participants who received SNAP benefits were less likely to be employed at baseline than participants who did not receive SNAP benefits (2 participants [1.8%] vs 4 participants [9.3%], $P = .048$). All outcomes were similar between participants who received SNAP benefits and participants who did not receive SNAP benefits (Table 4).

Discussion

Most SSI recipients we sampled successfully enrolled in SNAP in response to the June 2019 policy change that expanded eligibility to SSI recipients. Overall, compared with participants at baseline, participants at follow-up were more food secure and had better general health status, lower weekly food budget shortfall, less use of free food programs, and less cost-related medication nonadherence.

We did not observe a difference in outcomes between participants who received SNAP benefits and participants who did not receive SNAP benefits, which may be due to the small number of participants who did not receive SNAP benefits at follow-up. (High levels of program uptake is likely the result of robust outreach by local SNAP offices and suggests that SNAP is desirable in this population.) However, the changes in outcomes observed from baseline to follow-up may be related at least in part to SNAP enrollment, as most participants received SNAP at follow-up. This conclusion is supported by multiple other observations. First, participants who received higher SNAP benefit levels reported lower weekly food budget shortfalls. Second, a smaller percentage of participants at follow-up used free food program resources, suggesting that improvements observed were not related to use of programs other than SNAP.

The association between SNAP and improved general health and reduced cost-related medication nonadherence is consistent with previous research that examined the effect of interventions designed to improve food security (7–14). Our findings therefore extend the current literature on SNAP and its effect on health outcomes by suggesting that SSI recipients can also derive substantial health benefits from SNAP eligibility.

SNAP tends to affect the severity of poverty more than prevalence of poverty (3); its effects are greatest among those with the deepest poverty levels, but benefit levels in those households may be inadequate to allow a crossing of the poverty threshold. A similar phenomenon may have occurred in our study — many participants at follow-up improved their food insecurity score, but the improvements were insufficient to cross the threshold into food security. This hypothesis is supported by several lines of evidence. First, even among persistently food-insecure participants, continuous scores of food insecurity improved. Second, participants who were newly food secure at follow-up were less food insecure at baseline than those who remained food insecure at follow-up. Finally, the weekly food budget shortfall improved even among those participants who did not become food secure.

New food security was associated with lower levels of stress but not with improvements in other health outcomes, including general health status, number of unhealthy days, reliance on free food programs, or trade-offs between food and other basic necessities. Therefore, although minimal improvement in food insecurity, possibly as a result of SNAP enrollment, has numerous benefits, our findings suggest that additional improvements in health, lifestyle, and dietary intake may require higher benefit levels or additional interventions.

We did not observe improvements in dietary intake associated with the policy change. Low-income older adults and adults with disabilities often have additional barriers to healthy dietary intake in addition to food insecurity, including limitations in transportation, equipment to store and prepare food, and physical capacity to cook. SNAP enrollment may therefore address some, but not all, of the barriers preventing healthy dietary intake (23). Thus, SNAP benefits may be necessary but not sufficient for improving dietary intake in this population.

Our study has several limitations. First, variables other than changes in SNAP policy likely exist to explain the improvements in food security we observed. Although we found no significant difference in the self-reported number of unhealthy days between persistently food-insecure and newly food-secure participants at baseline or in the difference-in-differences analysis, participants who became newly food secure at follow-up may have had advantages, such as more resources or better health, that persistently food-insecure participants did not have and we did not measure.

Second, we recruited participants from a single urban setting, and most participants enrolled in SNAP soon after the policy change. Thus, our findings may not generalize to other populations. Third, biases are associated with the recruitment of participants primarily from housing sites and only those who are proficient in English. Some participants were also recruited from SNAP outreach events, skewing our sample to people more familiar with the SNAP policy change and more likely to participate in SNAP after the policy change went into effect. Fourth, almost half of participants had received SNAP benefits for less than 2 months at the time of their follow-up survey, which may have limited the time available for the intervention to significantly affect health and other outcomes.

Despite these limitations, our study contributes important findings to the SNAP literature. To our knowledge, ours is the first study to explore changes in food security among SSI recipients before and after new eligibility for SNAP. Our survey reached a population of adults at high risk of health decline, hospitalizations, and institutionalization. Additionally, our study provides valuable insight into factors associated with improvements in food security among SSI participants enrolled in SNAP and differential ways in which the opportunity to enroll in SNAP may affect people for whom benefit levels are adequate to achieve food security.

Disability is one of the strongest risk factors for food insecurity, and households with adults with disabilities have more severe food insecurity than households without adults with disabilities (24,25). We found that expansion of SNAP benefits to SSI recipients was associated with improved food security. Thus, interventions such as expansion of SNAP eligibility may be particularly important for reducing inequities in health outcomes in this population.

Future research should focus on exploring other variables that may improve food security among older adults and adults with disabilities. Additionally, future studies may benefit from longer duration between enrollment and follow-up to better examine the long-term potential benefits, including the health benefits, of SNAP expansion to newly eligible populations. Given that we did not observe changes in dietary intake in our study, future research could also explore the potential of SNAP programs that feature incentives for consuming fruits and vegetables. The change in SNAP eligibility investigated in our study is the kind of natural experiment that offers an important opportunity to examine the effect of SNAP on food security, health behaviors, and health outcomes.

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Tables

Table 1. Baseline Characteristics of Participants (N = 213) in Study of SNAP Eligibility, Food Security, and Health After a SNAP Policy Change, California, 2019–2020[a]

Characteristic	Value
Age, y	
<50	41 (19.2)
50–59	71 (33.3)
60–69	80 (37.6)
70–79	17 (8.0)
Missing data	4 (1.9)
Sex/gender	
Male	121 (56.8)
Female	88 (41.3)
Other	3 (1.4)
Missing data	1 (0.5)
Race/ethnicity[b]	
American Indian/Alaska Native	13 (6.1)
Asian	5 (2.3)
Black/African American	80 (37.6)
Hispanic/Latino	17 (8.0)
Native Hawaiian/Pacific Islander	1 (0.5)
White	73 (34.3)
Don't know/unknown/other	41 (19.3)
Education	
<High school diploma	54 (25.4)
High school graduate/GED	50 (23.5)
Some college/vocational degree	76 (35.7)
≥College graduate	31 (14.6)
Missing data	2 (0.9)
Veteran status	
Veteran	31 (14.6)
Nonveteran	179 (84.0)
Data missing	3 (1.4)

Abbreviation: SNAP, Supplemental Nutrition Assistance Program.
[a] Baseline survey administered to Supplemental Security Income recipients during May–August 2019; policy change in effect beginning June 1, 2019. All values are number (percentage) unless otherwise indicated; percentages may not sum to 100 because of rounding.
[b] Participants can be both Hispanic and one of the races.
[c] "Currently housed" defined as renting, owning, living in a single room occupancy unit/motel/hotel, low-income housing, or subsidized housing. "Unstably housed" defined as homeless, living in a shelter, or living in "someone else's house."
[d] Scored from 0 to 100 with higher numbers indicating more nutritious dietary intake; 153 participants answered question; total of 423 dietary recalls.
[e] Scored from 0 to 40: low, 0–13; moderate, 14–26; high, 27–40.
[f] Trade-offs defined as answering yes to 1 or 2 times per year, some months, or every month (compared with never); 10.4%–16.6% of data for these variables were missing; percentages based on number who answered question.

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Table 1. Baseline Characteristics of Participants (N = 213) in Study of SNAP Eligibility, Food Security, and Health After a SNAP Policy Change, California, 2019–2020[a]

Characteristic	Value
Employment status	
Employed	8 (3.8)
Not employed	203 (95.3)
Missing data	2 (0.9)
Housing status[c]	
Currently housed	191 (89.7)
Unstably housed	22 (10.3)
Annual household income, $	
≥15,000	24 (11.3)
<15,000	187 (87.8)
Missing data	2 (0.9)
General health status	
Excellent/very good	57 (26.8)
Good/fair/poor	156 (73.2)
Healthy Eating Index, mean (median)[d]	
Healthy Eating Index–2015	44.3 (43.8)
Alternative Healthy Eating Index–2010	45.4 (45.9)
No. of unhealthy days in past 30 days, mean (median)	17.1 (20.0)
Stress score, mean (median)[e]	
Mean (median)	19.8 (20.0)
Low	28 (13.1)
Medium	145 (68.1)
High	29 (13.6)
Missing data	11 (5.2)
Food insecurity	
Food secure	36 (16.9)
Food insecure	177 (83.1)
Cost-related medication nonadherence	
Yes	41 (19.2)
No	129 (60.6)
Missing data	43 (20.2)

Abbreviation: SNAP, Supplemental Nutrition Assistance Program.
[a] Baseline survey administered to Supplemental Security Income recipients during May–August 2019; policy change in effect beginning June 1, 2019. All values are number (percentage) unless otherwise indicated; percentages may not sum to 100 because of rounding.
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Table 1. Baseline Characteristics of Participants (N = 213) in Study of SNAP Eligibility, Food Security, and Health After a SNAP Policy Change, California, 2019–2020[a]

Characteristic	Value
Trade-offs[f]	
Mean (median)	1.3 (0)
Made trade-offs between food and medicine/medical care	76 (39.4)
Made trade-offs between food and utilities	65 (35.9)
Made trade-offs between food and housing	65 (34.6)
Made trade-offs between food and transportation	67 (35.8)
Use of community food resources in past 30 days	
Overall	171 (83.0)
Free groceries	110 (64.3)
Free dining room/soup kitchen	92 (53.8)
Home delivered meals	25 (14.6)
Weekly food budget shortfall (n = 171); mean, median, $	73.33 (50.00)

Abbreviation: SNAP, Supplemental Nutrition Assistance Program.
[a] Baseline survey administered to Supplemental Security Income recipients during May–August 2019; policy change in effect beginning June 1, 2019. All values are number (percentage) unless otherwise indicated; percentages may not sum to 100 because of rounding.
[b] Participants can be both Hispanic and one of the races.
[c] "Currently housed" defined as renting, owning, living in a single room occupancy unit/motel/hotel, low-income housing, or subsidized housing. "Unstably housed" defined as homeless, living in a shelter, or living in "someone else's house."
[d] Scored from 0 to 100 with higher numbers indicating more nutritious dietary intake; 153 participants answered question; total of 423 dietary recalls.
[e] Scored from 0 to 40: low, 0–13; moderate, 14–26; high, 27–40.
[f] Trade-offs defined as answering yes to 1 or 2 times per year, some months, or every month (compared with never); 10.4%–16.6% of data for these variables were missing; percentages based on number who answered question.

Table 2. Change in Outcomes Associated With New SNAP Eligibility Among SSI Recipients in Study of SNAP Eligibility, Food Security, and Health After a SNAP Policy Change, California, 2019–2020[a]

Factor	Baseline (n = 213)	Follow-up[b] (n = 157)	*P* Value[c]
Food insecurity, n (%)			
Food secure	36 (16.9)	51 (32.5)	<.001
Food insecure	177 (83.1)	106 (67.5)	
Healthy Food Index–2015, mean score[d]	44.3	43.6	.57
Alternative Healthy Food Index–2010, mean score[d]	45.4	44.8	.20
Stress, mean score[e]	19.8	18.5	.32
Mean no. of unhealthy days in past 30 days	17.1	16.5	.96
General health status excellent/very good, n (%)	57 (26.8)	43 (27.6)	<.001
Mean no. of trade-offs[f]	1.3	1.4	.82
Cost-related medication nonadherence, n (%)[g]	41 (24.1)	23 (17.7)	.001
Weekly food budget shortfall, mean, $	73.33	47.72	<.001
Used community food resources in past 30 days, n (%)	171 (83.0)	117 (75.5)	<.001

Abbreviations: SNAP, Supplemental Nutrition Assistance Program; SSI, Supplemental Security Income.
[a] Baseline survey administered to Supplemental Security Income recipients during May–August 2019; follow-up survey administered September 2019–January 2020. Policy change in effect beginning June 1, 2019.
[b] Among this group, 72.6% (n = 114) had received SNAP at time of follow-up survey.
[c] Fisher exact test used for bivariate variables and Mann–Whitney *U* test used for continuous variables.
[d] Scored from 0 to 100 with higher numbers indicating more nutritious dietary intake.
[e] Scored from 0 to 40: low, 0–13; moderate, 14–26; high, 27–40.
[f] Trade-offs defined as answering yes to 1 or 2 times per year, some months, or every month (compared with never).
[g] Denominator is number of participants who answered question.

Table 3. Baseline and Follow-up Differences Between Participants Who Were Newly Food Secure and Participants Who Were Persistently Food Insecure in Study of SNAP Eligibility, Food Security, and Health After a SNAP Policy Change, California, 2019–2020[a]

Item	Persistently Insecure (n = 100)	Newly Secure (n = 28)	*P* Value[b]
Baseline factor			
Food insecurity, mean[c]	7.2	6.7	.003
Healthy Food Index–2015, mean score[d]	45.6	43.2	.25
Alternative Healthy Food Index–2010, mean score[d]	46.9	44.3	.25
Stress, mean score[e]	20.1	16.7	.08
Mean no. of unhealthy days	16.9	11.9	.06
General health status excellent/very good, n (%)[b]	74 (75.5)	16 (57.1)	.10
Mean no. of trade-offs[f]	1.9	1.5	.08
Cost-related medication nonadherence, n (%)	26 (34.7)	4 (18.2)	.19
Weekly food budget shortfall, mean, $	80.00	54.70	.25
Used community food resources in past 30 days	78 (83.0)	24 (85.7)	>.99
Difference in difference from baseline to follow-up			
Food insecurity, mean[c]	−0.1	−5.3	<.001
Healthy Food Index–2015, mean score[d]	−0.3	−2.6	.49
Alternative Healthy Food Index–2010, mean score[d]	−2.1	−2.5	.54
Stress, mean score[e]	0.7	−9.0	.02
Mean no. of unhealthy days	2.1	−10.3	.52
General health status excellent/very good, n (%)[b]	8 (8.2)	1 (3.6)	.68
Mean no. of trade-offs[f]	−0.3	−1.3	.53
Cost-related medication nonadherence, n (%)	7 (11.5)	1 (4.5)	.68
Weekly food budget shortfall, mean, $	−34.76	−29.67	.87
Used community food resources in past 30 days, n (%)	7 (7.4)	1 (3.6)	.68

Abbreviations: SNAP, Supplemental Nutrition Assistance Program.
[a] Baseline survey administered to Supplemental Security Income recipients during May–August 2019; follow-up survey administered September 2019–January 2020. Policy change in effect beginning June 1, 2019.
[b] Fisher exact test used for bivariate variables and Mann–Whitney *U* test used for continuous variables.
[c] The US Department of Agriculture's US Household Food Security Survey Module: Six-Item Short Form was scored as a continuous variable (minimum value, 2.86; maximum, 8.48) by using the US Department of Agriculture's published weights derived from a Rasch model (15); the higher the score, the greater the food insecurity.
[d] Scored from 0 to 100 with higher numbers indicating more nutritious dietary intake.
[e] Scored from 0 to 40: low, 0–13; moderate, 14–26; high, 27–40.
[f] Trade-offs defined as answering yes to 1 or 2 times per year, some months, or every month (compared with never).

Table 4. Change in Outcomes Associated With Receipt of SNAP Benefits at Follow-Up Among SSI Recipients in Study of SNAP Eligibility, Food Security, and Health After a SNAP Policy Change, California, 2019–2020[a]

Factor	Did Not Receive SNAP Benefits (n = 43)	Received SNAP Benefits[b] (n = 114)	*P* Value[c]
Food insecurity, n (%)			
Food secure	15 (34.9)	36 (31.6)	.71
Food insecure	28 (65.1)	78 (68.4)	
Healthy Food Index–2015, mean score[d]	45.8	45.0	.57
Alternative Healthy Food Index–2010, mean score[d]	44.3	46.7	.20
Stress, mean score[e]	20.5	19.1	.65
Mean no. of unhealthy days	17.4	16.0	.69
General health status excellent/very good, n (%)[d]	10 (23.3)	33 (29.2)[f]	.55
Mean no. of trade-offs[g]	1.7	1.5	.45
Cost-related medication nonadherence, n (%)	6 (17.6)	17 (17.7)[f]	>.99
Weekly food budget shortfall, mean, $	73.68	41.85	.48
Used community food resources in past 30 days, n (%)	29 (70.7)	88 (77.2)	.41

Abbreviations: SNAP, Supplemental Nutrition Assistance Program; SSI, Supplemental Security Income.
[a] Baseline survey administered to Supplemental Security Income recipients during May–August 2019; follow-up survey administered September 2019–January 2020. Policy change in effect beginning June 1, 2019.
[b] Of this group, 72.6% (n = 114) had received SNAP at time of follow-up survey.
[c] Fisher exact test for bivariate variables and Mann–Whitney *U* Test for continuous variables.
[d] Scored from 0 to 100 with higher numbers indicating more nutritious dietary intake.
[e] Scored from 0 to 40: low, 0–13; moderate, 14–26; high, 27–40.
[f] Not all participants answered all questions; percentages based on number who answered question.
[g] Trade-offs defined as answering yes to 1 or 2 times per year, some months, or every month (compared with never).

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ORIGINAL RESEARCH

Interest in Receiving Nutrition Information Through Social Media Among Food-Security Program Participants in Washington, DC

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PEER REVIEWED

Summary

What is already known on this topic?

Previous studies evaluated the feasibility of incorporating social media communications into nutrition assistance programs, limiting the focus to age, sex, and barriers to use.

What is added by this report?

We demonstrated that characteristics such as self-efficacy and belief in the value of digital technology were closely associated with interest in receiving nutrition information through social media.

What are the implications for public health practice?

Our research provides insight into the characteristics of participants who may be responsive to receiving nutrition information through social media.

Abstract

Introduction

Effective communication approaches are necessary to reach food-security program participants. Accessing food-security programs has been especially challenging during the COVID-19 pandemic. Social media can play an important role in reducing some communication barriers. We examined interest in receiving nutrition information via social media among adults participating in food-security programs in Washington, DC.

Methods

We developed and administered a 22-item survey to adults participating in food-security programs (N = 375). Participants were recruited at Martha's Table, in Washington, DC, from January through March 2020. We performed bivariate analyses and multinomial logistic regressions to examine predictors of interest in receiving nutrition information via social media.

Results

Sixty-nine percent of participants reported using social media, and 49% expressed interest in receiving nutrition information via social media. Higher levels of self-efficacy and belief in the value of digital technology were associated with greater likelihood of interest in receiving nutrition information via social media (χ^2_6 = 139.0; Nagelkerke R^2 = 0.35; P < .001). We found no differences by sex or digital technology access in interest in receiving nutrition information via social media.

Conclusion

Social media is a widely used and a feasible method to reach food-security program participants. Understanding program participants' interest in receiving health information via social media may help food-security programs plan effective communication strategies to improve food security, especially when in-person participation is limited, such as during the COVID-19 pandemic.

