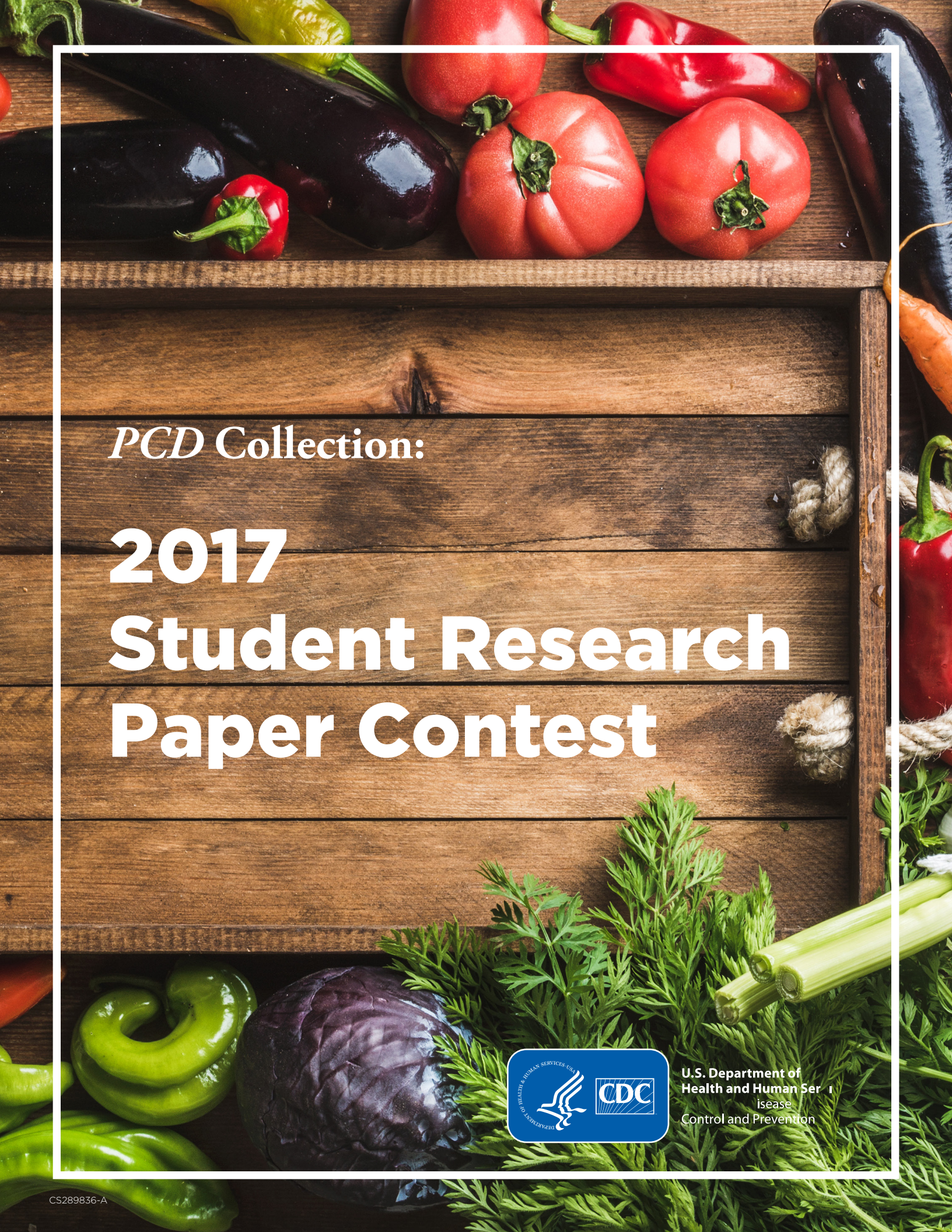

PCD Collection:

2017 Student Research Paper Contest

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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 proven and promising public health findings, innovations, and practices with editorial content respected for its integrity and relevance to chronic disease prevention.