Introduction

Food insecurity is a public health problem in the US that has been exacerbated by the COVID-19 pandemic. Food insecurity, defined as "the limited or uncertain availability of nutritionally adequate and safe foods or limited or uncertain ability to acquire acceptable foods in socially acceptable ways" (1), affects more than 11% of US households (2). The number of food-insecure people in the US is estimated to increase because of the pandemic to almost 20%, or 54.3 million Americans (3). In Washington, DC, food insecurity

increased from 10.6% in 2018 to 16.0% of the population in 2020 (4).

Differences in access to affordable and nutritious food across socioeconomic status also contribute to health disparities. Food insecurity has health consequences across the lifespan and is associated with increased risk for the development of chronic conditions such as obesity, diabetes, hypertension, coronary artery disease, and asthma (5–8). Furthermore, the pandemic disproportionately affects populations already at risk for food insecurity. In Washington, DC, Wards 7 and 8 account for 22.5% of the city's population (9), have the highest poverty rates (26.5% and 34.2%, respectively [10]), and are disproportionately affected by food insecurity (11). As of February 2021, residents of Wards 7 and 8 accounted for 35% of the total number of deaths attributable to COVID-19 in Washington, DC (12). During the pandemic, food security assistance programs modified their approaches to serve the community, including finding new locations to provide contactless food distribution (13).

Social media or social networking sites are web pages that allow users to create profiles, share content, and participate in discussions (14) to facilitate communication and community engagement (15). The number of social networking sites users in the US is increasing: 70% of adults use social networking sites today, compared with 5% in 2005 (16). Communication between an organization and its members could be enhanced by using social networking sites. However, access to and use of social networking sites is not necessarily an indication of interest in receiving nutrition information (17).

Studies that explored perceptions of social networking sites among food-security program participants limited their focus to rates of use of social networking sites and barriers to use. A study that examined technology use among participants in the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) found that 92% of participants had cell phones, yet only 23% accessed social networking sites using their cell phones (18). The study also found differences in the use of social networking sites by age, with "Millennials" (people born from 1982 through 1996, according to the Pew Research Center [19]) more likely to report accessing social networking sites than any other age group (18). In another cross-sectional study, of WIC recipients in remote communities of Alaska, more than 85% of participants reported it was useful to receive nutrition information on cell phones or computers, with email and online videos most preferred (20). Barriers to use of social networking sites for accessing nutrition information included technological problems, lack of access to computers or internet services, high cost, and slow internet connections (20). Furthermore, a 2018 systematic review identified the acquisition of new skills and knowledge by participants as a benefit of using social networking sites in health education programs (21). Exploring feasible, accessible, and innovative approaches to reach and engage participants is critical for food-security programs.

Our project was informed by the widely used Health Belief Model, originally derived from behavioral theory and developed to understand perceived barriers and benefits to adopting disease-prevention strategies (22). Proponents of the Health Belief Model argue that a person's self-efficacy and perceptions about disease prevention strategies and illness determine the adoption of healthy behaviors (22). In our study, the Health Belief Model offered a structure to discuss and organize findings into recommendations for practice and future research, particularly for increasing the effect of food security and nutrition programs through social networking sites. The objective of our study was to describe interest in receiving nutrition information via social networking sites among adults participating in food-security programs in Washington, DC.

Methods

We conducted this cross-sectional study from January through March 2020. We obtained institutional review board approval from American University in January 2020.

Recruitment

Researchers partnered with Martha's Table, a nonprofit organization that provides nutrition education and assistance to individuals and families in the Washington, DC, area. In 2018, the organization distributed 1.65 million healthy meals. Martha's Table hosts daily markets from 11 AM to 4 PM; fresh produce and pantry items are free. We recruited study participants from among Martha's Table market participants by using convenience sampling. Daily from January 14 to February 14, we invited market attendees aged 18 or older to complete a brief survey. We provided a consent form to assenting attendees, after which they completed anonymously a 22-item community social media and nutrition survey. Participants indicated whether they preferred to complete the survey by themselves or to have an interviewer read the survey questions aloud. We gave canvas bags and coloring posters to potential participants as an incentive for participation.

Data collection

Four graduate students were trained to recruit participants and administer the survey. To ensure fidelity, we provided an interviewer script to all interviewers. Every person waiting to attend the market was invited to participate in the study. A pilot test (n = 73) was conducted at Martha's Table Market in January 2020 to as-

sess clarity and appropriateness of the survey instrument and strategies to engage market attendees. During the first week of January, 80 shoppers at Martha's Table's daily market were invited to participate in the pilot survey, and 73 (91.3%) completed the survey. Of those, 35 (47.9%) completed the survey on their own; 38 participants (52.1%) preferred to have the interviewer read the questions aloud. We made 2 revisions after the pilot test. We added examples of non–social networking websites to the question "Do you use the internet?" to avoid confusing the terms "internet" and "social media," and we added skip-logic instructions, allowing respondents to skip questions that did not apply to them, based on answers to previous questions.

We invited 424 market attendees to participate; 381 agreed and completed the survey (89.9% response rate). We excluded 6 surveys because the respondents were Martha's Table employees. The final sample size was 375 surveys, of which most (60.3%, n = 226) were completed with the interviewer reading the questions out loud.

Measures

The development of the survey instrument was guided by the Health Belief Model (23) and input from leadership at Martha's Table. The instrument consisted of 3 sections: social media, nutrition, and demographic characteristics (Table 1). We adapted the social media questions from a 2018 Pew Research Center survey (14). The social media section included 13 questions to assess participants' use of social networking sites, frequency of use, access, and perceptions of the value of social networking sites. The questions in the social media section were used to calculate 3 digital technology subscores: technology use, technology access, and technology value. To calculate the technology use and technology access subscores, we used simple addition; each question had options valued at 0 (no) or 1 (yes). The subscore ranged from 0 to 3 for technology use and from 0 to 2 for technology access. For technology value, each of the 2 questions had options valued at 1 (never), 2 (almost never), 3 (sometimes) to 4 (almost always); the subscore ranged from 1 to 4. All participants were asked if and how they accessed nutrition information. We asked users of social networking sites about topics accessed and their interest in nutrition topics via social networking sites. We assessed participants' interest in receiving nutrition information via social networking sites, the dependent variable, with 1 question and 3 response options: yes, no, or maybe). We stratified responses by social networking site users and nonusers.

The 6 questions in the nutrition section were adapted from a previously validated Teacher Health Survey (24). We used the questions to calculate 2 nutrition subscores, for nutrition education belief and nutrition self-efficacy. For nutrition education belief, response options for the 2 questions were 1 (strongly disagree), 2 (disagree), 3 (agree), and 4 (strongly agree); subscores ranged from 1 to 4. For nutrition self-efficacy, response options to the 4 questions were 1 (very little), 2 (little), 3 (some), and 4 (very much); subscores ranged from 1 to 4. The demographic section asked about age, gender, and parental status. We defined "parent" as a parent or guardian of a child younger than 18 years.

Data analysis

We performed all statistical analyses using SPSS version 26 (IBM Corp) and set significance at $P < .05$ for all tests. We used descriptive statistics to examine individual items. We examined differences between the mean subscores for the social media and nutrition sections (technology use, technology access, technology value, nutrition education belief, nutrition self-efficacy) by gender and parental status using independent samples *t* tests. To determine reliability, we calculated the Kuder–Richardson Formula 20 (KR-20) for dichotomous measures and Cronbach α for nondichotomous measures. Following the approach of Rammstedt and Beierlein (25), we computed reliability for each subscale score, given that each was a separate construct. The technology use score had a KR-20 reliability of α = 0.66, and technology access had a KR-20 reliability score of α = 0.86. Cronbach α was calculated for technology value score (α = 0.82), nutrition education beliefs (α = 0.92), and nutrition self-efficacy score (α = 0.93). We used χ^2 tests to analyze the bivariate association between age groups, gender, and parental status and interest in receiving nutrition information delivered via social networking sites. A 1-way analysis of variance (ANOVA) test was performed to examine differences in the mean scores calculated between participants who answered yes, no, and maybe to the question on interest in receiving nutrition information via social networking sites. If the ANOVA revealed significant differences, we used post hoc Tukey multiple comparison tests to determine mean differences between social media and nutrition subscores. We performed multinomial logistic regression to predict the relationship between interest in receiving nutrition information via social networking sites and several gender, age, and social media and nutrition scores.

Results

Of 375 survey participants who completed the survey, 73.2% were women, and 49.3% were parents. Nearly all participants (98.6%) responded to all survey questions. The average participant age was 53.0 (SD, 16.6). Parents were younger (mean age, 47.2 [SD, 14.4]) than nonparents (mean age, 58.7 [SD, 16.7]) ($t_{373} = 7.14$, $P < .001$). The sample age distribution was consistent with the age distribution of Martha's Table's clients. Almost all participants (96.5%, n = 362) used cell phones, and most used social network-

ing sites (69.1%, n = 259) and the internet (80.5%, n = 302). Approximately 49.0% of the participants reported interest in receiving nutrition information via social networking sites, 30% of participants reported no interest, and 21% answered "maybe" to being interested. A total of 198 participants indicated use of social networking sites to find information about community events, 175 participants indicated use of social networking sites to find health information, and 168 indicated use of social networking sites to find nutrition information.

Women and parents had, on average, higher nutrition self-efficacy scores (3.3 and 3.4 respectively) than men and nonparents (3.1 both groups) (Table 2). Survey participants most often chose healthy recipes (n = 155) and farmers market calendars (n = 111) as topics they wanted to receive information on via social networking sites (Figure 1). The most common way to find nutrition information was through family and friends (n = 248) (Figure 2).

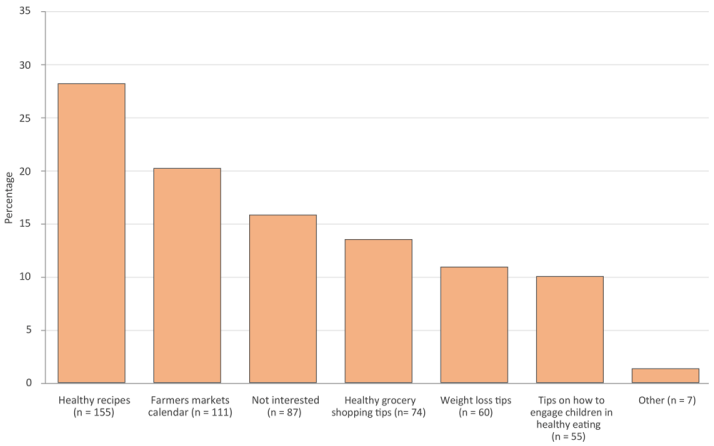

Figure 1. The distribution of survey responses (n = 549) among social media users (n = 259) in study of interest in receiving nutrition information through social media among food-security program participants in Washington, DC, January–March 2020. Survey participants were asked, "Please choose 2 nutrition topics that you would like to receive on your social media page." Results show the number of responses per topic.

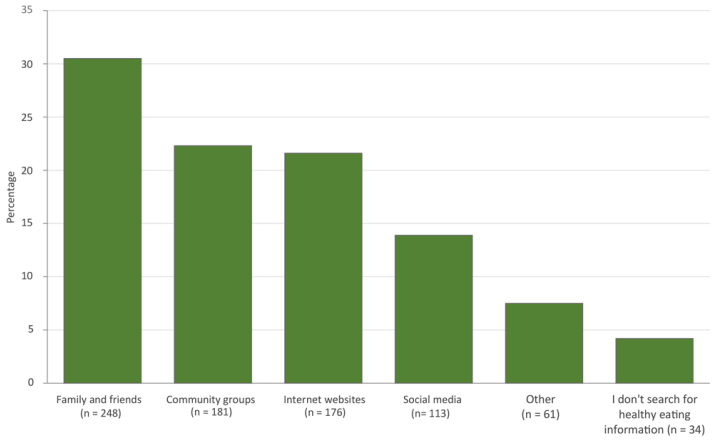

Figure 2. The distribution of survey responses (n = 813) among participants (n = 375) in study of interest in receiving nutrition information through social media among food-security program participants in Washington, DC, January–March 2020. The survey question was, "Do you search for healthy eating information using any of the following?" Participants were asked to check all that applied. Ns are number of responses.

Bivariate analyses

We found differences in interest in receiving nutrition information by age group ($\chi^2_{12} = 32.0$, $P = .001$) and parental status ($\chi^2_{22} = 12.5$, $P = .002$). The greatest interest was expressed by parents (57.8%) and participants in the group aged 35 to 44 (61.8%). The least interest was expressed by participants aged 75 or older (22%).

In the 1-way ANOVA to examine differences in the mean scores among participants who answered yes, no, and maybe to the question on interest in receiving nutrition information via social networking sites, we found significant differences in the technology use score ($F_{2, 372} = 79.18$, $P < .001$), the technology access score ($F_{2, 370} = 50.38$, $P < .001$), and the technology value score ($F_{2, 367} = 44.12$, $P < .001$). For all 3 scores, a Tukey post hoc test revealed that, on average, participants who responded yes and maybe had higher scores than participants who responded no. We also found significant differences in nutrition self-efficacy scores among the 3 groups ($F_{2, 372} = 14.51$, $P < .001$). A Tukey post hoc test revealed that, on average, participants who responded yes had a higher nutrition self-efficacy score (mean, 3.4) compared with participants who responded no (mean, 3.1) or maybe (mean, 3.0).

Multinomial logistic regression

We computed 3 multinomial logistic regression models to predict interest in receiving nutrition information via social networking sites. The best fit model included only nutrition self-efficacy, technology use, and technology value scores ($\chi^2_6 = 139.0$, $P < .001$, Nagelkerke $R^2 = 0.36$) (Table 3). The scores for nutrition self-

efficacy and technology use were significant predictors of interest among participants who answered yes, compared with those who answered no ($P = .004$ for nutrition self-efficacy and $P < .001$ for technology use) and those who answered maybe ($P < .001$ for nutrition self-efficacy and $P = .008$ for technology use). The score for technology value was significantly different in a comparison of participants who responded yes and those who responded maybe ($P < .001$). Participants who used digital technology (vs those who did not), highly valued digital technology (vs those who did not), and had high nutrition self-efficacy (vs those who had low nutrition self-efficacy) were more interested in receiving nutrition information through social networking sites.

Discussion

Our study indicated that social networking sites can provide an efficient and effective way to reach food-security program participants. The importance of access to nutrition information directly relates to healthy food choices and chronic disease prevention (26). Programs to reduce food insecurity and its associated chronic diseases rely on effective communication to support food access. Organizations that provide nutrition assistance in underresourced communities could reach participants with farmers market calendar reminders, 1 of the top 2 nutrition topics on which participants indicated they wanted to receive information via social media.

Our study showed that a high level of nutrition self-efficacy was associated with interest in receiving nutrition information via social networking sites. Participants who were interested in receiving nutrition information via social networking sites, on average, had higher self-efficacy scores than participants who said they were not interested or may be interested. According to Bandura et al (23), self-efficacy is a person's belief that they possess the ability to succeed in a particular situation. Martha's Table offers small group programs aimed at helping participants to make healthier decisions. Increasing the availability of these programs could be an effective way to increase nutrition self-efficacy among food-security program participants at Martha's Table. Previous research determined that age was an important factor in the use of social networking sites (18); however, we found that self-efficacy is a better predictor of interest than age in receiving nutrition information via social networking sites.

Although in our study younger people reported greater use of social networking sites than older participants, the results indicated that use of social networking sites was widely spread among study participants of all ages and is a desired method for receiving nutrition information. A high percentage of participants reported searching for health (43.2%) and nutrition (46.7%) information via social networking sites, and 49% of participants reported interest in receiving nutrition information via social networking sites. In 2014, younger people were the likely users of social networking sites, and the information shared and accessed through social networking sites reflected their interests (17). By 2020, people from a wider range of age groups had become social networking sites users (16); the type of information shared and accessed via social networking sites reflects this increased diversity. Our study found barriers to incorporating social networking sites in food programs, including slow internet speed and the high cost of internet connections, similar to those found by previous researchers (20). It is important that organizations using social networking sites as part of their community outreach efforts are aware of barriers to using these sites.

During the early days of the COVID-19 pandemic, Martha's Table had to modify its in-person food distribution activities. It increased information sharing via social networking sites, often announcing new locations or formats for food distribution shortly before they happened. COVID-19 caused unrest and forced food assistance organizations to quickly change food delivery strategies; social networking sites helped the organization reach some of their program participants in an equally fast way. Our research suggests that by focusing communication efforts on social networking sites, Martha's Table was more likely to reach participants with high self-efficacy levels than participants with lower levels of self-efficacy. As the number of users of social networking sites continues to increase in the US, it is essential to further our understanding of how to effectively reach food-security program participants through social networking sites.

Our study has several limitations. One methodologic limitation was that we used a convenience sample. Response bias and social desirability could have occurred given that Martha's Table programming provides access to nutritious food and our surveys were conducted at their location. The generalizability of our results is limited to food insecure participants in the Martha's Table's food assistance program who regularly attend food distribution days. Bias may have resulted from our study sampling approach; program participants who do not regularly attend food distribution days may have different characteristics from participants who regularly attend (ie, the latter engage in more health-seeking behaviors and are more aware of Martha's Table market offerings). The survey instrument was developed specifically for our study and has not been validated. Furthermore, although the Health Belief Model guided our study, we did not assess the cue-to-action construct, perceived severity construct, or susceptibility construct of the framework. Future studies should examine social factors and other external factors that influence the use of social networking sites and interest in nutrition information. The dependent variable,

interest in receiving healthy eating information through social media, could have been interpreted differently by different participants. However, during the pilot period, interviewers did not note any problems in the phrasing of the question or in participants' understanding of that question. We could not feasibly incorporate cognitive interviewing to identify interpretations of the survey questions among the intended population; such cognitive interviews could be useful in a follow-up study. Our study was cross-sectional; as such, it did not address cause and effect; it provides only a snapshot in time of the population surveyed. It cannot be concluded that interest in receiving information via social networking sites would predict access to and use of the information.

Our findings demonstrate differences between program participants interested in receiving nutrition information through social networking sites beyond age and sex. Characteristics such as self-efficacy and digital technology value are closely associated with interest in receiving nutrition information through social networking sites. In practice, researchers and organizations should consider evaluating several determinants of behavior, such as self-efficacy and digital technology value, when considering the use of social networking sites as a component of their program. Longitudinal studies are needed to determine causation and to examine whether tailoring social media messaging to participants' interests leads to increased access and interaction with information received via social media. In addition, future studies are needed to examine social networking sites as a method for program participants to receive nutrition information for health promotion using behavior change models, including the Health Belief Model. To our knowledge, our study is the first to explore possible predictors of interest in receiving nutrition information via social networking sites. Our findings can inform researchers and organizations interested in using social networking sites as communication or as a program delivery tool by providing insight into the characteristics of participants who would be responsive to using social networking sites. However, social media is constantly evolving and requires continuous monitoring for research and evaluation.

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Tables

Table 1. Instrument Questions, Response Options, and Scores, in a Survey Developed to Assess Interest in Receiving Nutrition Information via Social Networking Sites Among Adults Participating in Food-Security Programs in Washington, DC, January–March 2020

Category	Question	Response Options
Social media		
Technology use	1. Do you have a cell phone? 2. Do you use social media pages (ie, Facebook, Twitter, Instagram)? 3. Do you use the internet (ie, visit different sites such as Google, or news sites)?	Yes/no
Technology access	4. Do you access your social media pages using your cell phone? 5. Do you access the internet using your cell phone?	Yes/no
Technology value	6. Do you believe that social media pages give you access to valuable resources? 7. Do you believe that the internet gives you access to valuable resources?	• Never • Almost never • Sometimes • Almost always
Dependent variable	8. Would you be interested in receiving healthy eating information via social media?	• Yes • No • Maybe
Frequency of social media use	9. If you use social media. How often do you typically use it? (check ONE)	• Almost constantly • Several times a day • About once a day • Several times a week • Less than once a week
Open-ended question	10. If you don't use social media sites. Why? Please explain:	[Write in]
Multiple selection	11. If you use social media. Do you use social media for any of the following?	• Find healthy eating information • Find parenting advice • Find health information • Find information about community events • Do not use social media • Other (please specify)
Multiple selection	12. Do you access healthy eating information using any of the following? (check all that apply)	• Family and friends • Internet websites • Social media • Community Groups • I don't search for healthy eating information • Other (please specify)
Multiple selection	13. The following is a list of nutrition topics. If you use social media. Please choose 2 that you would like to receive on your social media page.	• Healthy recipes • Healthy grocery shopping tips • Weight loss tips • Tips on how to engage children in healthy eating • Farmers markets calendar • Other (please specify) • Not interested
Nutrition		
Nutrition education belief	1. It is important to me to learn about healthy eating. 2. Healthy eating education is an important issue.	• Strongly disagree • Disagree • Agree • Strongly agree
Nutrition self-efficacy	3. How much can you do to help your family and/or friends to engage in healthy eating? 4. How much can you do to help your family and/or friends to value healthy eating? 5. How much can you do to help your family and/or friends to believe they can engage in healthy eating? 6. For parents or guardians: As a parent/guardian, I feel prepared to talk about healthy eating with my child/children.	• Very Little • Little • Some • Very much

(continued on next page)

(continued)

Table 1. Instrument Questions, Response Options, and Scores, in a Survey Developed to Assess Interest in Receiving Nutrition Information via Social Networking Sites Among Adults Participating in Food-Security Programs in Washington, DC, January–March 2020

Category	Question	Response Options
Demographic characteristics		
Gender	1. Gender (please check one)	• Male • Female • Not listed
Parental status	2. Are you a parent or guardian of a child/children 0 to 18 years of age?	• Yes • No
Age	3. What year were you born? (please write)	[Write in]

Table 2. Mean Scores and Demographic Characteristics of Participants in a Survey Developed to Assess Interest in Receiving Nutrition Information via Social Networking Sites Among Adults Participating in Food-Security Programs in Washington, DC, January–March 2020

Category	Score Range	Men		Women		Parent[a]		Nonparent		All	
		n	Mean (SD)	n	Mean (SD)	n	Mean (SD)	n	Mean (SD)	n	Mean (SD)
Technology use	0–3	102	2.4 (0.9)	273	2.4 (0.8)	185	2.6[b] (0.8)	190	2.3[b] (0.9)	375	2.4 (0.8)
Technology access	0–2	102	1.2 (0.9)	271	1.3 (0.9)	184	1.5[b] (0.8)	189	1.1[b] (0.9)	373	1.3 (0.9)
Technology value	1–4	102	3.0 (0.9)	268	3.1 (0.8)	183	3.2[c] (0.8)	197	2.9[c] (0.9)	370	3.1 (0.9)
Nutrition education belief	1–4	102	3.4 (0.8)	273	3.6 (0.7)	185	3.6 (0.7)	190	3.6 (0.7)	375	3.6 (0.7)
Nutrition self-efficacy	1–4	102	3.1[c] (0.8)	273	3.3[c] (0.7)	185	3.4[c] (0.7)	190	3.1[c] (0.8)	375	3.2 (0.7)

[a] Defined as a parent or guardian of a child younger than 18 years.
[b] $P \leq .001$ between men and women or parents and nonparents.
[c] $P < .05$ between men and women or parents and nonparents.

Table 3. Multinomial Logistic Regression of Interest in Receiving Nutrition Information via Social Media Among Adults Participating in Food-Security Programs in Washington, DC, January–March 2020[a]

Independent Variable	B (SE)	Wald χ^2 (*df*) [*P* Value]	Exp (B) (95% CI)
Comparing participants who answered yes to participants who answered no			
Technology value	−0.59 (0.22)	7.1 (1) [.008]	0.56 (0.36–0.86)
Technology use	−1.21 (0.22)	30.0 (1) [<.001]	0.30 (0.19–0.46)
Nutrition self-efficacy	−0.60 (0.21)	8.2 (1) [.004]	0.55 (0.36–0.83)
Comparing participants who answered yes to participants who answered maybe			
Technology value	−0.60 (0.23)	7.0 (1) [.008]	0.55 (0.35–0.86)
Nutrition self-efficacy	0.75 (0.20)	14.6 (1) [.001]	0.47 (0.32–0.69)

[a] Survey participant were asked, "Would you be interested in receiving healthy eating information via social media?" Possible answers were yes, no, and maybe.

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ORIGINAL RESEARCH

Effect of Inadequate Sleep on Frequent Mental Distress

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PEER REVIEWED

Summary

What is already known on this topic?

One-third of US adults report that they sleep less than the recommended amount, and approximately 20% have received a diagnosis of a mental illness. The link between inadequate sleep and mental distress has been viewed historically as a symptom–disease association with sleep inadequacies deriving from preexisting mental distress.

What is added by this report?

We examined the association between inadequate sleep and frequent mental distress in a diverse, population-based sample of adults aged 18 to 65.

What are the implications for public health practice?

By identifying the correlation between inadequate sleep and frequent mental distress we can better understand this relationship as a risk factor instead of a symptom–disease relationship.

Abstract

Introduction

One-third of US adults report sleeping less than the recommended amount, and approximately 20% live with a mental illness. The objective of our study was to examine the association between inadequate sleep and frequent mental distress in a population-based sample of US adults.

Methods

We conducted a cross-sectional study by using 2018 Behavioral Risk Factor Surveillance System (BRFSS) data that included 273,695 US adults aged 18 to 64. Inadequate sleep was defined as 6 hours or less in a given night, and frequent mental distress was defined as self-reporting 14 days of mental health status as "not good" within the last month. We used weighted logistic regression to calculate odds ratios (ORs) and 95% CIs.

Results

Thirteen percent of study participants experienced inadequate sleep, and 14.1% experienced frequent mental distress. Participants who averaged 6 hours or less of sleep per night were about 2.5 times more likely to have frequent mental distress when controlling for confounders (OR, 2.52; 95% CI, 2.32–2.73) than those who slept more than 6 hours.

Conclusion

Inadequate sleep was associated with significantly increased odds of frequent mental distress. Our findings suggest that further research is necessary to evaluate the temporal relationship between inadequate sleep and frequent mental distress.

Introduction

Poor mental health is common in the US. Nearly 1 in 5 US adults live with mental illness (1). Furthermore, an estimated 50% of all Americans will be diagnosed with a mental illness or disorder at some point in their life (1,2). Mental health illness includes many different conditions and symptoms, such as anxiety, depression, stress, and other psychological illnesses. Moderate and severe mental disorders that need psychological treatment require regular visits to a health care provider, thus lowering workplace productivity (3). Furthermore, depression, schizophrenia, and bipolar disorder are risk factors for coronary heart disease, hypertension, diabetes, dyslipidemia, metabolic syndrome, obesity, stroke, and substance abuse disorders (3,4). Depression and anxiety alone cost over $1 trillion annually for medications, outpatient and primary care visits, and inpatient care (3,4).

The Centers for Disease Control and Prevention (CDC) and the American Academy of Sleep Medicine emphasize the importance of an adequate night's sleep, which is defined as 7 or more hours per night with no upper limit (5,6). Anything less than this amount may lead to the development of various chronic diseases. More than one-third of the US population does not get adequate sleep

(5). The people that most often get inadequate sleep are Native Hawaiian/Pacific Islander people, non-Hispanic Black people, and multiracial people (6). Those who most often get adequate sleep are married people and people with a college degree or more.

Studies have demonstrated an association between inadequate sleep and frequent mental distress (7,8), and sleep deprivation causes substantial negative health outcomes (4). The link between inadequate sleep and frequent mental distress has been viewed historically as a symptom–disease association with sleep inadequacies deriving from preexisting mental distress (9). However, at least 1 study researched the opposite hypothesis, evaluating frequent mental distress leading to a lack of sleep (10). These studies found that in certain populations, risk for inadequate sleep is increased if a person is experiencing depression or anxiety. Most current research on the potential association between inadequate sleep and mental distress focuses on a specifically defined group, such as college students, nurses, or people with diagnosed sleep disorders (9,11,12). Furthermore, current research focuses primarily on diagnosed mental health disorders (4,8). The purpose of our study was to examine the association between inadequate sleep and frequent mental distress in a diverse, population-based sample of adults aged 18 to 64.

Methods

We used 2018 Behavioral Risk Factor Surveillance System (BRFSS) data to analyze the association between sleep and self-reported mental distress. BRFSS is a cross-sectional survey that uses a standardized questionnaire to collect prevalence data regarding risk behaviors and preventive behavioral health practices among adult US residents (13). Participants self-report information during telephone interviews conducted by trained personnel. Interviewers make calls for interviews 7 days a week during the day and evening (14). BRFSS raw data, which are collected during the survey, are submitted to CDC each year for processing and are made available to researchers the following calendar year through annual reports available on the CDC website (https://www.cdc.gov/brfss/index.html). BRFSS is conducted in all 50 states, the District of Columbia, and 3 US territories. Noninstitutionalized adults aged 18 or older are eligible to complete the BRFSS survey (15). Over 400,000 adults are interviewed each year. The land line response rate for BRFSS is 53.3%, and the cellular telephone response rate is 43.3% (16). A total of 437,436 people completed the BRFSS survey in 2018. After excluding those participants who were not aged 18 to 64 (n = 160,115) and those who did not have information on frequent mental distress (n = 3,626), 273,695 survey participants remained for analysis.

The survey question used to identify the exposure variable of interest reads, “On average, how many hours of sleep do you get in a 24-hour period?” Participants were asked to provide a value from 1 to 24 hours. Sleep values were recorded as whole numbers, and values greater than 30 minutes were rounded up per BRFSS coding. Inadequate sleep was defined as 6 hours or less of sleep in a given 24-hour period, which is 1 hour less than the minimum recommended number of hours of sleep for adults (5,17,18). We chose this definition of inadequate sleep because the rounding done by BRFSS personnel could have created situations where people who actually had inadequate sleep were classified as having the minimum recommended hours. Furthermore, previous studies also defined inadequate sleep as 6 hours or less per night (5,17). Thus, using this same definition allows for better comparison across studies.

The survey question selected to identify the outcome of interest, frequent mental distress, was “Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?” (13). The responses were recorded as the number of days (ie, 1–30 days). Frequent mental distress was considered present if 14 or more days were reported as mental health “not good” in the previous month. This definition was based on recommendations from previous studies on frequent mental distress (19) and guidance from the American Psychiatric Association on the necessary duration of symptoms to diagnose depression (20).

Potential confounders were selected on the basis of prior research and included age, race/ethnicity, sex, current smoking status, binge drinking, marital status, education, income, and loss of insurance (21–28). Study participants were asked the following question regarding alcohol consumption: “One drink is equivalent to a 12-ounce beer, a 5-ounce glass of wine, or a drink with one shot of liquor. During the past 30 days, on the days when you drank, about how many drinks did you drink on the average?” (13). We used this information to create a dichotomous binge drinking variable; in the past 30 days on the days when they drank, men who had 5 or more drinks and women who had 4 or more drinks were classified as binge drinkers (29). To assess current smoking, participants were asked, “Do you now smoke cigarettes every day, some days, or not at all?” Ultimately, this variable was dichotomized into people who smoked every day or some days and people who did not smoke at all.

A primary univariate analysis was performed to obtain frequencies and weighted percentages of the exposure, outcome, and potential confounders at the $P < .20$ level. We used logistic regression to assess the association between self-reported sleep and frequent mental distress and to identify other risk factors for frequent mental distress. Multivariate logistic regression was used to ob-

tain the odds ratio for the association between inadequate sleep and frequent mental distress while adjusting for potential confounders. A backward elimination approach was used to retain confounders at the $P < .05$ level. Ultimately, age, marital status, income, smoking status, and education level were identified as confounders. Because of the complex sampling design used by BRFSS, weighted analyses were performed using Stata version 15.1 (StataCorp LLC).

Results

Most study participants were non-Hispanic White (59.1%), female (50.2%), married (49.3%), and had at least a high school diploma (87.4%) (Table 1). Most participants reported that they had adequate nightly sleep (87.0%), and 14.1% experienced frequent mental distress (≥14 d/mo). Mean hours of sleep per 24-hour period were similar across age groups (18–34: 6.9 h; 35–49: 6.8 h; 50–64: 6.9 h).

People with inadequate sleep had nearly a threefold increased odds of frequent mental distress compared with those who had adequate sleep, and this finding was significant (OR, 2.67; 95% CI, 2.51–2.84) (Table 2). Participants who were divorced/separated/widowed had twice the odds of frequent mental distress compared with study participants who were married (OR, 2.14; 95% CI, 2.01–2.29). There was a dose–response association between education level and frequent mental distress. As education levels decreased, the odds of frequent mental distress increased (high school diploma, GED, associate degree, or no university degree: OR, 2.06; 95% CI, 1.95–2.18; no high school diploma: OR, 3.35; 95% CI, 3.06–3.67).

After adjustment for age, marital status, income, smoking status, and education level, the inadequate sleep–frequent mental distress association was attenuated but remained significant. Participants with inadequate sleep had nearly 2.5 times increased odds of frequent mental distress compared with those with adequate sleep (OR, 2.52; 95% CI, 2.32–2.73; $P < .001$).

Discussion

In our population-based study of US adults, inadequate sleep was associated with significantly increased odds of mental distress after controlling for confounding variables. Our findings align with previous research with the caveat that prior research has often looked at sleep as the outcome (8). Because our study used a large sample of adults and excluded only those who did not respond to qualifying questions, our results further confirm a potential association between inadequate sleep and mental health in a broader population.

Our study findings suggest an association between inadequate sleep and frequent mental distress. Because BRFSS is a cross-sectional study design, determining the true temporal sequence is not possible. Previous research has not closely examined the association between inadequate sleep as a risk factor for frequent mental distress. However, inadequate sleep has been linked to poor biological measures, including hypertension, anemia, and dyslipidemia (7). Low amounts of sleep and the attributed chronic conditions could possibly have a negative impact on depressive symptoms (7).

Limitations to this study include the potential for nondifferential misclassification of both the exposure and outcome variables; failure to recall information or misunderstanding questions asked possibly resulted in inaccurate responses. Also, self-reporting of mental distress is subjective. People may differ in their self-reporting and interpretation of what is "not good" for mental health. Furthermore, the use of a telephone interview could possibly influence self-reporting of mental distress. However, research demonstrates that the reporting of mental health information does not differ between face-to-face interviews and telephone interviews (31,32). In some instances, telephone interviews reduced embarrassment to participants when discussing mental health. We used a cut point of 6 hours to determine inadequate sleep rather than 7 hours, which is the minimum recommended hours of sleep for adults. We reran our model using 7 hours as the cut point for inadequate sleep, and our findings were of similar magnitude and remained significant. Given our aforementioned concerns that the rounding done by BRFSS personnel as it relates to the sleep duration variable could have incorrectly classified participants, we ultimately decided to retain our 6-hour cut point. In addition, because this definition of inadequate sleep has been used by others, it allows for better comparison across studies (5,17). Regardless, any nondifferential misclassification in our study would likely bias the results toward the null. Because we used a secondary data source, we were limited to the questions asked in the BRFSS survey. Thus, confounding by variables not measured in the BRFSS was possible. Selection bias is possible given that the response rate for BRFSS was 53.3% for landline responses and 43.3% for cellular telephone responses (15). The extent to which participation in BRFSS would be related to inadequate sleep and frequent mental distress is unknown; however, BRFSS is widely considered to be a valid and reliable measure of mental health and health behaviors (33).

Our study had numerous strengths. Information bias is unlikely because of the use of trained interviewers and standardization of interview methods. The exposure question may capture sleep data with more precision because it asks how many hours the participant slept in a 24-hour period. Thus, naps are included in the reporting. In addition, the wording enables the sleeping habits of

people who do not work traditional day-time jobs to be more accurately reported. Establishing hours slept in a 24-hour period is consistent with prior research, giving a continuity of comparison across studies (4,7,8). Finally, our study included all participants aged 18 to 64 and did not focus only on those with preexisting conditions or on populations at risk for inadequate sleep (4,8). Thus, given the large sample size and the complex sampling design used by BRFSS, our findings are likely generalizable to adults living in the US.

Because one-third of the US population is not attaining adequate sleep, our findings warrant further research to expand on the true association between inadequate sleep and frequent mental distress (5). Thorough clinical assessment of sleep by age and length and quality of sleep could strengthen the measurement of the exposure. More thorough follow-up questions related to mental distress, including clinical diagnoses, may allow for a clearer evaluation of the temporal sequence between inadequate sleep and mental distress.

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Tables

Table 1. Demographic Characteristics of Participants (N = 273,695) Experiencing Frequent Mental Distress, Behavioral Risk Factor Surveillance System, 2018

Variable	Unweighted n[a]	Weighted %
Average[b] sleep		
Adequate	239,750	87.0
Inadequate	33,945	13.0
Days mental health not good		
Normal, <14 d/mo	235,570	85.9
High, ≥14 d/mo	38,125	14.1
Sex		
Female	143,771	50.2
Male	129,480	49.8
Age, y		
18–34	71,614	38.3
35–49	79,602	29.5
50–64	122,479	32.2
Race/ethnicity		
Non-Hispanic White	193,757	59.1
Non-Hispanic Black	25,117	12.5
Asian	8,138	5.8
American Indian/Alaska Native	5,843	1.1
Hispanic	30,725	19.3
Other races	10,115	2.2
Education		
College degree or above	104,228	28.6
High school diploma, GED, or some college	149,023	58.8
No high school diploma	19,911	12.6
Marital status		
Married	142,638	49.3
Divorced/separated	56,972	18.7
Widowed/never married	72,748	32.1
Annual household income, $		
<35,000	65,453	30.8
35,000–75,000	66,469	28.7
>75,000	91,722	40.5
Binge drank[c] in past 30 days		

[a] Some totals may not equal the total number of participants because of missing data.
[b] Inadequate average sleep was defined as 6 hours or less in a 24-hour period.
[c] In the past 30 days on the days when they drank, men who had 5 or more drinks and women who had 4 or more drinks.