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PREVENTING CHRONIC DISEASE
PUBLIC HEALTH RESEARCH, PRACTICE, AND POLICY

COLLECTION: PCD 2017 STUDENT RESEARCH PAPER CONTEST

EDITORIAL

Shaping Future Generations of Public Health Researchers: *Preventing Chronic Disease*'s Student Research Paper Contest

Leonard Jack Jr, PhD, MSc

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Compañeros: High School Students Mentor Middle School Students to Address Obesity Among Hispanic Adolescents

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Early Onset Obesity and Risk of Metabolic Syndrome Among Chilean Adolescents

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PREVENTING CHRONIC DISEASE
PUBLIC HEALTH RESEARCH, PRACTICE, AND POLICY
Volume 14, E96 OCTOBER 2017

COMMENTARY

Shaping Future Generations of Public Health Researchers: *Preventing Chronic Disease*'s Student Research Paper Contest

Leonard Jack Jr, PhD, MSc

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Leonard Jack, Jr, PhD, MSc, Editor in Chief

Preventing Chronic Disease (*PCD*) is committed to providing opportunities for future generations of researchers to contribute to public health and develop critical writing and reviewing skills. Since its introduction in 2011, *PCD*'s Student Research Paper Contest has been a success; each year the journal receives manuscripts prepared by students from around the world, and the number of entries continues to increase. This year, *PCD* set a record of 72 student submissions. With so many entries, we decided that the only fair way to judge the submissions would be to establish 4 winning categories by level of education: high school, undergraduate, graduate, and doctoral. This year's submissions addressed a range of topics related to the screening, surveillance, and use of population-based approaches to prevent and control chronic diseases and focused on such health conditions as arthritis, asthma, cancer, diabetes, cardiovascular health, obesity, depression, and others.

Goals of the *PCD* Student Research Paper Contest

There are 5 primary goals of *PCD*'s Student Research Paper Contest:

- Provide students with an opportunity to become familiar with a journal's manuscript submission requirements and peer-review process
- Assist students to connect their knowledge and training on conducting quality research with a journal's publication expectations
- Develop students' research and scientific writing skills to become producers of knowledge rather than just consumers of knowledge
- Provide students with an opportunity to become a first author on a peer-reviewed article
- Promote supportive, respectful, and mutually beneficial student–mentor relationships that strengthen students' ability to generate and submit scholarly manuscripts throughout their professional career

Developing Critical Skills in Research and Scholarly Publishing

Conducting sound research and summarizing findings for a scholarly publication requires patience, resilience, sound ethical judgement, and scientific writing skills that meet a journal's high standards. *PCD* recognizes that this process can be both an exciting and

an anxiety-producing experience for student authors. *PCD* provides guidance and support through every stage of the publication process to help student authors gain experience and confidence. *PCD*'s website offers comprehensive guidance to authors in preparing manuscripts for submission, including helpful submission checklists, detailed descriptions of various article types and requirements, and guidelines on structuring abstracts and creating tables and figures from the *AMA Manual of Style: A Guide for Authors and Editors, 10th Edition* (1).

The contest also helps students during the early stages of their academic career in working with colleagues and responding to critique. In preparing their manuscripts, students have an opportunity to work with mentors to explore the public health landscape and identify original ideas that contribute to public health. The peer-review process student manuscripts undergo at *PCD* allows students to talk about appropriate ways to respond professionally to feedback. Novice authors can be discouraged by negative feedback, but through the peer review and revision process students learn the value of feedback in strengthening their arguments, clarifying their narrative story, and gaining knowledge and insight from peer reviewers who are subject matter experts in their field.

Another key aspect of the contest is helping students gain a greater understanding of the ethical parameters of peer-reviewed research, so that they develop good judgement in presenting and interpreting data. Students work with their mentors to better understand what it means to execute sound ethical judgement. *PCD* encourages and facilitates these conversations by providing guidance from the American Medical Association, the International Committee of Medical Journal Editors, and the Committee on Publication Ethics on topics such as duplicate publication, definitions of authorship, conflicts of interest, copyright and permissions, institutional review board approval, differences between honest scientific errors and research misconduct, and a detailed understanding of a peer-reviewed journal's process for responding to allegations of possible misconduct.

And finally, every stage of *PCD*'s Student Research Paper Contest requires students to take responsibility in responding to deadlines. Students must submit their manuscript to *PCD* on or before the due date, respond to feedback from peer reviewers and the editor in chief, and work with *PCD*'s experienced staff of technical editors through all stages of editing and production. Manuscripts may undergo multiple rewrites as students respond to comments and suggestions related to the strengths and weaknesses of their study, statistical tests used, presentation of data in tables and figures, accuracy of data analyses, and implication of the study's findings on public health research and practice. In advancing through these stages and meeting these deadlines, students develop two of the most critical skills of successful public health professionals: patience and persistence.

Contest Categories and Stages of Review

This year's winners in the high school, undergraduate, graduate, and doctoral categories should be commended for demonstrating maturity and professionalism throughout this comprehensive and intense manuscript submission and review process. *PCD*'s student papers progress through 6 stages. First, the editorial office screens entries to determine whether they meet contest requirements. In the second stage, the editor in chief reviews the entries to determine whether they align with the journal's mission and vision and are of high enough quality to advance to the third stage. In the third stage, members of the *PCD* editorial board identify which submissions should be considered as potential winners for the various categories. Submissions not advancing as potential winners are assigned to *PCD*'s standard peer-review process, so that those students still have an opportunity for publication. In the fourth stage, the editorial board conducts a comprehensive review of a few selected manuscripts and provides feedback to the student contestants, who then must address the feedback and submit a revised manuscript. In the fifth stage, the editorial board assesses the revised manuscripts to identify which should be selected as the winner in each category. Editorial board members must provide strong justifications to support their selections to the editor in chief, who makes the final decision. The sixth and final stage is notifying authors of winners. In addition to having an article published, winning authors are featured through a *PCD* podcast, "*PCD* Sound Bites," to discuss key aspects of their research. *PCD* also mentors winners by providing an opportunity for them to become a reviewer and serve on a selection panel for the next year's contest.

2017 *PCD* Student Research Paper Contest Winners

PCD identified 5 winners in the 2017 Student Research Paper Contest. Two entries were selected as winners in the doctoral category. In one, Pacheco and colleagues conducted a study that followed a cohort of 673 participants in Chile from infancy to adolescence to understand the association between early obesity and risk of metabolic syndrome in adolescence (2). Researchers found that the age of onset of obesity is a strong risk factor for metabolic syndrome. In the other winning entry, Arlinghaus and colleagues conducted a 6-month obesity program for Hispanic middle school students in Houston, Texas, to determine the feasibility of using high

school students as trained peer health mentors called *compañeros* to promote and sustain reductions in body mass index (3). Researchers found that the use of *compañeros* was a promising approach in helping Hispanic children achieve healthier body weight.

The winning entry in the graduate category, by Mendoza-Herrera and colleagues, described the development of a diabetic retinopathy screening tool based on a predictive model for use among low-income adults in Mexico (4). Researchers collected biomedical, clinical, anthropometric, and sociodemographic data from 1,000 low-income adults with diabetes. Four risk factors predicted diabetic retinopathy: time since diabetes diagnosis, hyperglycemia, systolic hypertension, and physical inactivity.

The winning entry in the undergraduate category, by Smurthwaite and Nasser, explored the geographic convergence of chronic conditions at the neighborhood level (5). The study used a cross-sectional design to estimate the prevalence of obesity, cardiovascular disease, and type 2 diabetes in western Adelaide, Australia. The authors used Moran's *I* method to identify significant clusters of these 3 chronic conditions and observed diverse spatial variation in their prevalence.

PCD is delighted to have its first winner in the high school category. Liu and colleagues conducted a social marketing campaign that used environmental prompts to influence purchases of fruits and vegetables (6). The social marketing campaign was implemented and evaluated in 17 grocery stores during 4 months in 5 rural counties in Kentucky. By using surveys collected from 240 participants, the authors found that recipe cards influenced participants' desire to purchase fruits and vegetables.

Parting Thoughts

Students and mentors submitting manuscripts in this year's Student Research Paper Contest — regardless of whether their entry was selected as a winner — should be proud of their efforts. Student authors of manuscripts not accepted for publication in *PCD* were encouraged to seek consideration elsewhere. *PCD* has just announced the call for student research papers for its 2018 contest. Please see our Announcements page (www.cdc.gov/pcd/announcements.htm) for more information. *PCD*'s Student Research Paper Contest has proven to be a well-received scientific writing experience. We ask *PCD* readers to encourage students to consider submitting a manuscript for consideration in next year's contest.

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WINNING STUDENT PAPERS

PREVENTING CHRONIC DISEASE
PUBLIC HEALTH RESEARCH, PRACTICE, AND POLICY
Volume 14, E92 OCTOBER 2017

ORIGINAL RESEARCH

Compañeros: High School Students Mentor Middle School Students to Address Obesity Among Hispanic Adolescents

Katherine R. Arlinghaus, MS, RD[1]; Jennette P. Moreno, PhD[2]; Layton Reesor[1]; Daphne C. Hernandez, PhD, MSEd[1]; Craig A. Johnston, PhD[1]

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PEER REVIEWED

Editor's Note: This article is 1 of 2 winners of the 2017 Student Research Paper Contest in the Doctoral category.