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Table 1. Demographic Characteristics of Participants (N = 273,695) Experiencing Frequent Mental Distress, Behavioral Risk Factor Surveillance System, 2018

Variable	Unweighted n[a]	Weighted %
No	96,053	64.5
Yes	47,478	35.5
Smoke		
No	58,416	53.6
Yes	47,318	46.4
Lost health coverage within past year		
No	28,314	91.1
Yes	2,270	8.9

[a] Some totals may not equal the total number of participants because of missing data.
[b] Inadequate average sleep was defined as 6 hours or less in a 24-hour period.
[c] In the past 30 days on the days when they drank, men who had 5 or more drinks and women who had 4 or more drinks.

Table 2. Association Between Selected Variables and Frequent Mental Distress Among Participants (N = 273,695), Behavioral Risk Factor Surveillance System, 2018

Variable	Weighted Odds Ratio (95% CI)
Average[a] sleep	
Adequate	1 [Reference]
Inadequate	2.67 (2.51–2.84)[b]
Sex	
Female	1 [Reference]
Male	0.91 (0.87–0.96)[b]
Age, y	
18–34	1 [Reference]
35–49	1.00 (0.95–1.06)
50–64	1.27 (1.20–1.34)[b]
Race/ethnicity	
Non-Hispanic White	1 [Reference]
Non-Hispanic Black	1.12 (1.04–1.21)[b]
Asian	0.52 (0.44–0.62)[b]
American Indian/Alaska Native	1.61 (1.35–1.90)[b]
Hispanic	1.05 (0.96–1.13)
Other races	1.35 (1.21–1.51)[b]
Education	
College degree or above	1 [Reference]
High school diploma, GED, or some college	2.06 (1.95–2.18)[b]
No high school diploma	3.35 (3.06–3.67)[b]
Marital status	
Married	1 [Reference]
Divorced/separated/	2.14 (2.01–2.29)[b]
Widowed/never married	1.29 (1.22–1.36)[b]
Annual household income, $	
<35,000	2.71 (2.54–2.91)[b]
35,000–75,000	1.56 (1.45–1.68)[b]
>75,000	1 [Reference]
Binge drank[c] in past 30 days	
No	1 [Reference]
Yes	1.21 (1.13–1.30)[b]
Smoke	
No	1 [Reference]

[a] Inadequate average sleep was defined as 6 hours or less in a 24-hour period.
[b] Significant at $P < .20$.
[c] In the past 30 days on the days when they drank, men who had 5 or more drinks and women who had 4 or more drinks.

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Table 2. Association Between Selected Variables and Frequent Mental Distress Among Participants (N = 273,695), Behavioral Risk Factor Surveillance System, 2018

Variable	Weighted Odds Ratio (95% CI)
Yes	1.80 (1.68–1.93)[b]
Lost health coverage within past year	
No	1 [Reference]
Yes	1.40 (1.17–1.69)[b]

[a] Inadequate average sleep was defined as 6 hours or less in a 24-hour period.
[b] Significant at $P < .20$.
[c] In the past 30 days on the days when they drank, men who had 5 or more drinks and women who had 4 or more drinks.

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ORIGINAL RESEARCH

Association of the Neighborhood Built Environment With Incident and Prevalent Depression in the Rural South

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PEER REVIEWED

Summary

What is already known on this topic?

Features of the built environment are associated with physical activity in urban and rural communities and with depression in urban communities.

What is added by this report?

Features of the built environment, including aesthetics, destinations, and security, were associated with depression in a rural population in Louisiana, and these associations were not mediated by physical activity.

What are the implications for public health practice?

Improvements in the built environment that promote physical activity among rural populations should take neighborhood context into consideration to minimize negative side effects on mental health.

Abstract

Introduction

A neighborhood's built environment is associated with physical activity among its residents, and physical activity is associated with depression. Our study aimed to determine whether the built environment was associated with depression among residents of the rural South and whether observed associations were mediated by physical activity.

Methods

We selected 2,000 participants from the Bogalusa Heart Study who had a valid residential address, self-reported physical activity (minutes/week), and a complete Center for Epidemiologic Study–Depression (CES-D) scale assessment from 1 or more study visits between 1998 and 2013. We assessed the built environment with the Rural Active Living Assessment street segment audit tool and developed built environment scores. The association between built environment scores and depression (CES-D ≥16) in geographic buffers of various radii were evaluated by using modified Poisson regression, and mediation by physical activity was evaluated with mixed-effects models.

Results

Depression was observed in 37% of study participants at the first study visit. One-point higher physical security and aesthetic scores for the street segment of residence were associated with 1.07 times higher (95% CI, 1.02–1.11) and 0.96 times lower (95% CI, 0.92–1.00) baseline depression prevalence. One-point higher destination scores (ie, more commercial and civic facilities) in radius buffers of 0.25 miles or more were associated with 1.06 times (95% CI, 1.00–1.13) the risk of depression during follow-up. Neighborhood poverty (defined as percentage of residents with incomes below the federal poverty level and dichotomized at 28.3%) modified cross-sectional and longitudinal associations. Associations were not mediated by physical activity.

Conclusion

The built environment was associated with prevalence and risk of depression, and associations were stronger in high-poverty neighborhoods. Built environment improvements to promote physical activity should take neighborhood context into consideration to minimize negative side effects on mental health in high-poverty communities.

Introduction

Depression is among the leading causes of years lived with disability worldwide (1). Nearly 10% of US adults experience depression, a substantial public health problem (2). Residents of rural areas are less likely to engage in sufficient physical activity than urban residents (3), contributing to elevated prevalence of chronic disease and health disparities among rural populations (4). However, rural populations experience fewer mental health disorders than intermediate-size urban areas (5).

Depression is associated with disorder and violence in the neighborhood environment and less consistently with structural features of the built environment (6). Most prior analyses of the relationship between depression and the built environment were of urban areas and were cross-sectional, with little consideration of spatial scale (6,7). Built environments may influence depressive symptoms as a neighborhood stressor (8) or along pathways mediated by behaviors (eg, physical activity) that result from the interactions of individuals with their environment (9). Built environment features that impede physical activity are more prevalent in rural locales than in urban ones. For example, rural residents may have greater distances to travel, roads with higher speed limits, and fewer pedestrian or cyclist safety features (10). Research has not determined whether depression among rural populations is associated with the built environment and whether it is mediated by physical activity.

We evaluated cross-sectional and longitudinal associations between structural features of the rural built environment and depressive symptoms among participants in the Bogalusa Heart Study. Previous research in this population identified significant associations between scores for features of the neighborhood built environment and physical activity (11). We hypothesized that higher scores (environments more conducive to physical activity) would be associated with lower baseline prevalence of depression and lower depression incidence and that these associations would be mediated by physical activity.

Methods

The Bogalusa Heart Study is a longitudinal study of cardiovascular risk factors conducted in rural Washington Parish, Louisiana, that began in 1973 (12). Our cross-sectional analysis consisted of participants with a valid address of residence who had complete data on depressive symptoms and physical activity assessed in at least 1 study visit since 1998 (n = 2,000). Participants in the longitudinal analysis had more than 1 observation (range, 2–5 observations; mean, 2.55). Depressive symptoms were reported by study participants by using the Centers for Epidemiologic Studies–Depression (CES-D) scale, which has high validity in noninstitutionalized adult populations (13). Continuous CES-D scores were used in mixed models for the association of neighborhood environment with changes in severity of depressive symptoms, and CES-D was dichotomized (≥16, depressed; <16, not depressed) (14) for Poisson regression for cross-sectional (at the first CES-D assessment for each participant) and longitudinal associations of neighborhood environment with depression.

We audited built environment features of street segments of residence (n =1,340) by using Google Street View for each available image (n = 2,648) for all study participants (n = 2,000) by using the Rural Active Living Assessment (RALA) street segment audit tool (15). Built environment audits were merged to participant study data by date, with the most temporally proximate street segment image used for built environment exposure at each study visit. Reliability of built environment audits using Google Street View has been reported as high (16). Neighborhood scales were developed for all features assessed, and for features in domains of path, pedestrian safety, aesthetics, commercial and civic destinations, physical security, and land use. Reliability of the neighborhood scales, assessed with intraclass correlation coefficients for duplicate audits of 196 street segments, has previously been reported to be acceptable for all domains except physical security features (11).

Covariates

Participants were characterized with anthropometric, demographic, socioeconomic, behavioral, and health covariates. Age, body mass index (BMI) (weight in kg/height in m^2), and total physical activity were available as continuous variables. Self-reported data were dichotomized for education (≥high school degree, <than a high school degree), annual income (≥$15,000, <$15,000), marital status (married, unmarried), health insurance (yes, no), home ownership (yes, no), employment status (employed, unemployed), and alcohol consumption in the past 12 months (yes, no). Race was self-reported as White or Black. Smoking was self-reported and categorized (current, former, never). Neighborhood contextual variables were obtained for the census tract of residence from the American Community Survey 5-year estimates and the 2010 census (17). Variables for neighborhood poverty (the percentage of residents in a census tract living in a household with an income below the federal poverty level [FPL]) and population density (residents per square mile) were calculated and used as continuous variables and dichotomized at the sample mean for the evaluation of effect modification. High and low categories were defined for neighborhood population density (high density, ≥586 people/sq mi; low density, <586 people/sq mi) and percentage of residents living in neighborhood poverty (high poverty, ≥28.3%; low poverty, <28.3%).

Analysis

We developed scales for built environment overall in 6 domains of street segment features identified a priori and refined following principal components analysis. This process has been reported in detail elsewhere (11). Briefly, scales were developed by creating 1 variable for features that were assessed across multiple RALA variables (eg, sidewalks, paths), with all variables coded so higher values indicated features that promote physical activity. We calculated variable means, and 1 point was added to a preliminary segment score for each variable for which the segment value exceeded the sample mean. The mean preliminary score was then calculated for segments with values above and below the sample mean for every variable, and these means were compared. We flagged variables for removal where the difference in mean preliminary score between segments above and below the sample mean was less than 1. A final segment score was calculated by adding 1 point for each unflagged variable where the segment value exceeded the sample mean for that variable. This process was done for all variables assessed (overall), and repeated within domains of features (ie, path, pedestrian safety, aesthetics, physical security, destinations, and land use). A built environment score of 0 indicated that the segment had no additional features that promote physical activity relative to the average street segment. This scoring process has been used in the development of walkability and playground indexes (18,19). The higher the score for a segment, the more features the segment contained thought to promote physical activity, with higher land use scores indicating more dense residential development, better-condition residences than the average street segment, and the absence of hills or other geographic or land development barriers to physical activity. Buffers — the area around each audited street segment — with radii of 0.25, 0.50, 1.00, and 1.50 miles were used to define neighborhood exposures. Overall neighborhood scores were calculated as the average, weighted by the inverse of the distance from the centroid, of street segments within these buffers.

We evaluated the association between neighborhood built environment scores and longitudinal change in severity of depressive symptoms by using a hierarchical, mixed-effects, linear growth model, including all study participants with 2 or more CES-D assessments (n = 1,006), with differences in the rate of change (slope) being the outcome of interest. Mixed-effects models were conducted for each built environment score, with an interaction between the score and age and random intercepts and coefficients for age for each subject nested in street segments and census tracts and adjusted for sex, education, smoking, neighborhood poverty, and population density. The average duration of follow-up for participants in the longitudinal analysis exceeded 10 years, so the slope differences were expressed as the number of CES-D points per 10-years of follow-up. The percentage of each association between built environment scores and depressive symptoms mediated by physical activity was evaluated in mixed effects linear growth regression models by using a product of coefficients method (20), and 95% CIs for the resultant percentage mediation were calculated with a specialized program (21) in SAS version 9.4 (SAS Institute).

The association between neighborhood built environment scores and depression was evaluated by using modified Poisson regression models with robust standard error estimation, which accommodated clustering in street segments and census tracts (22). We reported the cross-sectional association between the built environment and depression in the baseline examination as prevalence rate ratios (PRRs) and 95% CIs, adjusted for age, sex, education, smoking, neighborhood poverty, and population density. Models for the longitudinal association between neighborhood built environment and depression included all subjects with more than 1 depression assessment (n = 1,006), giving risk ratios (RR) and 95% CIs, adjusted for age at baseline, sex, baseline CES-D score, education, smoking, duration of time elapsed since baseline (follow-up duration), neighborhood poverty, and population density.

Neighborhood poverty and population density were identified a priori as potential effect modifiers. Modification of the effect of built environment scores on depression in Poisson regression models and depressive symptoms in mixed effects regression models was evaluated by interacting built environment scores with dichotomized percentage of neighborhood poverty or population density. All analyses were conducted by using SAS version 9.4. *P* values of <.05 were considered significant.

Results

The mean values for subjects included in our cross-sectional analysis were on average age, 38.3; BMI, 29.8; CES-D score, 15.1; and reported weekly physical activity, 175.8 minutes (Table 1). A minority of the sample was male (43.1%), Black (33.6%), and had at least a high school education (41.9%). Most reported being a current or former smoker (55.7%), drinking alcohol in the past year (61.3%), having an annual household income at or above $15,000 (64.3%), owning their home (72.3%), being employed (79.8%), being married (53.2%), and being in good health (64.4%). Because subjects included in longitudinal analyses represent a subset of those in the cross-sectional analysis, they will not be described separately. Cross-sectional study participants who were older, more educated, and did not own their homes lived on street segments with significantly higher overall built environment scores, whereas only home ownership was significantly associated with lower overall built environment scores for the longit-

udinal sample. Cross-sectional analyses for depression at the baseline examination identified 740 depressed subjects (37.0% of 2,000 total subjects); longitudinal analyses for depression identified 568 depressed subjects and 438 nondepressed subjects at the end of follow-up (Table 2).

Depressed subjects in the cross-sectional sample lived on street segments with lower aesthetics ($P < .001$) and higher physical security ($P < .001$) scores than nondepressed subjects (Table 2). Depressed subjects in the cross-sectional sample lived in census tracts with higher neighborhood poverty ($P < .001$) than nondepressed subjects. We observed no significant differences between street segment scores or neighborhood contextual variables between depressed and nondepressed subjects included in the longitudinal sample.

Significant associations were observed for aesthetics and physical security built environment scales on the street segment of residence (Table 3). For each 1-point higher aesthetics score on the street segment of residence, the prevalence of depression was 4% lower (PRR = 0.96, 95% CI, 0.92–1.00), and while similar magnitude associations were observed in larger neighborhood buffers, these were not significant. For each 1-point higher physical security score on the street segment of residence, the prevalence of depression was 7% higher (PRR = 1.07, 95% CI, 1.02–1.11).

Significant associations were observed between higher destination scores and increased risk of depression. For each 1-point higher destination score, the risk of depression was 1.06 (95% CI, 1.00–1.13), 1.07 (95% CI, 1.01–1.14), 1.08 (95% CI, 1.01–1.15), and 1.07 (95% CI, 1.00–1.15) times higher in buffers of radii of 0.25, 0.50, 1.00, and 1.50 miles, respectively (Table 3). No significant associations of built environment scales with depression were observed for the overall built environment, paths, pedestrian safety, aesthetics, physical security, and land use in longitudinal analyses.

Significant effect modification by neighborhood poverty was identified for the pedestrian safety features scale in 0.25-mile, 0.50-mile, 1.00-mile, and 1.50-mile buffers in cross-sectional Poisson regression models, with 1-point higher pedestrian safety score associated with significant increased prevalence of depression in high-poverty neighborhoods but not low-poverty neighborhoods (Figure). Neighborhood poverty significantly modified the relationship between the destination scale and depression in longitudinal analyses, with 1-point higher destination scores in buffer radii of 0.25 mile, 0.50 mile, 1.00 mile, and 1.50 miles associated with higher risk of depression in high-poverty but not low-poverty neighborhoods. Associations between built environment scales and depression were not significantly modified by population density, though a 1-point higher aesthetic score was associated with significantly lower prevalence of depression in buffer radii of 0, 0.25 mile, and 0.50 of a mile in high-density neighborhoods but not in low-density neighborhoods (Figure).

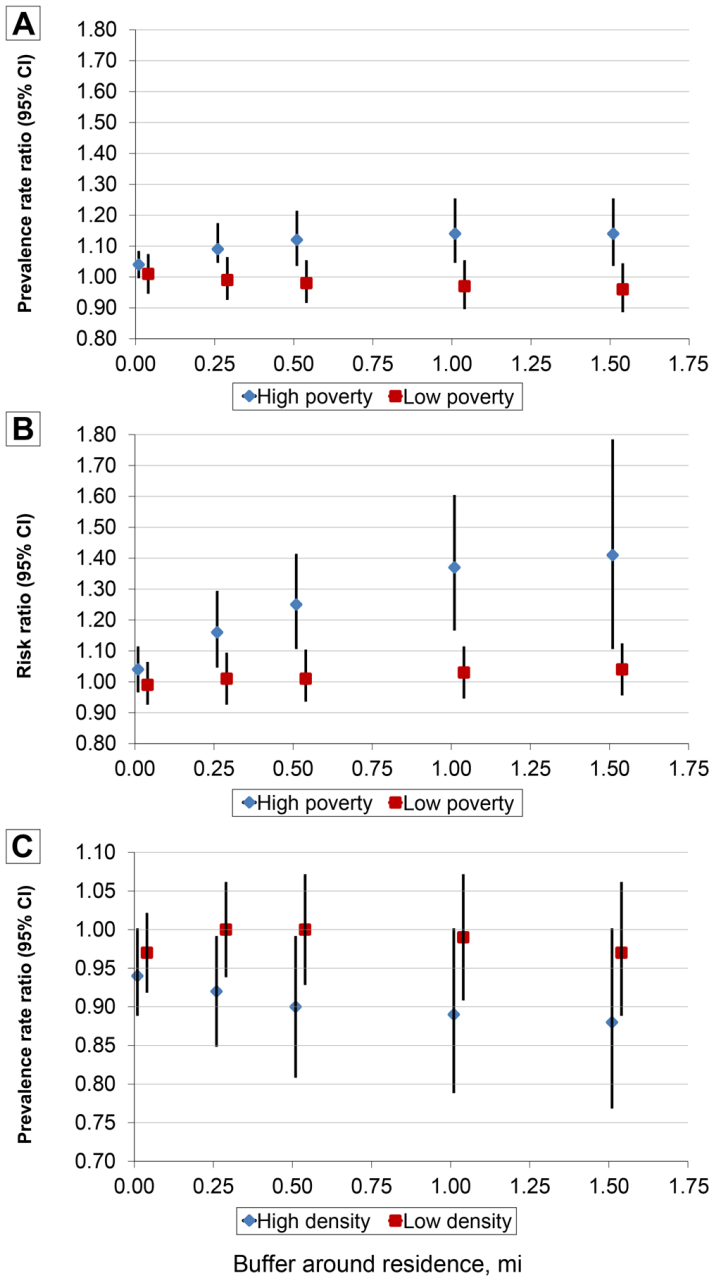

Figure 1. Association between built environment scores in buffers around residence and incident and prevalent depression among participants (N = 2,000) in the Bogalusa Heart Study, 1998–2013. High poverty is defined as ≥28.3% of residents (of a census tract) living below the federal poverty level; low poverty is defined as <28.3% of residents (of a census tract) living below the federal poverty level. High density is defined as ≥586 residents (of a

census tract) per square mile of area; low density is defined as <586 residents (of a census tract) per square mile of area. Graph A shows prevalence rate ratio (PRR) for a 1-point increase in pedestrian safety score. Graph B shows the risk ratio (RR) for a 1-point increase in destination score, and graph C shows the PRR for a 1-point increase in aesthetics score.

Over an average of 2.55 assessments, we found significant associations between the 10-year rate of change in depressive symptom severity and scales for the overall built environment and for paths, pedestrian safety, aesthetics, physical security, and land use (Table 4). In a buffer of 1.50 miles around the residence, a 1-point–higher overall and path scores were associated with 0.17 and 0.40 CES-D points/10-years slower increase in depressive symptom severity, respectively. Each 1-point higher pedestrian safety score was associated with 0.35, 0.52 and 0.57 CES-D points/10-years slower increase in depressive symptom severity in 0.50 mile, 1.00 mile, and 1.50 mile buffers, respectively. Neighborhood aesthetics were significantly associated with more rapid increases in severity of depressive symptom in all buffer radius sizes, with each 1-point higher aesthetics score associated with a 0.76 CES-D-points/10-years faster increase in depressive symptom severity in a 1.50-mile buffer radius. On the street segment of residence, each 1-point higher physical security score was associated with a 0.44 CES-D point/10-years faster increase in depressive symptom severity. In a 1-mile buffer radius, each 1-point higher land use score was associated with a 0.69 CES-D-points/10-years faster increase in depressive symptom severity. Of the significant slope differences, the only one mediated by physical activity was the aesthetics score on the street segment of residence (−2.83% mediated by physical activity) (Table 5).

Discussion

Our study identified significant associations between the built environment around a residence and depression and severity of depressive symptoms in the rural South. A more aesthetically pleasing street segment of residence was associated with a 4% lower prevalence of depression, and more security features (eg, window bars) were associated with a 7% higher prevalence of depression at the baseline visit. Each 1-point higher destination score within 0.25-mile, 0.50-mile, 1.00-mile, and 1.50-mile buffer radii around a residence was associated with a significant 6% to 8% higher risk of depression over an average of 10 years of follow-up. Effect modification by neighborhood poverty was identified, with significant associations observed exclusively in high-poverty neighborhoods between more pedestrian safety features and higher prevalence of baseline depression. Significant associations between more neighborhood destinations and higher risk of depression were identified exclusively in high poverty neighborhoods. No significant effect modification by neighborhood population density was observed.

Several studies have reported associations between the built environment and depressive symptoms (6,7). Among older adults, more walkable neighborhoods were associated with low cross-sectional odds of depression among men but not women (23). Neighborhood problems such as noise, vandalism, poor residential quality, incivilities (eg, trash on street), and heavy traffic were associated with more depressive symptoms at baseline but no changes in depressive symptoms over follow-up (24). A study among low-income Black and White residents of the southeastern US identified nonsignificantly higher odds of depression, with those in neighborhoods with the highest walkability index having 6% higher odds of CES-D–defined depression compared with those in the lowest walkability index neighborhoods (25). Our study did not identify associations between the overall built environment score and depression in cross-sectional or longitudinal analyses; however, the association between higher destination scores and increased risk of depression in our study is in accord with the higher odds of depression in the prior study (25). Differences between studies in the way neighborhood walkability was determined (by GIS mapping or street segment audit), the way scores were developed, and population density may explain the absence of an association between the overall score and depression in our study. The association between a high physical security score on the street segment of residence and increased depression prevalence at baseline is likely due to an inverse association of these features with residents' perception of safety. Inverse associations between objective and perceived neighborhood safety measures and depressive symptoms have been reported previously (24,26). In our study, living on a more aesthetically pleasing street segment was associated with lower prevalence of depression at baseline, in accord with prior reports that less aesthetically pleasing environments such as those with trash in the streets (24) or with less greenspace (27) are associated with greater depression.

Reasons for differences in associations between built environment scores and depression at baseline and over follow-up are unclear, but similar patterns have been reported previously (6,26). In a prior study high neighborhood and individual level safety measures were associated with low CES-D scores at baseline, but neither was significantly associated with changes in that score over a 10-year period (26). In our study, aesthetics and physical security scores for the street segment of residence were associated with decreased and increased prevalence of depression at baseline, respectively, but not over follow-up. The absence of longitudinal associations is consistent with the prior claim that changes to built environment exposures may be more important to incidence of depressive symptoms than static exposure (26).

We identified significant effect modification by the percentage of residents in a neighborhood with incomes below the FPL. This is

in accord with a previous study that found significant associations between increased walkability and increased depression only in the most socioeconomically deprived neighborhoods (25). Similarly, in the present study, significant associations between higher pedestrian safety scores and increased depression prevalence at baseline were identified only in high-poverty neighborhoods. Significant associations between higher destination scores and increased depression risk over follow-up were also identified only in high-poverty neighborhoods in the present study. This may be due to the associations between high neighborhood socioeconomic disadvantage (and poverty), low neighborhood social capital, and high depressive symptom (7). In our study, at baseline, each 10% increase in the prevalence of poverty in a census tract was associated with 12% higher prevalence of depression. The stronger associations between the built environment and depression in these neighborhoods may be due to a sense of vulnerability resulting from psychological stress, to which financial concerns are a significant contributor (28).

The mechanisms that underlie the association between higher physical security scores and increased prevalence of depression, between higher aesthetic scores and decreased prevalence of depression, and between higher destination scores and increased risk of depression are unknown. The associations between built environment scores and the rate of change in CES-D scores were not mediated by physical activity in our study population. Previous research has suggested that chronic stress, and associated hypocortisolism, among residents in neighborhoods with more objective and perceived stress-inducing features may explain relationships between neighborhood social disadvantage and negative health outcomes (29). Another study identified alteration of resting-state neural oscillatory activity in the cerebellum as a mechanism that could explain associations between environmental factors and depression (30). A study of the built environment and perceived social support and psychological distress among residents identified associations of features that promote direct social interaction with increased perceived social support and potential benefits for mental health (31). Associations between scores for built environment features and depression found in our study may therefore be mediated by influences on perceived social support or chronic stress.

Our study has several strengths. The sample was a well-characterized rural population with longitudinal data on physical activity, the built environment, and depression, and analyses were adjusted for potential individual and contextual confounders. Depression was assessed with a validated instrument (13), and the built environment scales were both reliable and associated with physical activity. Analyses evaluated cross-sectional and longitudinal associations. The density of street segments included in built environment audits allowed the construction of scales for the built environment within buffers of various radii around the residence, which has been a limitation in much of the prior literature (6). Our study also has limitations. Observed associations were based on an observational study design, and causality could not be inferred. No measure of the perceived built environment was available, so we could not assess mediation of associations between the objectively assessed built environment and depression by residents' perception of the built environment. Also, no measure of social support was included in our analysis. The uncertain geographic context problem, in which the true geographic context relevant to the health outcome being studied for participants is unknown, may have contributed to underestimation of the strengths of the observed associations. Most study participants lived in one rural parish in Louisiana, so generalizability of the results may be limited.

Our study contributes to prior findings of cross-sectional associations between built environment features thought to promote physical activity (ie, walkability) and increased prevalence of depression in the southern United States. Additionally, significant associations of more overall built environment features, more pedestrian safety features, more physical security features, and more destinations with greater depression only in high-poverty neighborhoods supports prior reports about the modifying influence of neighborhood socioeconomic status on the relationship between the built environment and depression. Relationships between built environment features thought to promote physical activity and negative mental health outcomes in low-socioeconomic–status neighborhoods may be due to relationships between these features and increased stressors among people who perceive themselves as marginalized (25,28). Built environment improvements tailored to neighborhood contexts and residents' wants and needs may have more broadly positive effects on community health. Further research is needed to identify mechanisms underlying associations between the built environment and depression and to explain why neighborhood socioeconomic status modifies the relationship between the built environment and depression.

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Tables

Table 1. Characteristics of Participants (N = 2,000) Included in Analyses Evaluating the Cross-Sectional and Longitudinal Associations of the Built Environment Around the Residence and Depression in a Rural Population, Bogalusa Heart Study, 1998–2013

Characteristic	Cross Sectional		Longitudinal	
	N = 2,000	*P* Value[a]	N = 1,006[b]	*P* Value[a]
Age, y, mean (SD)	38.27 (8.63)	.03	36.79 (4.96)	.05
BMI, mean (SD)	29.79 (8.03)	.18	29.63 (8.20)	.89
Follow-up duration, y, mean (SD)	0.00 (0.00)	1.00	10.68 (3.17)	.90
CES-D score[c] at baseline, mean (SD)	15.08 (10.27)	.93	13.24 (9.84)	.75
Depressed at baseline, n (%)	740 (37.00)	.77	321 (31.91)	.46
Male, n (%)	862 (43.10)	.15	410 (41.46)	.77
Black, n (%)	672 (33.60)	.22	303 (30.64)	.79
≥High school education, n (%)	838 (41.90)	.002	548 (58.80)	.64
Household income ≥$15,000, n (%)	1,285 (64.25)	.87	718 (72.67)	.99
Married, n (%)	1,063 (53.15)	.19	611 (61.78)	.22
Have health insurance, n (%)	1,216 (60.80)	.08	635 (68.13)	.06
Employed, n (%)	1,596 (79.80)	.54	833 (84.23)	.26
Home owner, n (%)	1,445 (72.25)	<.001	779 (78.77)	.008
In good health, n (%)	1,288 (64.40)	.22	878 (89.32)	.76
Current smoker, n (%)	590 (29.50)	.06	292 (29.03)	.91
Former smoker, n (%)	523 (26.15)	.06	300 (29.82)	.91
Consumed alcohol in last year, n (%)	1,206 (61.25)	.22	628 (63.50)	.18
Any physical activity, n (%)	1,436 (72.90)	.67	858 (86.75)	.79
Walking (min/wk), mean (SD)	83.29 (245.56)	.76	82.45 (250.18)	.27
Physical activity (min/wk), mean (SD)	175.77 (386.90)	.38	181.34 (375.15)	.07

Abbreviations: BMI, body mass index; CES-D, Centers for Epidemiologic Studies–Depression.
[a] *P* values were assessed with analysis of variance for categorical variables and Pearson correlation coefficient for continuous variables and are for the association of participant characteristics with the (continuous) overall built environment score for the street segment of residence.
[b] Longitudinal sample; includes only those study subjects with 2 or more observations.
[c] CES-D score ≥16 indicates depression. CES-D scores can range from 0 to 60.

Table 2. Neighborhood Characteristics of Participants (N = 2,000) Included In Analyses Evaluating the Cross-Sectional and Longitudinal Associations of the Built Environment Around the Residence and Depression in a Rural Population, by Depression Status, Bogalusa Heart Study, 1998–2013

Variable	Cross Sectional			Longitudinal[a]		
	Depressed[b] (n = 740)	Not Depressed (n = 1,260)	*P* Value[c]	Depressed[b] (n = 568)	Not Depressed (n = 438)	*P* Value[c]
Street segment of built environment[d]						
All features, mean (SD)	10.55 (4.32)	10.49 (4.49)	.77	10.41 (4.17)	10.34 (4.43)	.78
Path, mean (SD)	2.31 (2.35)	2.20 (2.40)	.32	2.08 (2.22)	2.11 (2.37)	.83
Pedestrian safety features, mean (SD)	3.21 (1.81)	3.03 (1.81)	.03	3.02 (1.83)	2.94 (1.89)	.51
Aesthetics, mean (SD)	2.99 (1.47)	3.28 (1.60)	<.001	3.33 (1.55)	3.30 (1.57)	.76
Destinations[e], mean (SD)	0.61 (1.22)	0.54 (1.14)	.20	2.92 (1.11)	2.94 (1.11)	.90
Physical security, mean (SD)	3.41 (1.45)	3.19 (1.32)	<.001	0.52 (1.10)	0.51 (1.13)	.73
Land use, mean (SD)	1.61 (0.90)	1.67 (0.95)	.17	1.67 (0.98)	1.66 (0.90)	.85
Contextual variables						
Population density, mean (SD)	556.75 (1,575.20)	603.25 (1,189.66)	.46	536.30 (1,774.73)	520.84 (839.53)	.86
Percentage poverty[f], mean (SD)	30.06 (10.23)	27.20 (11.22)	<.001	28.75 (10.58)	28.41 (11.00)	.39

Abbreviation: CES-D, Centers for Epidemiologic Studies–Depression.
[a] Longitudinal sample; includes only those study subjects with 2 or more observations.
[b] CES-D score ≥16 indicates depression. CES-D scores can range from 0 to 60.
[c] *P* values for comparison of depressed and not-depressed subjects are from *t* tests.
[d] Built environment scores summarize features of street segments assessed with the Rural Active Living Assessment street segment audit tool, overall and within domains of features, with higher numeric scores indicating the presence of more features thought to promote physical activity. Scores have the following ranges: overall (2–29), path (0–9), pedestrian safety (0–10), aesthetics (0–6), destinations (0–11), physical security (0–6), and land use (0–5).
[e] Includes commercial and civic facilities.
[f] Neighborhood poverty was defined as the percentage of residents in a census tract living below the federal poverty level.

Table 3. Association of Neighborhood Built Environment Scores[a] With Prevalence and Incidence of Depression Among Participants (N = 2,000), Bogalusa Heart Study, 1998–2013

Built Environment Score	Buffer Around Residence Unit				
	0.00 mi	0.25 mi	0.50 mi	1.00 mi	1.50 mi
Cross-sectional, prevalence rate ratio (95% CI)					
Overall	1.01 (0.99–1.02)	1.01 (0.99–1.03)	1.01 (0.99–1.03)	1.00 (0.98–1.03)	1.00 (0.98–1.02)
Path	1.01 (0.98–1.04)	1.02 (0.99–1.05)	1.02 (0.98–1.05)	1.01 (0.97–1.05)	1.01 (0.97–1.06)
Pedestrian safety	1.03 (1.00–1.06)	1.03 (0.99–1.08)	1.04 (0.98–1.09)	1.03 (0.97–1.09)	1.02 (0.96–1.08)
Aesthetics	0.96 (0.92–1.00)	0.97 (0.92–1.02)	0.97 (0.91–1.02)	0.96 (0.90–1.02)	0.95 (0.88–1.02)
Destinations[b]	1.04 (0.99–1.10)	1.04 (0.97–1.10)	1.04 (0.97–1.12)	1.02 (0.94–1.12)	1.02 (0.93–1.13)
Physical security	1.07 (1.02–1.11)	0.97 (0.84–1.12)	1.02 (0.87–1.21)	1.03 (0.86–1.24)	1.00 (0.82–1.22)
Land use	0.98 (0.92–1.04)	0.97 (0.89–1.05)	0.95 (0.86–1.05)	0.92 (0.83–1.03)	0.95 (0.85–1.06)
Longitudinal, risk ratio (95% CI)					
Overall	1.00 (0.99–1.01)	1.01 (0.99–1.02)	1.01 (0.99–1.03)	1.01 (0.98–1.03)	1.00 (0.98–1.03)
Path	1.00 (0.97–1.02)	1.00 (0.97–1.03)	1.01 (0.97–1.04)	1.00 (0.96–1.04)	0.99 (0.95–1.04)
Pedestrian safety	1.01 (0.98–1.04)	1.00 (0.97–1.04)	1.01 (0.97–1.05)	1.00 (0.96–1.04)	1.00 (0.95–1.05)
Aesthetics	1.00 (0.97–1.04)	1.01 (0.97–1.06)	1.02 (0.97–1.07)	1.02 (0.97–1.08)	1.02 (0.96–1.08)
Destinations[b]	1.01 (0.97–1.06)	1.06 (1.00–1.13)	1.07 (1.01–1.14)	1.08 (1.01–1.15)	1.07 (1.00–1.15)
Physical security	1.00 (0.96–1.05)	1.11 (0.96–1.28)	1.15 (0.97–1.36)	1.13 (0.94–1.37)	1.10 (0.90–1.35)
Land use	1.00 (0.95–1.06)	0.99 (0.92–1.05)	0.99 (0.93–1.07)	0.97 (0.90–1.05)	0.96 (0.88–1.05)

[a] Built environment scores summarize features of street segments assessed with the Rural Active Living Assessment street segment audit tool, overall and within domains of features, with higher numeric scores indicating the presence of more features thought to promote physical activity. Measures of association represent the relative prevalence or risk of depression associated with a 1-point increase in the specified built environment score. Scores have the following ranges: overall (2–29), path (0–9) pedestrian safety (0–10), aesthetics (0–6), destinations (0–11), physical security (0–6), and land use (05).
[b] Includes commercial and civic facilities.

Table 4. Association Between Neighborhood Built Environment Scores and Change in CES-D[a], Participants (N = 1,006)[a], Bogalusa Heart Study, 1998–2013

Built Environment Score[c]	CES-D Slope Difference[b] for 1-Point Increase in Built Environment Score									
	Buffer Around Residence Unit									
	0.00 mi		0.25 mi		0.50 mi		1.00 mi		1.50 mi	
	β (SE)	*P* Value	β (SE)	*P* Value	β (SE)	*P* Value	β (SE)	*P* Value	β (SE)	*P* Value
Overall	0.02 (0.05)	.67	0.00 (0.06)	.98	−0.03 (0.07)	.69	−0.11 (0.08)	.16	−0.17 (0.08)	.04
Path	−0.07 (0.09)	.40	−0.09 (0.11)	.41	−0.09 (0.12)	.46	−0.22 (0.14)	.13	−0.40 (0.16)	.01
Pedestrian safety	−0.06 (0.11)	.60	−0.20 (0.14)	.16	−0.35 (0.16)	.03	−0.52 (0.17)	<.01	−0.57 (0.19)	<.01
Aesthetics	0.26 (0.13)	.04	0.51 (0.16)	<.01	0.67 (0.19)	<.01	0.71 (0.23)	<.01	0.76 (0.26)	<.01
Destinations[d]	0.08 (0.16)	.64	0.17 (0.24)	.49	0.05 (0.27)	.86	−0.10 (0.33)	.76	−0.36 (0.41)	.38
Physical security	0.44 (0.14)	<.01	0.22 (0.53)	.69	0.57 (0.62)	.36	0.46 (0.74)	.54	0.54 (0.84)	.52
Land use	0.27 (0.22)	.21	0.47 (0.27)	.08	0.55 (0.30)	.07	0.69 (0.34)	.04	0.71 (0.38)	.06

Abbreviation: CES-D, Centers for Epidemiologic Studies–Depression.
[a] Longitudinal sample; includes only those study subjects with 2 or more observations.
[b] CES-D slope was expressed as the rate of change in depressive symptom severity per 10 years of follow-up (depressive symptom severity was assessed as a continuous CES-D score that can range from 0 to 60, with higher scores indicating more severe depressive symptoms).
[c] Built environment scores summarize features of street segments assessed with the Rural Active Living Assessment street segment audit tool, overall and within domains of features, with higher numeric scores indicating the presence of more features thought to promote physical activity. Associations represent the difference in the rate of change of depressive symptom severity over 10 years for a 1-point increase in the specified built environment score. Scores have the following ranges: overall (2–29), path (0–9), pedestrian safety (0–10), aesthetics (0–6), destinations (0–11), physical security (0–6), and land use (05).
[d] Includes commercial and civic facilities.