Abstract

Introduction

Promotoras, Hispanic community health workers, are frequently employed to promote health behavioral change with culturally bound Hispanic lifestyle behaviors. Peer health mentors have been used in schools to promote healthy nutrition and physical activity behaviors among students. This study investigates the efficacy of combining these 2 approaches by training high school health mentors, called *compañeros*, to engage Hispanic middle school students in a school-based obesity intervention as a strategy to promote and sustain reductions in standardized body mass index (zBMI).

Methods

High school *compañeros* were trained to participate in a 6-month obesity program alongside middle school students in Houston, Texas. Middle school students were randomized to participate in the program either with *compañeros* (n = 94) or without *compañeros* (n = 95). The intervention was conducted from 2013 through 2016 in 3 cohorts of students, 1 each school year. Students were followed for 12 months. The primary outcome was zBMI, which was analyzed at baseline, 6 months, and 12 months.

Results

Significant differences were found between conditions across time ($F = 4.58$, $P = .01$). After the 6-month intervention, students in the condition with *compañeros* had a larger decrease in zBMI ($F = 6.94$, $P = .01$) than students in the condition without *compañeros*. Furthermore, students who received the intervention with *compañeros* showed greater sustained results at 12 months ($F = 7.65$, $P = .01$).

Conclusion

Using high school *compañeros* in an obesity intervention for Hispanic middle school students could be effective in promoting and maintaining reductions in zBMI.

Introduction

Although one of the strengths of school-based interventions for obesity is the ability to reach racial/ethnic minority groups who are at elevated risk, the success of school-based weight management interventions is not equivalent across races/ethnicities, and few obesity intervention programs exist that are tailored for racial/ethnic minority groups (1,2). A cost-effective public health strategy frequently used in Hispanic communities is to train community health workers, called *promotoras,* to promote healthy lifestyle behaviors (3,4). *Promotoras* are familiar with the population they serve and are typically well-respected members of the target community. These factors enable them to communicate health messages in a relatable way (5). Adapting the *promotoras* model to the

middle school setting by training high school students as health mentors, called *compañeros*, may be one strategy to more effectively tailor weight management interventions for Hispanic adolescents.

Peer perception of lifestyle behaviors is important to adolescents (6), and evidence is beginning to establish teenagers as effective health mentors (7). However, few studies have assessed anthropometric measurements as an outcome (8–10). Of those that have, none were conducted with low-income, Hispanic adolescents, and none included a follow-up after the intervention to determine whether results were sustained. Our study aimed to examine whether the assistance of *compañeros* in the implementation of nutrition and physical activity lessons could be an effective strategy for delivering an obesity prevention program to middle school students in a predominantly Hispanic school system.

Methods

Sixth-grade and seventh-grade students (n = 506) were recruited from a charter school in Houston, Texas, that serves students in grades 6 through 12. Although all students who provided verbal assent and had parental consent were given the opportunity to participate in the intervention, only those who were overweight or obese (n = 189), defined as having a body mass index (BMI, kg/m^2) at or above the 85th percentile for age and sex according to the guidelines of the Centers for Disease Control and Prevention (CDC) (11) were included in this analysis. This sample size satisfied the 200 participants (100 in each condition) that were calculated to be needed to have an 80% likelihood of detecting a 0.09-unit difference in zBMI (standardized BMI) between conditions. The power analysis assumed nominal values for type I and type II error rates (5% and 20% respectively; 2-tailed) and an attrition rate of 20%. Students were randomized to receive either an obesity intervention with *compañeros* (n = 94) or without *compañeros* (n = 95). All students self-identified as Hispanic.

Study design

Participants in both conditions received an obesity intervention for 50 minutes, 5 days a week, for 6 months during students' physical education (PE) class period. The intervention was conducted from 2013 through 2016 in 3 cohorts, 1 each school year, and participants were followed for 12 months. Because of the school calendar, the intervention was interrupted by various school breaks. To prevent contamination, students' schedules were developed before the beginning of the school year so that all students randomized to a particular condition were in classes only with students who were also randomized to the same condition. Interventions were led by PE teachers who were trained by research staff members as described elsewhere (12). Each week, the students participated in 1 day of healthy eating activities and 4 days of physical activity. This program was based on a school-based obesity intervention with demonstrated efficacy among this population (13,14). Details about the intervention and curriculum are available elsewhere (12,14,15). In addition to the physical activity and nutrition components, the intervention included behavioral modification through a token economy system in which the students received points for participation that they could accumulate and redeem for prizes. The only difference between the 2 conditions was the presence or absence of *compañeros*.