Table 5. Percentage of the Observed Association of Neighborhood Built Environment Scores[a] With CES-D Slope[b] Mediated by Physical Activity, Participants (N = 1,006)[c] Bogalusa Heart Study, 1998–2013

Built Environment	CES-D Slope Difference[b], Percentage Mediation (95% CI) by Physical Activity				
	Buffer Around Residence Unit				
	0.00 mi	0.25 mi	0.50 mi	1.00 mi	1.50 mi
Overall	−5.92 (−20.12 to 4.33)	16.4 (−167.44 to 211.48)	−1.44 (8.23 to −12.09)	−0.06 (2.71 to −2.87)	0.23 (2.21 to −1.60)
Path	1.55 (7.87 to −3.70)	−0.51 (4.48 to −5.87)	0.50 (6.32 to −4.98)	0.40 (3.16 to −2.09)	0.35 (2.06 to −1.13)
Pedestrian safety	−0.84 (7.40 to −9.65)	0.40 (3.71 to −2.62)	0.24 (2.32 to −1.67)	0.35 (1.92 to −0.98)	0.55 (2.17 to −0.70)
Aesthetics	−2.83 (−6.59 to −0.29)	-0.31 (−1.83 to 1.01)	−0.13 (−1.38 to 1.04)	−0.15 (−1.53 to 1.12)	−0.18 (−1.59 to 1.10)
Destinations[d]	1.72 (−8.11 to 12.72)	0.79 (−5.58 to 7.70)	5.94 (−17.02 to 32.96)	−2.47 (10.41 to −17.04)	−0.92 (3.16 to −5.63)
Physical security	1.07 (−0.12 to 2.97)	−3.20 (−14.77 to 6.20)	−2.03 (−7.17 to 1.75)	−2.19 (−9.18 to 3.31)	−0.96 (−7.01 to 4.43)
Land use	2.48 (−0.66 to 7.21)	2.27 (−0.05 to 5.89)	2.29 (0.06 to 5.76)	1.83 (−0.05 to 4.78)	1.65 (−0.25 to 4.60)

Abbreviation: CES-D, Centers for Epidemiological Studies–Depression.

[a] Built environment scores summarize features of street segments assessed with the Rural Active Living Assessment street segment audit tool, overall and within domains of features, with higher numeric scores indicating the presence of more features thought to promote physical activity. Associations represent the percentage of the slope difference for a 1-point increase in the specified built environment score that is mediated by physical activity. Scores have the following ranges: overall (2–29), path (0–9), pedestrian safety (0–10), aesthetics (0–6), destinations (0–11), physical security (0–6), and land use (05).

[b] CES-D slope was expressed as the rate of change in depressive symptom severity per 10 years of follow-up (depressive symptom severity was assessed as a continuous CES-D score that can range from 0 to 60, with higher scores indicating more severe depressive symptoms).

[c] Longitudinal sample; includes only those study subjects with 2 or more observations.

[d] Includes commercial and civic facilities.

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ORIGINAL RESEARCH

Colorectal Cancer Risk Factors and Screening Among the Uninsured of Tampa Bay: A Free Clinic Study

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PEER REVIEWED

Summary

What is already known on this topic?

Patients with low socioeconomic status have a high likelihood of developing colorectal cancer (CRC) due to associated risk factors and lower reported rates of screening.

What is added by this report?

This study is among the first to analyze the prevalence of CRC risk factors and screening rates of low-income and uninsured patients at free clinics in Florida.

What are the implications for public health practice?

Community-based health centers and free medical clinics are uniquely positioned to treat and care for this vulnerable population through the development of sustainable and cost-effective primary and secondary prevention strategies.

Abstract

Introduction

Uninsured patients with low socioeconomic status are at high risk for developing colorectal cancer (CRC), and data on risk factors and prevalence of CRC in this population are limited. The purpose of this study was to assess the risk factors for CRC in uninsured patients from free clinics in the Tampa Bay area of Florida.

Methods

We conducted a retrospective cohort study among patients 50 years or older who were provided service at 9 free clinics in the Tampa Bay area between 2016 and 2018. Demographics, chronic disease characteristics, and screening data were collected via a query of paper and electronic medical records.

Results

Of the 13,982 patients seen, 5,139 (36.8%) were aged 50 years or older. Most were female (56.8%), non-Hispanic White (41.1%), and unemployed (54.9%). Patients with CRC screening were more likely to be employed compared with patients without CRC screening (54.4% vs 44.4%, $P = .01$). Within the cohort, 725 (22.7%) patients were active smokers, 771 (29.2%) patients currently consumed alcohol, and 23 patients (0.4%) had a history of inflammatory bowel disease. Patients had a median body mass index of 29.4 (interquartile range, 25.4–34.2) kg/m^2, and 1,455 (28.3%) had diabetes. Documented CRC screening was found among 341 (6.6%) patients.

Conclusion

Uninsured patients had a high prevalence of CRC risk factors but a low reported screening rate for CRC. Free clinics are uniquely positioned to provide patients at high risk for CRC with strategies to decrease their risk and to be screened for CRC.

Introduction

Colorectal cancer (CRC) is the third leading cause of cancer-related deaths in the United States (1) and is most prevalent in patients aged 50 years or older. Despite significant strides in overall cancer survival, several factors such as low income, lack of insurance, and being in a racial or ethnic minority group prevent many Americans from receiving optimal care (1–3).

Patients with low socioeconomic status have a higher likelihood of developing CRC because of associated risk factors such as alcohol intake, obesity, and smoking (4). Another social determinant of health associated with poor outcomes in patients is lack of health insurance (2). It is well documented that cancer screening rates are lowest in people without health insurance, which leads to high numbers of late-stage cancers (5–7). Patients with Medicaid or those who are uninsured are more likely to have metastatic disease as well as lower rates of definitive surgery and resection (8). Furthermore, patients of racial and ethnic minority groups experience higher incidence and mortality rates of CRC compared with White patients (3,6).

Community-based health centers (CHC) and free medical clinics (FMC) provide primary care services to a large proportion of underinsured and uninsured individuals. They serve as first-line care for the prevention and management of many CRC risk factors such as diet, smoking, alcohol use, and type 2 diabetes (9). However, data on the burden of CRC risk factors in patients of these clinics are limited. The purpose of this study was to assess the prevalence of known risk factors and screening rates of CRC in low-income and uninsured patients of free clinics around Tampa Bay, Florida.

Methods

We included all uninsured patients served at 9 free clinics in the Tampa Bay area of Florida from January 1, 2016, through December 31, 2018, in this retrospective cohort study. We included patients aged 50 years or older served at any point during the study period, on the basis of US Preventive Services Task Force guidelines that recommend screening for CRC starting at age 50 because of the increased risk of colorectal cancer in this age group (10). We obtained data from paper and electronic medical records and used REDCap software for analyses (11). We compared patients who had documented CRC screening and those who did not by socioeconomic variables (ie, age, sex, race/ethnicity, employment status) and known CRC risk factors, including biometrics (ie, weight and body mass index), alcohol or tobacco use, and comorbidities (ie, diabetes and inflammatory bowel disease [IBD]). We present numeric variables as median (interquartile range [IQR]) and categorical variables as number (%). We used Mann–Whitney-Wilcoxon tests for numeric variables and χ^2 tests for categorical variables; missing values were not included in tests of significance. Significance was set at $P < .05$.

All participating clinics consented to the use of their data. This study was approved by the University of South Florida institutional review board.

Results

Of the 13,982 patients seen during the study period, 5,139 (36.8%) were aged 50 years or older and included for further analysis (Table 1). Of those with nonmissing demographic data, most were female (n = 2,896, 56.8%) and unemployed (n = 1,327, 54.9%), and nearly equal proportions were non-Hispanic White (n = 1,649, 41.1%) and Hispanic of any race (n = 1,639, 40.8%). Of those who reported their smoking status, 725 (22.7%) were active smokers, and 594 (18.6%) were past smokers (Table 2). Current and past smokers reported a median history of 15 pack-years (IQR, 5–35 pack-years). Of those who reported their history of alcohol consumption, 771 (29.2%) were active consumers, and 192 (7.3%) were past consumers. The median body mass index (BMI, kg/m^2) of patients was 29.4 (IQR, 25.4–34.2). The sample included 1,455 (28.3%) patients with diabetes and 23 (0.4%) patients with IBD.

Of all patients, 341 (6.6%) had a documented CRC screening. Patients with a documented CRC screening were more likely to be employed that those without a screening (54.4% vs 44.4%, $P = .01$) (Table 1). Patients who had a CRC screening were more likely than those without screening to be active (39.9% vs 28.0%) or past (10.7% vs 6.9%, $P < .001$) consumers of alcohol (Table 2). Diabetes was more prevalent among patients who received CRC screening than those without (33.1% vs 28.0%, $P = .047$). IBD was more prevalent among patients with a documented CRC screening than among those without (1.8% vs 0.4%, $P < .001$).

Discussion

We found a high prevalence of CRC risk factors among uninsured patients in Tampa Bay's free clinics. More than half of the patients were unemployed and consisted of a largely Hispanic population. We also found a 28.3% prevalence of diabetes and a median BMI of 29.4, suggesting the continued need for management of chronic health conditions.

The prevalence of several known modifiable risk factors for CRC, including smoking, alcohol usage, poor diet, obesity, and lack of physical activity, is higher in low socioeconomic populations (12–14). Hereditary and personal factors associated with CRC include type 2 diabetes, chronic IBD, and family history of CRC (15–18), and many of these risk factors are seen in higher rates within racial and ethnic minority groups (19). A meta-analysis of 29 articles by Luo and colleagues found that type 2 diabetes was associated with a relative risk of 1.37 (95% CI, 1.28–1.42) of developing CRC (15). Notably, previous epidemiologic studies show that Hispanics have a high prevalence of overweight and type 2 diabetes (20,21).

Patients who are at high risk for CRC and meet US Preventive Services Task Force guidelines are recommended to have routine CRC screening. However, CRC screening compliance remains a challenge in uninsured patients. Shapiro et al reported that 40% of Americans aged 50–75 years had not received recommended CRC screening and that the percentage was higher among those without insurance (80%) (22). Another study by Mojica et al reported that cancer screening rates for Latina women are lower than for non-Latino White women (23). CRC screening rates have been historically lower among Hispanic individuals compared with those who are non-Hispanic White (24). Our results are consistent with the literature, as our patient population was predominantly Hispanic and CRC screening was low, with only 6.6% of patients undergoing routine screening. Additionally, we found that unemployed patients were more likely not to have CRC screening, emphasizing the need for additional resources or better screening strategies for this population. We have previously reported that epidemiologic estimates may be affected by barriers to health care access, such as transportation, work leave, and the severity of disease (25). Furthermore, although colonoscopy is the gold standard for CRC screening, it is expensive. Socioeconomic status may affect providers' prescription patterns as well as patient compliance. Cheaper alternatives such as the fecal immunochemical test (FIT) and fecal occult blood test (FOBT) can be offered, but these sometimes result in false positive test results (26).

CHCs and FMCs are uniquely positioned to reduce CRC burden because of the large proportion of underinsured and uninsured individuals they serve. Studies show that having a routine source of care is a predictor of CRC test use in these populations (27,28), and several community interventions to increase CRC screening in uninsured patient populations have been successful (29–32). A study by Lairson et al used community health workers, video interventions, or both to increase awareness for colon cancer screening in low-income, uninsured Hispanic patients in El Paso, Texas. These interventions achieved screening rates between 75% and 87% compared with 10% in the comparison group (30). A program for uninsured patients in South Carolina found that FIT screening was more fiscally appropriate for a state's budget and also an effective choice compared with colonoscopy (29). Patients may experience barriers to access to care, such as lack of transportation, so mail-in FOBT can be used to promote screening in low-income populations (31). One of our contributing clinics in Florida has documented screening rates as high as 64% with the help of a dedicated gastroenterologist and a partnership with the Colon Cancer Alliance (32).

Our study has several limitations, including its retrospective nature and potential for selection bias. Other barriers to health care utilization may exist and may be differentially distributed in the uninsured population, so our study sample may not be representative of the uninsured population at large. Because the clinics operate independently and have different patient health recording methods, we could not collect and analyze certain data, such as diet and exercise. Study variables often contained large numbers of missing values, which could introduce bias beyond that which occurs with the collection of administrative data. Patients who received CRC screening had lower proportions of missing data on risk factors. Patient or provider knowledge of these risk factors may have increased the likelihood of CRC screening (ie, the presence of multiple risk factors was an apparent requisite for screening), and patients with CRC screening may have been more engaged with their primary care center in general. Another consideration is that although our original study focused on a spectrum of chronic diseases, our database did not capture the entire granularity of screening methods (eg, colonoscopy, FIT, FOBT) for CRC.

Nevertheless, our study is among the few that have reported the burden of risk factors and screening rates for CRC in FMCs in Florida (32). Overall, our study further elucidates the disparity of risk factors and CRC burden in the low-income and uninsured population. Because CHCs and FMCs are uniquely positioned to treat and care for this population, our findings should encourage the development of sustainable and cost-effective primary and secondary prevention strategies for this vulnerable group.

Conclusion

Low-income and uninsured patients of the free clinics in Tampa Bay are at a higher risk of developing CRC because of higher rates of predisposing comorbidities. Continued management of risk factors and increased screening efforts should be made for this vulnerable population. Subsidized screening, including FIT tests and colonoscopies, would strongly benefit these high-risk patients and increase the resources available at free clinics for such preventive measures.

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Tables

Table 1. Demographics of Uninsured Patients Serviced at 9 Free Clinics in Tampa Bay, Florida, 2016–2018[a]

Demographic Characteristic	All Patients (N = 5,139)	No CRC Screening (n = 4,798)	CRC Screening (n = 341)	*P* Value
Age, median, y (IQR)	58 (54–62)	58 (54–62)	58 (54–61)	.35
Sex				
Male	2,206 (43.2)	2,074 (43.6)	132 (38.7)	.09
Female	2,896 (56.8)	2,687 (56.4)	209 (61.3)	
Missing	37 (0)	37 (0)	0	
Race/ethnicity				
White	1,649 (41.1)	1,504 (40.6)	145 (47.1)	.04
Black	507 (12.6)	465 (12.5)	42 (13.6)	
Asian	194 (4.8)	183 (4.9)	11 (3.6)	
Hispanic, all races	1,639 (40.8)	1,533 (41.4)	106 (34.4)	
Other	26 (0.7)	22 (0.6)	4 (1.3)	
Missing	1,124 (0)	1,091 (0)	33 (0)	
Employment				
Employed	1,091 (45.1)	998 (44.4)	93 (54.4)	.01
Unemployed	1,327 (54.9)	1,249 (55.6)	78 (45.6)	
Missing	2,721 (0)	2,551 (0)	170 (0)	

Abbreviations: CRC, colorectal cancer: IQR, interquartile range (quartile 1–quartile 3).
[a] Values are no. (%) unless otherwise indicated.

Table 2. Clinical Colorectal Cancer Risk Factors of Uninsured Patients Serviced at 9 Free Clinics in Tampa Bay, Florida, 2016–2018[a]

Risk Factor	All Patients (N = 5,139)	No CRC Screening (n = 4,798)	CRC Screening (n = 341)	*P* Value
BMI, median, kg/m^2 (IQR)				
Sample	29.4 (25.4–34.2)	29.3 (25.4–34.2)	29.7 (25.6–34.4)	.94
Missing	1,546 (0)	1,527 (0)	19 (0)	
Smoking status				
Active	725 (22.7)	656 (22.6)	69 (23.0)	.09
Past	594 (18.6)	525 (18.1)	69 (23.0)	
Never	1,879 (58.8)	1,717 (59.2)	162 (54.0)	
Missing	1,941 (0)	1,900 (0)	41 (0)	
Alcohol consumption				
Active	771 (29.2)	663 (28.0)	108 (39.9)	<.001
Past	192 (7.3)	163 (6.9)	29 (10.7)	
Never	1,676 (63.5)	1,542 (65.1)	134 (49.4)	
Missing	2,500 (0)	2,430 (0)	70 (0)	
Chronic illness				
Diabetes	1,455 (28.3)	1,342 (28.0)	113 (33.1)	.047
Inflammatory bowel disease	23 (0.4)	17 (0.4)	6 (1.8)	<.001

Abbreviations: CRC, colorectal cancer; BMI, body mass index; IQR, interquartile range.
[a] Values are no. (%) unless otherwise indicated.

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GIS SNAPSHOTS

Visualizing Potential Effects of Dentist Retirements on Accessibility to Dental Care Among Children in Alabama, 2019

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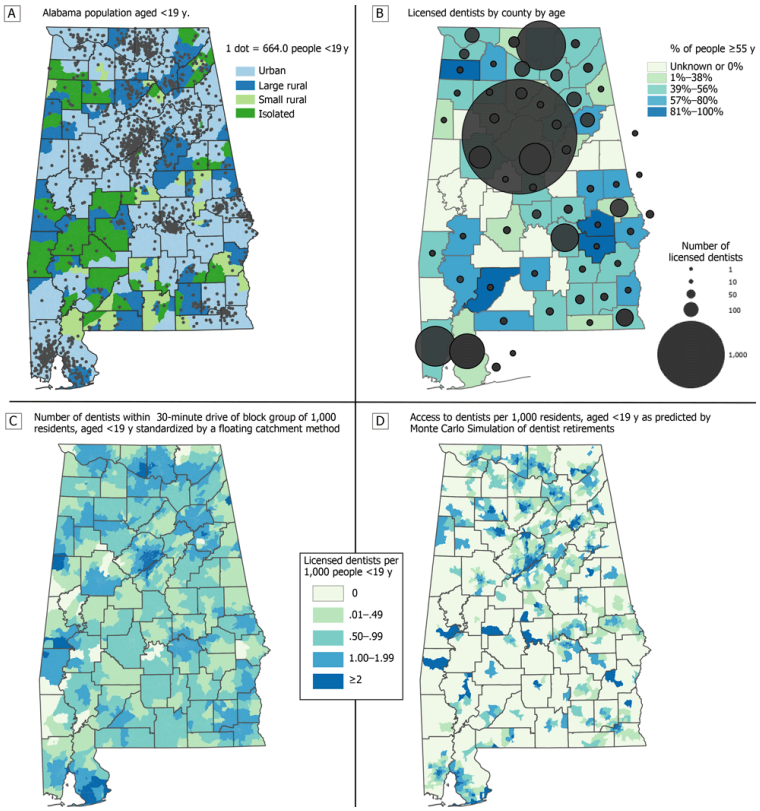

Four maps show the distribution of population and dentists in Alabama. Map A shows the distribution of the population aged 20 or younger; Map B, the distribution of licensed dentists by age across counties (counties with fewer than 3 dentists are not included); Map C, the number of dentists within a 30-minute drive of a block group of 1,000 residents aged 20 or younger, standardized by a floating catchment method; and Map D, shows access to dentists per 1,000 residents aged 20 or younger, as predicted by a Monte Carlo simulation of dentist retirements. Maps B and C include dentists' data at the latitude and longitude point-level. Sources: 2018 American Community Survey 5-Year Estimates (8), Alabama Board of Dental Examiners (9), Rural Health Research Center (13), ESRI StreetMap Premium ArcGIS Pro version 2.5.0 (Esri), Python version 3.4 (Jupyter Project), and NAD 1983 HARN StatePlane Alabama West FIPS 0102 (Esri).