High school students were selected to be *compañeros* if they met the following criteria: were recommended by a teacher, had an opening in their schedule during intervention periods, and expressed a desire to be involved. Weight was not a criterion for either *compañeros* or middle school students to participate in the study. *Compañeros* and middle school students were not matched by weight or racial/ethnic characteristics. However, because the school has a predominantly Hispanic student body, all *compañeros* and middle school students were Hispanic. In this school district, high school and middle school students were taught in the same building.

Compañeros meeting criteria were trained daily for 2 weeks on how to lead all of the intervention activities. This training approach was similar to that used to train the PE teachers (12). The training curriculum mirrored the intervention curriculum, included basic nutrition and physical activity education, and was designed to help *compañeros* identify strengths and weaknesses in their own diets and physical activity habits. Training provided *compañeros* with ideas to use when talking with middle school students about how to make improvements in their diets and activity behaviors. *Compañeros* were trained on each intervention activity until they were able to perform each themselves and explain to others how to do it. *Compañeros* were provided with conversation starters and practiced initiating conversations about the curriculum with peers. Lastly, *compañeros* were trained in how to provide praise and the importance of modeling. *Compañeros* were considered to be proficient in this activity when they were able to demonstrate the use of praise correctly in 3 different student scenarios.

Once trained, *compañeros* were instructed to engage in intervention activities with the middle school students. Before each class, the PE teacher informed *compañeros* of the topic of focus for the day (eg, strategies to eat more vegetables, ways to be more active throughout the day). During class, *compañeros* were to initiate a discussion of the selected topic with their group of middle school

studentss. For example, between exercise stations *compañeros* might talk about what they were going to eat for lunch that day or discuss their favorite vegetables. PE teachers regularly met with *compañeros* to provide feedback on how they were doing and give guidance as needed.

In the without *compañeros* condition, all variables were held constant between conditions with the exception of the *compañeros* component. A trained PE teacher provided the same lessons as with the *compañeros* condition. The only difference was that they conducted class without *compañeros* assistance.

Researchers monitored the implementation fidelity of each condition. For both conditions, researchers recorded the number of nutrition and physical activity sessions conducted. They also randomly assessed 10% of classes to record how frequently the PE teacher provided positive reinforcement and constructive feedback to students. Weekly meetings were conducted with the PE teacher to discuss issues related to intervention adherence. The fidelity check process was the same for both conditions except that in the *compañeros* condition, the implementation of fidelity of the *compañero* role was also monitored. Specifically, researchers randomly observed 10% of classes to record how frequently *compañeros* modeled healthy behavior and provided praise to the middle school students.

Measures

Middle school students' height and weight were regularly measured throughout the study. Baseline, 6-month, and 12-month assessments were included in this analysis. At each assessment point, height was measured without footwear using a SECA 213 stadiometer (SECA). Weight was assessed in light clothing and without footwear using a Tanita BWB-800 digital scale (Tanita Corp). BMI was calculated from students' weight and height. BMI percentiles were determined by using the students' age and sex and were classified according to CDC guidelines (11). BMI percentiles were standardized to sex and age norms to determine zBMI.

The interpretation of height and weight for adolescents is complicated because adolescents are growing and developing. To enable a more comprehensive interpretation of anthropometric changes in adolescents, zBMI, BMI percentile, and BMI were included as outcomes. The primary outcome was zBMI, because the use of this metric is standard practice in research (16). Both zBMI and BMI percentiles account for age, sex, and the expected growth and development of adolescents. Possibly because pediatricians often speak to parents about their child's growth in terms of percentiles, the meaning of BMI percentile is more interpretable for a larger audience than the meaning of zBMI. Although zBMI is more sensitive than BMI percentile, neither of these metrics is sensitive to change at extreme ranges, such as that indicative of extreme obesity. BMI was included as an outcome to overcome this shortcoming because, although BMI does not account for age, sex, or the expected growth of adolescents, its sensitivity does not diminish at ranges suggestive of extreme obesity.