Background

Regular dental visits can prevent dental problems (1,2). Under half of the US population aged 44 or younger is estimated to have untreated dental caries (3), and regular dental care during childhood can benefit oral health outcomes as an adult (2). Despite this evidence, access to dental care in the United States remains a challenge, especially among economically or socially marginalized groups (4). In 2018, only 230,490 of 736,103 (31.3%) beneficiaries under age 21 enrolled in Alabama's Medicaid program used dental services (5). A crucial, but often overlooked barrier to dental accessibility in the United States is the aging of the dental workforce. In 2016, an estimated 40% of US dentists were aged 55 or older compared with 27% in 2001 (6). Data suggest that more than half of Alabama dentists are aged 50 or older (7), which indicates that a large number are expected to retire in the near future, which could result in a shortage of dentists.

The objective of our analysis was 2-fold. First, we aimed to highlight access to dentists among Alabamians aged 20 or younger in the context of evaluating a dental network adequacy policy that promotes access to dental care for all people aged 20 or younger, living 30 minutes or less of driving time from a licensed dentist. We then used national dentist retirement rates to describe the implications of such retirements on access to dental care.

Data and methods

Our study focuses on dental accessibility among young Alabama residents (<21 y) where each block group (n = 3,437) population count of young residents, as recorded in American Community Survey 5-year estimates of the 2018 US Census (8), was represented as the geometric center of its respective block group. We define accessibility as geospatial proximity to a state-licensed dentist in relation to a person's home residence. The Alabama Board of Dental Examiners (9) provided 2020 data that was deidentified and geocoded at latitude and longitude point-levels. Statistics from the American Dental Association's Health Policy Institute (7) were used to estimate the likelihood of a dentist retiring in the upcoming year, based on the age provided in the dental provider data (10).

We used a 30-trial Monte Carlo simulation to simulate the effects of dentist retirements on access to dental care for residents aged 20 or younger. Similar to previous analyses (11), a 2-step floating catchment area method was employed to estimate accessibility to dentists in Alabama, and we used Monte Carlo methods to simulate future accessibility. We generated retirement scenarios that allowed us to assess the potential effect of dentist retirements on accessibility on the basis of the ages of currently practicing dentists and published retirement rates (10). Full systematic details on how this analysis was conducted with statistical formulas and Python code can be found at https://bit.ly/githubAccessBama.

Average differences and variances in accessibility estimates were observed in a simulation of dentist retirements to better understand differences in geospatial accessibility after accounting for the retirements. Comparisons of physical access to dental care by rurality augmented the retirement scenario. Rurality was operationalized by using the 2019 rural–urban commuting area codes from the Rural Health Research Center's 4-level categorization (Rural Health Research Center). Automobile travel times were generated by using ESRI Streetmap Premium 2019 (Esri). All analyses were generated with ArcGIS Pro 2.5.0 (Esri) and Python 3.4 (Jupyter Project) by using multiple libraries. We used the Kruskal–Wallis test to examine differences in accessibility scores by rurality. Although findings presented in this article reflect modeling assumptions (eg, applying a drive-time catchment threshold of 30 minutes) used by the American Dental Association in an earlier study (11), interactive maps with the ability to manipulate various assumptions are available on a Tableau Software public dashboard (Supplemental file at https://public.tableau.com/shared/23ZDYJ77R).

Highlights

The percentage of dentists who were likely to retire within the calendar year was 2.5% for those aged 34 or younger; 2.3%, 35 to 44; 4.0%, 45 to 54; 15.9%, 55 to 64; 40.9%, 65 to 74; 61.4%, 75 to 84; and 80.6%, 85 or older. On the basis of map analyses describing accessibility, we came to 3 conclusions. First, young people's access to dentists appeared to be higher in Alabama urban areas than in rural areas ($P < .001$) (Table). The average accessibility score of an urban census block was about 1.28 dentists per 1,000 young people compared with about 0.85 dentists per 1,000 youths in rural areas. Second, considering our simulation of dentist retirements, rural regions on average would be more affected by retirements than urban regions. Third, although the retirement of aging dentists appeared, potentially, to affect various areas of Alabama, the southwest corner of the state appeared to be the most vulnerable.

Observation of the Tableau software public dashboard suggested that modifying the travel time threshold to operationalize access had a greater effect on young people in urban areas than young people in the rural southwestern and lower-central regions of Alabama. The high density of dentists working in urban regions most likely accounts for this difference. Although we focused on the outflow of dentists, some studies suggest that dental school graduates are more likely to seek employment in urban areas than in rural areas (12), which suggests that our results would be more pronounced if we included inflow estimation rates. Our maps and

the online Tableau Software dashboard provide evidence that the potential retirement of aging dentists jeopardizes dental care access for young people in Alabama, especially those in rural areas. Stakeholders including the US Public Health Service (USPHS), the Alabama Medicaid Agency, and the Alabama Department of Public Health can utilize these preliminary findings to develop strategies for targeted investigations on possible clinical effects of this phenomenon. USPHS often provides incentives, such as scholarships and student loan forgiveness for enrolled clinicians willing to practice in underserved areas. The Alabama Medicaid Agency provides a significant amount of dental care to young people in Alabama, particularly those in rural areas where a large portion of citizens are enrolled in Medicaid.

Actions

Our study has limitations. First, only license information for dentists in Alabama were used in analyses. Young people in counties that border the neighboring states might choose to use the service of a dentist not licensed in Alabama. Our analyses, therefore, may have edge effect biases. Another limitation is that we focus on dentists retiring (outflow) and do not consider new dentists joining the workforce (inflow). We do this to provide a worst-case estimation of future dental care accessibility; however, future studies may also incorporate the inflow of dentists. Nonetheless, strengths in our analyses balance its limitations.

Our study is one of the few analyses in Alabama to assess the relationship between dentist age and access to dental care. To our knowledge, this is the first study to visualize the effect of dentist retirements on dental care accessibility, which has the potential to serve as a preliminary step in a planning management strategy for the allocation of dentists in areas of need. Institutions outside of Alabama can use our methods to estimate accessibility in their regions to examine the effects of key policy decisions before implementation.

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Table

Table. Potential Effects of Dentist Retirements on Children in Alabama: Descriptives and Accessibility Scores[b,c,d] by Rural Status[a]

Population	Urban	Large Rural	Small Rural	Isolated	Statewide
<20 y, n (%)	1,022,520 (78.5)	201,338 (15.5)	25,895 (2.0)	52,413 (4.0)	1,302,166 (100.0)
Block groups, n (%)	2,571 (74.8)	583 (17.0)	91 (2.6)	191 (5.6)	3,436 (100.0)
Percentile ranked baseline accessibility scores, providers per 1,000 population aged <18 y					
10th	0.46	0.44	0.32	0.25	0.43
25th	0.84	0.64	0.46	0.56	0.72
Median	1.28	0.80	0.64	0.77	1.12
75th	1.70	0.97	0.88	0.92	1.54
90th	2.24	1.42	1.09	1.32	2.11
Percentile ranked retirement simulated accessibility scores, providers per 1,000 population aged <18 y					
10th	0	0	0	0	0
25th	0.18	0	0	0	0.05
Median	0.71	0.70	0	0	0.66
75th	1.61	1.14	0.72	0.87	1.46
90th	2.58	1.90	1.26	1.79	2.41

[a] Rurality based on the Rural Health Research Center's 4-Level Categorization at https://depts.washington.edu/uwruca/ruca-maps.php.
[b] Baseline accessibility scores calculated using a 2-step floating catchment area.
[c] Simulated accessibility scores calculated using a 30-trial Monte Carlo simulation of a 2-step floating catchment area.
[d] Details on this analysis, including formulas and Python code can be found at https://bit.ly/githubAccessBama.

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ORIGINAL RESEARCH

Needs of Individuals Living With Hepatitis Delta Virus and Their Caregivers, 2016–2019

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Summary

What is already known on this topic?

Hepatitis delta virus (HDV) is a rare viral infection of the liver with potentially life-threatening consequences. Because of the rarity of the disease and a general lack of awareness, many patients may have gaps in critical disease-specific knowledge.

What is added by this report?

Little is known about the experiences of patients living with HDV. This qualitative study may be among the first to examine experiences of patients living with HDV and their caregivers to assess this population's unique needs and challenges to care.

What are the implications for public health practice?

Identifying challenges to care and needs of HDV patients and their caregivers may help improve provider and public health practitioners' ability to educate and care for this population.

Abstract

Introduction

Hepatitis delta virus (HDV) is a serious coinfection of the hepatitis B virus (HBV) that is estimated to affect between 48 to 72 million people worldwide. Data are limited on the informational needs of people living with HDV. The Hepatitis B Foundation, a US-based nonprofit organization that provides support to people living with HBV and HDV, receives emails (queries) as part of a helpline, a service to provide information, resources, and support to people affected by HBV and HDV.

Methods

Query content was analyzed to assess the impact of HDV at the individual level. A total of 65 HDV-related queries from 17 countries were received from October 2016 to January 2019, and all were analyzed for this study.

Results

Thematic analysis of queries indicated 4 dominant themes. Three were related to a need for information about 1) the disease and prevention of it, 2) disease symptoms and outcomes, and 3) treatment options. The fourth theme was related to barriers and quality of life. Individuals requested information on treatment options, medication access, diagnostic test interpretation, and clinical trials.

Conclusion

Our study highlights the needs and lived experience of patients with HDV and summarizes critical information gaps. Findings can inform health care providers, public health professionals, and the pharmaceutical and biotechnology industries about the informational needs and lived experiences of individuals living with HDV and help create future HDV-related educational resources, care, and clinical trials.

Introduction

Viral hepatitis accounts for an estimated 1.34 million deaths worldwide per year. Since 1990, viral hepatitis mortality has increased by 63%, and in 2017, hepatitis was the seventh leading cause of death in the world (1–4). Hepatitis delta virus (HDV) is a serious coinfection of HBV that is estimated to affect between 48 and 72 million people (13%–14.5%) (5–7) of the 292 million people living with chronic hepatitis B (CHB) worldwide (8).

Available data suggest that HBV–HDV coinfection is most prevalent in Central Asia, Eastern Europe, Central Latin America, and West and Central Africa (5–7). People most at risk for HBV–HDV coinfection are likely to be living in or have emigrated from these regions, have a history of intravenous drug use, are men who have

sex with men, have HIV or hepatitis C virus (HCV), or have multiple sex partners (9,10). The rates of coinfection with HDV range from more than 10% to as high as 70% in countries in Africa, Asia, and parts of South America (11). In industrialized countries, such as Germany, England, and France, studies have shown recent increases in HDV prevalence (12,13). Epidemiologic and clinical research on HDV is sparse, contributing to an incomplete understanding of the actual disease burden, low global testing rates, and lack of effective treatments (12–14). Only people who already have CHB, or people who contract HBV and HDV through simultaneous exposure, can become infected (14), creating a defined risk group. Despite these factors, awareness among patients and providers is low, and treatment of HDV is far behind medical advancements for HBV and HCV (15,16).

No US Food and Drug Administration–approved treatment of HDV exists, and the only somewhat effective treatment is pegylated interferon, with only 25% to 30% of patients able to control the virus with weekly injections administered for at least 1 year (17,18). When coinfection is poorly controlled, patients are 3 times as likely to develop cirrhosis and liver cancer, compared with HBV infection alone. Approximately 70% to 90% of coinfected patients develop cirrhosis within 5 to 10 years (19–22). Despite its discovery more than 40 years ago, knowledge of HDV is limited, and little is known about the informational needs and experiences of people living with HDV.

Methods

We analyzed HDV-related email queries sent to the Hepatitis B Foundation, a US-based nonprofit organization, from October 2016 through January 2019 to identify information gaps and understand the lived experience of patients with HDV. The nonprofit organization receives queries as part of a free helpline, a service to provide information, resources, and support to people affected by HBV–HDV coinfection. The helpline is run by trained community health education specialists who are knowledgeable about HBV and HBV–HDV coinfection, and it provides patients with general guidance, disease information, and referrals to physicians or other health care providers.

All HDV-related queries received over 28 months were collected and de-identified by a trained researcher (S.P.). Queries that initially were not in English (n = 2) were translated using an online translation tool. Codes were developed in 2 ways: a priori (informed by the literature) and through line-by-line reading of a subsample of queries. Each code was given an explicit definition to ensure coding accuracy and improve intercoder reliability (23,24). Coding was performed by using NVivo12 software (QRS International), and all data were independently coded by 2 members of the research team (S.F., P.K.). Intercoder reliability was assessed by using the κ coefficient to identify coding discrepancies. The analysis team met (P.K., S.F., C.F., R.F.) throughout the coding process to discuss and resolve coding discrepancies until an acceptable final κ was achieved. Three of 19 codes had a mean κ of less than 0.75. These codes were examined in more detail by the analysis team so that coding discrepancies could be resolved, and κ scores were recalculated. This study was approved by the Heartland institutional review board and acknowledged by the Thomas Jefferson University institutional review board.

Results

A total of 65 HDV-related queries were received from October 2016 to September 2019 and were included in this analysis. Most queries were from Romania (n = 11, 16.9%), Pakistan (n =10, 15.4%), and the United States (n = 9, 13.8%) (Table). Just over half of individuals identified themselves within the queries; of these, 31% self-identified as living with HBV–HDV coinfection (n = 20), and the remainder reported being caregivers, family, or friends of those with HDV (n = 10, 15%) or providers (n = 4, 6%). The mean adjusted final κ was 0.91 (range, 0.78–1.00), corresponding to near perfect intercoder agreement. Thematic analysis of queries identified 4 dominant themes, 3 related to a need for information about 1) the disease and its prevention, 2) disease symptoms and outcomes, and 3) treatment options.

Need for information on HDV diagnosis and prevention

People living with HDV and their family, friends, and caregivers often had questions about a new diagnosis of HDV, explicitly conveying questions about how to interpret diagnostic laboratory findings. For instance, one individual was unsure whether HDV-positive results meant a worsening or spread of an existing disease (HBV) or was a new infection. An example of this theme came from the following query: “I tested positive for HBV in 2012, and all I was told is that it would clear. No medication was prescribed. Yesterday I went for another test and was told that [it is] HDV. . . I do not understand what this means. [Is] this a new infection, or the disease is spreading?” After being diagnosed with both HBV and HDV, one patient wondered why their hepatitis results had drastically changed, despite being on medications, and asked for clarification of these results: “I have been on peg-Interferon for 12 weeks and Baraclude for 1 year. Now my enzymes are sky high, but my HBsAg has dropped to 26,000. At the same time, [my] HBV viral load has increased significantly. My question is, why has my viral load increased?”

Individuals receiving an initial diagnosis of HDV tended to have general questions about the disease. These questions asked either

for advice on immediate next steps to take (eg, "What do I need to do?") or for clarification about an HDV diagnosis (eg, "What [is] the meaning of delta virus?") After receiving a diagnosis of HDV from their physician, another patient was notified of the rarity of the disease and re-emphasized the need for more information (eg, "Do you know of people with both hep B and D [and basal core mutation] or have any information on this?") Patients and family members of those with HDV also had concerns about disease transmission. One query asked about how HDV was contracted in order to avoid the disease. Other patients and family members had questions about specific modes of disease transmission. For instance, another individual, the fiancé of someone living with HDV, had concerns about sexual transmission. This individual described, "My fiancé has just been presently diagnosed with hepatitis D infection. Am I safe or at risk of infection after sex/intimacy with him? Please, I need clarification." Those living with HDV and family members wanted additional information about how to prevent HDV ("Please, how is hep D contracted and [what are] ways to avoid contracting the virus?") or expressed confusion about an HBV–HDV diagnosis, despite taking preventive measures. "I kindly need [some] help to figure this [out,] as [I] am not sure why [I] was negative . . . got the preventive shots and all of a sudden now the results are showing positive as in having a chronic hep B infection." A pregnant woman worried about transmission to her newborn and asked for methods to prevent potential harm from the disease for her child: "We're expecting a baby in a month's time. What can I do to protect the baby?"

Understanding disease symptoms and outcomes

Patients with HDV described concerns about the risk of liver cancer or liver damage due to the disease. Sometimes patients asked about mechanisms through which HDV increased liver damage (eg, "I would like to know how hepatitis D [coinfection] comes about increasing the severity of the liver condition") or shared information about newly diagnosed liver damage that surprised them. One participant stated, "I have what I've been told is a rare situation. Early this year tests came back that I had cirrhosis and another hepatitis, hep D (delta), along with the hep B, plus a basal core mutation, making me at high risk for liver cancer." Often, patients and family members were curious about specific symptoms and wondered whether these could be attributed to HDV or other causes. "I have chronic hepatitis B and also 'have' hepatitis D (delta). I have multiple symptoms (abdominal pain, back pain, nausea, etc) that may or may not be related to my hepatitis. . . . We've been trying to determine the cause of my symptoms for years, thus if you happen to have any information on the above or are able to point me to where I can get more info, that would be greatly appreciated."

Treatment options

The need for clinical trials was the most salient aspect of "Treatment Options" and represented 16.9% (n = 11) of all queries that were included (N = 65). Patients and caregivers in many countries wanted to know about the availability of clinical trials in their own country and asked for information on how to register for and participate in these trials. One individual asked, "Is there [an] open phase 3 hepatitis delta clinical trial? Could you tell me how to register to participate?"

Patients also showed interest in finding curative treatments for HDV, especially when faced with a new diagnosis of the disease. "I have had hepatitis B for nearly 10 years and recently found out that I also have hepatitis D. I can't say I am feeling well. Isn't there any cure found for these?" Queries contained a variety of questions on medication, including recommendations for the newest and best medications, medication availability in certain countries, and advice on current medication regimens. The following is an excerpt from a query about the best medication recommendations after a patient was given a diagnosis of HDV.

"[Could] you please help me to find or recommend [to] me any latest best medication for this diagnosis?" Patients and family members of those with HDV were also very interested in treatment options. Questions included whether there were any treatments for HDV and what new treatments were available. "My mom is suffering from Hepatitis Delta. Is there any treatment for that virus?"

When faced with a new diagnosis of HDV, patients asked whether there were any lifestyle modifications they could make to improve the quality of life with the disease or discussed lifestyle modifications they had already implemented. These lifestyle modifications were often made in conjunction with medications and included eating healthy and abstaining from certain habits, such as smoking and drinking. "Right now, I take only those medicines, I try to eat healthy and I try to rest how much I can. I don't drink alcohol and I don't smoke. Should I do other things?"

In addition to Western medicine or treatment modalities, some patients opted to try alternative therapies for their HBV–HDV, which included herbal or plant-based supplements. Patients using herbal or "natural" treatments often used these in conjunction with Western medications and reported using herbal treatments after they had tried other treatment options. "After I searched other treatment for my diseases, I discovered a clinic with natural drugs: SECOM. I was there and the doctor gave me a personal treatment. After 2 months taking these, ALT has normal value and AST is bigger with only 11 units."

Barriers to care and quality of life

Patients and caregivers or other family members sometimes noted different barriers to adequate care, including poverty, access to doctors or medication, or language barriers. Poverty was the most commonly noted reason for requesting help and more information. One individual described, "I need your help because [I] belong to a [low-income] family." People living with HDV and their family members often felt worried, shocked, scared, and uncertain after receiving a diagnosis of HDV. One person living with HDV was very worried and expressed explicit concerns about how long they could live with the disease, stating, "I just found out that I have hepatitis B and D together. . . . How long can I live? What should I do? [Please], help me! I'm so scared."

Discussion

Qualitative analysis of queries received by the Hepatitis B Foundation indicated that people living with HDV and their family members had considerable concerns and the need for information that were related to 4 distinct thematic categories: 1) disease knowledge and prevention, 2) disease symptoms and outcomes, 3) treatment options, and 4) barriers and quality of life. People living with HDV and their family members and friends requested information on treatment options, medication access, diagnostic test interpretation, and availability of clinical trials. Questions about the availability of clinical trials and how to register for such trials was the most common topic among all queries.

To our knowledge, this study is the only one that qualitatively examines the experiences and needs of people living with HDV and their family members to assess needs and barriers in this population. Prior studies have used qualitative methods to explore various HBV patient experiences, including initial responses to disease, stigma associated with the disease, stress and anxiety about one's health, and concerns about premature death (25–30), but to our knowledge none have examined the impact of HBV–HDV coinfection. This study showed similar sentiments and family members expressed worry about loved ones with HDV, which often manifested in searches for treatment options. People who received an initial diagnosis of HDV also expressed fear and anxiety, which was reflected in concerns about lifespan with the disease and confusion about the diagnosis. Despite these similarities, HDV patient experiences may be unique from those with HBV, HCV, or both because of the rareness of the condition and a lack of disease awareness among the general public. Future research should examine the differences between HDV patient experiences compared with HCV and HBV patient experiences.

Another notable commonality between this study's findings and those of others is the lack of disease knowledge and lack of knowledge of treatment and screening options for viral hepatitis (27,29,31). People who sent queries about HDV had little knowledge of HDV but showed interest in furthering their knowledge, especially with regard to treatments and clinical trial research. These findings indicate the need for improved efforts to educate people who are diagnosed with HDV about their disease with the goal of increasing patient and caregiver knowledge. More knowledge about the disease among people living with HBV increases patient acceptance of disease and self-efficacy in disease management (29), which, based on our findings, could also be the case for those living with HDV. Future research should explore the relationship between HDV disease knowledge and patient self-efficacy in disease management.

Most qualitative literature about people living with viral hepatitis focuses on varied aspects of HBV and HCV patient experiences, in particular, the stigma associated with the disease, lack of disease knowledge, poor quality of life, and the complex emotions associated with having the disease. None of the queries we analyzed contained questions or content that referred to stigma or discrimination associated with HDV, possibly because patients had more immediate concerns about managing their health condition. No qualitative study has explored the needs and barriers of HDV patients, who may face more urgent needs related to treating and controlling disease progression (26,32), so more research is needed to understand stigma in the context of HDV.

In our study, people affected by HDV needed information about types of treatment options available to them, medication access, diagnostic test interpretation, and availability and location of clinical trials, the latter being the most common topic of all queries. These questions suggest that individuals with HDV may have challenges accessing medication, physicians with adequate knowledge about the disease, and clinical trials, and more work is needed to fully understand these challenges. Our findings also suggest that the subset of individuals who emailed queries specifically related to treatment may have already done online research about HDV before sending an email query. For example, many individuals who inquired about clinical trials mentioned hepatitis-specific medications and prepared detailed questions about interpretations of laboratory test results.

Results of this study emphasize the importance of targeted, patient-centered education for patients with HDV, and future education should focus on clarifying laboratory results, treatment options, medication access, and clinical trial resources for this population. Given the complex set of emotional, medical, and lifestyle factors that affect patients with HDV, materials should also be delivered accessibly and at the appropriate level of health literacy for those affected. Globally, patients with HBV–HDV coinfection may be more likely to be from more rural, isolated, or lower-

income countries. Providers, especially those managing patients with HBV–HDV coinfection (primarily hepatologists), and public health professionals have a critical role in disseminating this information to patients because of their disease-specific knowledge and areas of expertise.

Strengths and limitations

Our sample was people with HDV who sent email queries to a nonprofit helpline, so it may not be representative of the larger HDV-affected population. The queries analyzed in this study were limited to those received by the Hepatitis B Foundation. Many queries were from the United States, an industrialized country with a known lower incidence of HDV but with higher awareness. Because the Hepatitis B Foundation is US-based, Americans living with HDV and their caregivers may be more familiar with the foundation's work and have more access to their resources, so our results are subject to regional bias.

Our data consisted only of email queries and did not include other forms of correspondence, such as in-person visits or queries received via mail, telephone, or social media platforms, so our sample may be less representative of the total population of patients with HDV. However, telephone calls to the Hepatitis B Foundation, are not recorded, so the ability to obtain these data was limited. Email queries were chosen for this analysis as the initial stage of this research. In the future, we hope to expand on this research to explore queries sent via social media platforms, including Instagram, Facebook, and Twitter. We expect that concerns will be similar to those of people using email. The sole use of email-based correspondence also may have affected sample representativeness because it limits the sample to people who have access to working internet (or electricity) and email accounts. Given the distribution of HDV in industrialized countries in Asia and Africa, many HDV patients may tend to live in less resource-rich environments. Our sample may not be representative of the larger HDV-affected population.

Conclusion

This qualitative research indicated knowledge gaps among patients with HDV related to disease prevention, transmission risk to close family members, disease symptoms and long-term outcomes, and treatment options as well as barriers to care and overall quality of life. Our findings expand on the needs and barriers of individuals directly affected by HDV. A summary of these queries will be shared with providers who treat patients with HDV to help them expand their knowledge and understanding of the needs of their patients and their caregivers, and the data will be used to create more resources tailored to meet the unique needs of people living with HDV. Our findings may also be used to better understand the information needs, challenges, and quality of life implications of patients with HDV to inform clinical trial designs and the development of new treatments. Like other chronic viral hepatitis patients, those affected by HDV need more education on certain aspects of their disease. Although our findings are not representative of the larger HDV global population, we believe that they support the claim of a larger knowledge gap that exists surrounding HDV. Because people living with HDV and their family members tended to need more information on treatment options, medication access, diagnostic test interpretation, and clinical trials, providers and public health organizations therefore have the most crucial role in educating people with HDV and their families. Ultimately, targeted education interventions for this patient population are important because they can improve self-efficacy in disease management and overall quality of life. Future research is needed to fully understand the impact HDV has on the lives of people who are affected, and the knowledge gained from this research will help guide future research projects and outreach initiatives for those affected by HDV. We hope our findings can help educate providers, public health professionals, and the pharmaceutical and biotechnology industries on the needs of individuals living with HDV, so we can collectively address them.

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Table

Table. Frequency of HDV-Related Queries (N = 65) to the Hepatitis B Foundation[a], by Country (n = 17), 2016–2019

Country	Query Frequency (%) (n = 65)
Romania	11 (16.9)
Pakistan	10 (15.4)
United States	9 (13.8)
Mongolia	4 (6.2)
Uzbekistan	3 (4.6)
Brazil	2 (3.1)
Ghana	2 (3.1)
Egypt	1 (1.5)
Finland	1 (1.5)
Germany	1 (1.5)
India	1 (1.5)
Kenya	1 (1.5)
Mauritania	1 (1.5)
Netherlands	1 (1.5)
Singapore	1 (1.5)
Spain	1 (1.5)
Uganda	1 (1.5)

Abbreviation: HDV, hepatitis delta virus.
[a] The Hepatitis B Foundation is a US-based nonprofit organization.

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GIS SNAPSHOTS

A Comparison of Community Resources for Chinese Immigrants Across Philadelphia Neighborhoods

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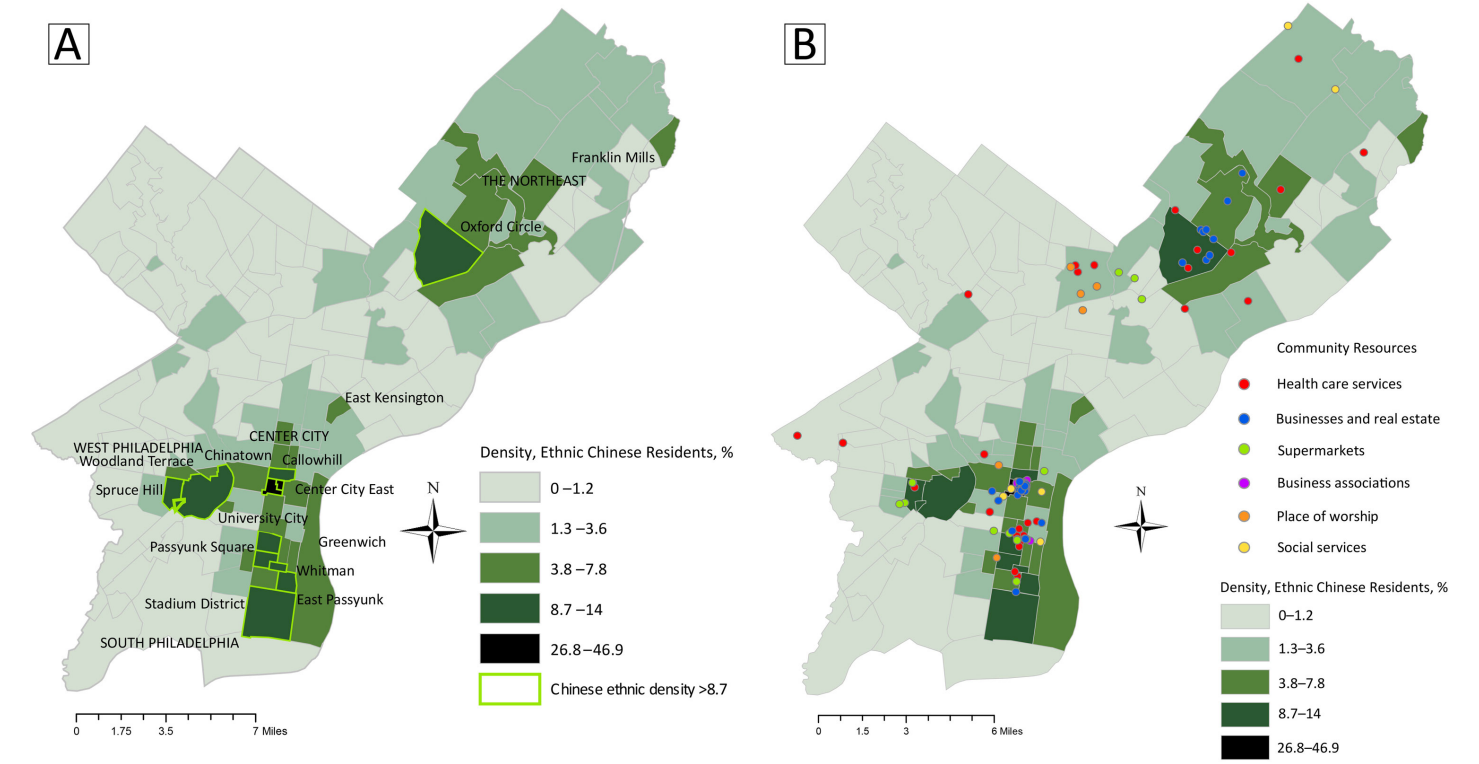

Distribution of neighborhoods and services in Philadelphia, Pennsylvania, by density of ethnic Chinese residents, from 2014–2018 estimates. Map A shows percentages by neighborhood, highlighting those with a density of 8.7% or more. Map B shows locations of 6 types of community resources for Chinese residents overlaid on Map A to illustrate resource distribution in relation to population density. Geographic proximity of resources corresponds overall to neighborhood density of Chinese residents. However, not all types of resources are equally distributed, indicating they are unavailable to residents of some neighborhoods. Data sources: Chinese demographic data are from the American Community Survey 2018 (5-Year Estimates), prepared by Social Explorer (1). Boundaries for Philadelphia neighborhoods data are from OpenDataPhilly, developed by Azavea Inc (2). Community resource data are from the Chinese *Philadelphia Yellow Pages* (3).

Background

Chinese immigrants are the third-largest non-US–born population in the US (4). Although these immigrants have lower rates of obesity and obesity-related conditions than people of other races/ethnicities, such health advantages decrease with increasing length of US residence (5,6). This increased risk for chronic disease has been attributed primarily to acculturation to Western lifestyle norms; however, trajectories may vary depending on the environment in which immigrants reside (7). Ethnic enclaves are ethnically, spatially, and socially distinctive communities with sizable immigrant populations that have been shown to promote well-being with their concentration of health-related, cultural, and social resources (8). Such resources include health care providers and retail food stores that share their language and culture, and gathering spaces for social interactions, such as churches (9,10). Research among elderly immigrants has shown that the incorporation of Chinese cultural symbols in the physical spaces they inhabit increases immigrants' sense of belonging (11). Access to cultural resources, such as places of worship and schools, may also yield tangible health benefits over time (12). The interpersonal connections, social networks, and sense of cohesion and belonging fostered in environments that are socially and culturally resource-rich may increase Chinese residents' social capital, which has been associated with a wide range of positive health outcomes, including reduced risk for chronic disease (10,13).

The Philadelphia metropolitan area is among the top 10 destinations for Chinese immigrants to the US. Of the approximately 37,000 ethnic Chinese people who resided in Philadelphia according to 2014–2018 estimates, 60% were non-US–born (1). The availability and locations of various types of community resources in neighborhoods of high ethnic Chinese density could help direct immigrants toward the resources they need and help determine where resources are still needed. However, such information is largely unavailable. As part of a study of Chinese immigrants residing in Philadelphia, we mapped the spatial distribution of 8 types of health-related Chinese community resources, overlayed on the density of Chinese residents in neighborhoods across the city. Our objective was to show the relative proximity of such resources to the neighborhoods with high concentrations of ethnic Chinese residents and areas with high density but few resources.

Data and Methods

To identify community resources for the largely non-US–born Chinese population residing in Philadelphia, we used the most current online Chinese version of the *Philadelphia Yellow Pages* (3). We further investigated these resources by using Google searches to verify that they targeted Chinese clients through Chinese-language advertising or other information. We then categorized each as one of 6 types of resources: primary health care provider (n = 46) (ie, family medicine, internal medicine, pediatrics, Chinese medicine, dentistry), places of worship (n = 14), business and cultural associations (n = 16), supermarkets (n = 29), other businesses (n = 43) (ie, accounting, insurance, banks, real estate), or other services (n = 10) (ie, employment, funeral, English language, education). The address of each resource was geocoded and color-coded, then mapped as a layer in ArcGIS 10.8 (ESRI). Each resource map was then overlaid on a map showing neighborhoods by density of ethnic Chinese residents.

We defined geospatial neighborhood boundaries by using a web map (2) of Philadelphia neighborhoods. We used 2018 American Community Survey 5-year estimates to calculate census tract–level density of ethnic Chinese residents as the number of people of Chinese origin, excluding Taiwanese people, divided by the total population of the census tract (1). The census tract–level data were aggregated within neighborhood boundaries according to the proportion of their spatial areas that fell within the boundaries. For example, a census tract that fell completely within a given neighborhood was included in its entirety, but for a census tract that fell only halfway within a given neighborhood, only 50% of its population was included. We categorized ethnic Chinese density in 5 ranges (0%–1.2%, 1.3%–3.6%, 3.8%–7.8%, 8.7%–14.0%, and 26.8%–46.8%) by using the Jenks method, which identified natural breaks in the distribution of ethnic density. We used a grayscale to illustrate the levels of ethnic density. We designated neighborhoods in the top 2 categories (>8.7%) as having high ethnic Chinese density.

Highlights

Across 157 Philadelphia neighborhoods, 3 contiguous neighborhoods in Center City had the highest concentrations of ethnic Chinese residents: Chinatown, 46.9%; Center City East, 26.8%; and Callowhill, 14.0%. They were followed by 3 clusters of adjacent neighborhoods: South Philadelphia (Greenwich, 13.4%; Passyunk Square, 12.7%; East Passyunk, 12.0%; Stadium District, 9.9%; Whitman, 9.1%), West Philadelphia (Spruce Hill, 11.1%; University City, 9.1%; Woodland Terrace, 8.7%), and the Northeast (Oxford Circle, 10.1%). Community resources were heavily concentrated in these 4 areas. In particular, of the 158 resources that we mapped, 76 (48.1%) were located in the 3 Center City neighborhoods centered on Chinatown — mostly supermarkets, businesses, and business and cultural associations. These 3 Center City neighborhoods were the only ones that also contained all 6 resource types, primarily because 15 of the 16 business and cultural associations were located in these neighborhoods.

Chinese-speaking health care providers, although concentrated in Chinatown and near South Philadelphia, were widely distributed

across the city, even in areas of low ethnic Chinese density. In contrast, businesses were concentrated in Center City, South Philadelphia, and Oxford Circle, although Oxford Circle did not have supermarkets. The West and South Philadelphia neighborhoods and Oxford Circle had fewer places of worship; places of worship in the Northeast were located in the neighborhood of Olney, which is southwest of Oxford Circle. The neighborhoods of Franklin Mills and East Kensington lacked any resources despite their relatively high ethnic density (7.5% and 7.4%, respectively).

Action

Our maps have 2 primary implications for preventing chronic disease among Chinese immigrants. First, they help identify neighborhoods of high ethnic Chinese density with few nearby culture-specific resources, and they highlight the specific types of resources that are lacking. As such, the maps can complement needs assessments targeting neighborhoods with Chinese immigrants to determine the types of resources that might be fostered in these areas. In turn, needs assessments can inform future iterations of these maps by incorporating additional types of resources and ways to categorize these resources. Second, the maps inform Chinese immigrants in these areas who might not be aware of the full range of social and cultural resources in the city beyond their immediate neighborhoods.

These maps also suggest that Chinese immigrants do not limit themselves to the resources in their immediate residential environment. This idea of "heterolocality" (14) points to the importance of studying how immigrants navigate their environments to meet their social and cultural needs and preferences.

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