Data analysis

Statistical analyses were performed using SPSS, version 19.0 (SPSS, Inc); χ^2 and independent samples *t* tests were conducted to compare differences between conditions at baseline and between those with and without measures at 6 and 12 months. A 2 × 3 repeated measures analysis of covariance (ANCOVA) was used to determine differences in weight outcomes between conditions across all periods. Post-hoc analyses (2 × 2 repeated measures ANCOVA) were conducted at both 6 and 12 months. To be consistent with the Consolidated Standards of Reporting Trials 2010 Statement (17), in addition to the model developed for the main analysis, the last observation carried forward (LOCF) method was used to create an intention-to-treat model to include those without 6-month or 12-month measurements. This method replaces missing data with the data most recently collected. Mean change scores for height, weight, BMI, BMI percentile, and zBMI were computed for each condition, from baseline to 6 months and from baseline to 12 months for both the main analysis and the intention-to-treat analysis. This study was approved by the Institutional Review Board for Human Subjects at the Baylor College of Medicine.

Results

Of the 189 students initially included in the study (94 in the *compañeros* condition and 95 in the without *compañeros* condition), 140 were available for assessment at 6 and 12 months, 71 students in the with *compañeros* condition and 69 in the without *compañeros* condition (Figure 1). The 49 students who were unavailable for assessment were excluded from our main assessment. No significant differences in age, sex, height, weight, or BMI were observed at baseline between conditions (Table 1). There was a 74.1% retention rate at 12 months (n = 140 students remained). Attrition did not differ significantly among the 71 students remaining in the *compañeros* condition (24.5% attrition) and the 69 students remaining in the condition without *compañeros* (27.4% attrition). Students excluded from analysis (those unavailable for measurements at both 6 and 12 months) had a higher initial weight, BMI, and zBMI than did those whom we were able to assess at each time point (Table 1). Because of this, baseline weight was used as a covariate during all analyses.

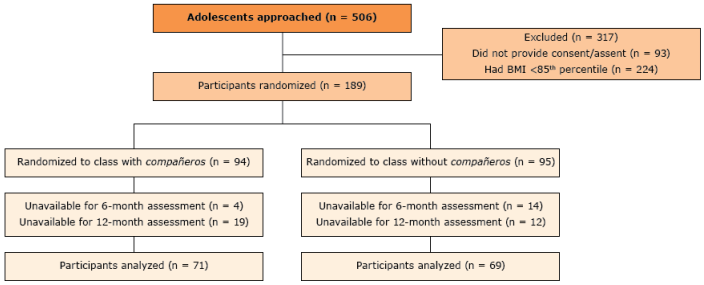

Figure 1. CONSORT diagram illustrating the flow of participants through the study, an obesity prevention intervention using *compañeros*, Houston, Texas, 2013–2016. Participants included in the main analysis had baseline, 6-month, and 12-month assessment data. Abbreviation: CONSORT, the Consolidated Standards of Reporting Trials.

Implementation fidelity was high overall for both conditions. In both conditions, all 24 nutrition sessions and 96 physical activity sessions were conducted, and PE teachers provided constructive feedback in 100% of the observed classes. PE teachers provided positive reinforcement in 90% of the observed classes in the *compañeros* condition and in 95% of the observed classes in the condition without *compañeros* condition. In the *compañeros* condition, *compañeros* modeled healthy behaviors in 98% of the observed classes and provided praise in 94% of the observed classes.

Results from the ANCOVA analysis indicated that, compared with students in the condition without *compañeros*, students in the *compañeros* condition decreased their zBMI ($F = 4.58$, $P = .01$) (Figure 2).

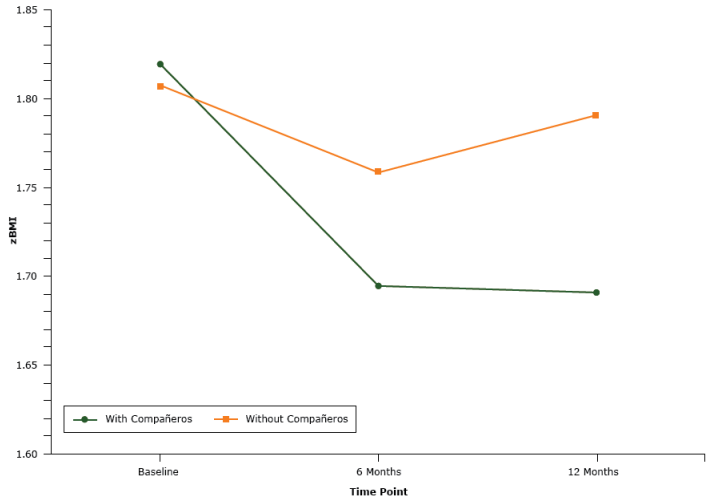

Figure 2. Comparison by study group of mean zBMI of participants at baseline, 6 months, and 12 months for participants in the with *compañeros* condition and participants in the without *compañeros* condition, an obesity prevention intervention using *compañeros*, Houston, Texas, 2013–2016.

Post hoc analyses from baseline to 6 months and baseline to 12 months indicated differences in zBMI between conditions ($F = 6.94$, $P = .01$ and $F = 7.65$, $P = .01$, respectively). Eighty percent of students in the *compañeros* condition and 64% of students in the condition without *compañeros* decreased or maintained zBMI from baseline to 6 months. At 12 months, 68% of students in the *compañeros* condition and 55% of students in the condition without *compañeros* had decreased or maintained zBMI from baseline.

BMI scores did not decrease for all outcome variables between conditions from baseline to 6 months and 12 months for either condition (Table 2). The mean change in BMI from baseline to 12 months was significantly different between conditions; zBMI and BMI percentile decreased from baseline to 6 months and from baseline to 12 months for both conditions. The *compañeros* condition had a significantly greater decrease in zBMI at both 6 months and 12 months than the condition without *compañeros*.

As with the main analysis, the intention-to-treat ANCOVA showed that compared with students in the condition without *compañeros*, students in the *compañeros* condition had a significantly decreased zBMI ($F = 3.27$, $P = .04$). The change in zBMI between conditions for both 6- and 12-month post hoc analyses also showed significant differences between conditions ($F = 5.08$, $P = .04$; $F = 5.62$, $P = .02$, respectively).

Discussion

The purpose of this randomized controlled trial was to see if the addition of *compañeros* to an established teacher-led, school-based obesity intervention (12) for middle school Hispanic students would be a more effective strategy for delivering the intervention than teachers delivering the intervention without *compañeros.* At both 6 months and 12 months, students in the *compañeros* condition had a significantly lower zBMI than those in the condition without *compañeros.* The paucity of school-based interventions for Hispanic adolescents makes it difficult to directly compare the findings of this study to other studies (18). However, the results of this study are consistent with obesity interventions for adolescents in general, in which zBMI has been estimated to decrease by less than 0.1 units from baseline to intervention end (19).

Mean weight, height, and BMI increased from baseline to 12 months in both conditions. This change is expected because adolescents are still growing. The goal of adolescent obesity interventions is not necessarily weight loss, but a slowed weight gain relative to height. The statistically smaller increase in BMI observed in the condition with *compañeros* compared with the condition without *compañeros* indicates that the presence of *compañeros* was more effective at changing the trajectory of weight gain relative to height.

Although school-based interventions have generally been able to create short-term reductions in zBMI, few have been able to accomplish maintenance of zBMI (19). Maintenance of results is particularly discouraging when intervention implementation is translated from research professionals to teachers and staff at a school (12). The results of this study are compelling because students who received the intervention with *compañeros* demonstrated greater maintenance in zBMI reduction at a year than those who received the intervention without *compañeros.* The addition of *compañeros* appears to be a possible solution to bridge the maintenance gap in the translation of intervention implementation from research professionals to a school's teachers and staff.

One potential explanation for why the *compañeros* condition was more successful than the condition without *compañeros* is the possibility that *compañeros* were able to individually tailor the program for the middle school students in a way PE teachers were unable to. This suggestion is consistent with hypothesized reasons for the success of *promotoras* in community-based programs. As members of the community that they serve, *promotoras* are able to relate to program participants in a way medical professionals are often unable to (5). Because *compañeros* attended the same school and had similar socioeconomic and racial/ethnic backgrounds as the middle students, they likely had a fuller understanding of the middle students' school, familial, and social environments. Although no data were collected to determine how middle school students perceived *compañeros*, the endorsement of healthy behaviors by high students, who are thought to be respected and admired by middle students, likely contributed to intervention engagement and sustained behavior change (20). Another plausible explanation for the differences seen between the 2 conditions is that students who received the intervention with *compañeros* received more attention, and this additional attention could have contributed to improved outcomes.

Because of the population of our study (ie, low income, Hispanic adolescents attending a charter school), additional research is needed to determine the generalizability of this type of intervention in other settings. However, the strategy of using peers to promote and sustain weight outcomes is likely generalizable to a variety of populations. For example, findings from this study are consistent with those of peer health mentoring interventions with Appalachian youths (21). Collectively, these studies support the notion that for interventions to be successful in the short and long term, they need to be relevant to the population being observed.

Strengths of this study include its being a randomized controlled trial with a pre, post, and one-year follow up design that targeted Hispanic adolescents, a group at increased risk for obesity. Limitations include the lack of a no-treatment control condition, though practical considerations and school requirements made this unfeasible. Although being able to randomize students at the individual level is a strength of the study, the randomization does not control for the possibility of contamination. Steps were taken to prevent contamination. All students assigned to a particular condition had identical class schedules so that they had class only with students also randomized to the same intervention condition. Although students ate lunch by grade level, students had assigned tables for lunch so that they ate lunch only with students randomized to the same intervention condition. It was not feasible to keep students separated according to condition during free times or extracurricular activities, and it is probable that those in the condition without *compañeros* knew that there was another condition and vice versa. Lastly, the health outcomes of *compañeros* were not assessed. Results from other studies that have measured the effects of peer health mentorship on the mentor suggest that health mentorship programs have health benefits for both parties involved (8).

More research is needed in the area of maintenance and translation of effective interventions for the school setting. School health initiatives are often deprioritized because of the pressures schools are under for students to perform well on standardized tests and because of resource constraints (22). Low-cost strategies that require little additional effort from the school's staff are needed for school-based health programs to be sustainable. The findings of

this study indicate that the addition of *compañeros* to an obesity program was an effective strategy among Hispanic adolescents to facilitate sustained reductions in zBMI for a year. Considering the effectiveness *compañeros* demonstrated in this study and the minimal extra resources needed to support them, the *compañeros* model warrants further investigation as a possible strategy for addressing practical concerns schools face when implementing health initiatives.

Notes

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Tables

Table 1. Comparison of Baseline Characteristics of Participants (N = 189), by 12-month Attrition and by Treatment Condition[a], *Compañeros* Obesity Intervention, Houston, Texas 2013–2016

Characteristic	Included in Main Analysis	Excluded From Main Analysis[b]	*P* Value[c]	With *Compañeros* Condition	Without *Compañeros* Condition	*P* Value[d]
Total, n	140	49	—	94	95	—
Age, y	13.02 (0.56)	12.90 (0.56)	.17	12.91 (0.48)	12.94 (0.63)	.71
Female, n (%)	66 (47)	31 (63)	.07	48 (51)	49 (52)	—
Height, cm	157.93 (6.67)	158.10 (7.25)	.88	157.54 (6.97)	158.57 (7.20)	.32
Weight, kg	65.68 (9.30)	69.92 (13.83)	.02	68.32 (13.04)	69.31 (12.84)	.60
BMI, kg/m^2	26.30 (3.10)	27.86 (4.56)	.01	27.40 (4.03)	27.51 (4.53)	.85
zBMI	1.64 (0.37)	1.81 (0.45)	.01	1.78 (0.41)	1.76 (0.46)	.77
BMI percentile	93.86 (3.97)	95.13 (4.04)	.06	95.04 (3.82)	94.57 (4.27)	.43
Attrition at 12 mos, n (%)	0 (0)	49 (100)	—	23 (24.5)	26 (27.4)	.74

Abbreviations: —, not applicable; BMI, body mass index; zBMI, standardized BMI.
[a] Values are mean (standard deviation) unless otherwise noted.
[b] Participants randomized into a study condition were not included in the analysis if they were unavailable for both 6-month or 12-month assessments.
[c] *P* values were determined by an independent samples *t* test and χ^2 tests between participants who were and were not included in the main analysis.
[d] *P* values were determined by independent samples *t* tests and χ^2 tests between with *compañeros* and without *compañeros* conditions.

Table 2. Changes in Body Characteristics of Participants (N = 189) at 6 Months and 12 Months by, Treatment Condition[a], *Compañeros* Obesity Intervention, Houston, Texas 2013–2016

Characteristic	With *Compañeros* (n = 71)	Without *Compañeros* (n = 69)	*P* Value[b]	With *Compañeros* (n = 94)	Without *Compañeros* (n = 95)	*P* Value[b]
	Main Analysis[a], Mean (SD)			Intention-to-Treat[c], Mean (SD)		
Change in values from baseline to 6 months						
Height, cm	2.25 (2.02)	2.62 (1.92)	.27	2.17 (1.95)	2.27 (1.96)	.73
Weight, kg	0.88 (2.92)	2.61 (3.88)	.001	1.18 (2.89)	2.03 (3.82)	.09
BMI, kg/m^2	−0.42 (1.23)	0.13 (1.45)	.02	−0.27 (1.20)	0.03 (1.41)	.12
*z*BMI	−0.12 (0.18)	−0.05 (0.16)	.01	−0.10 (0.17)	−0.05 (0.16)	.04
BMI percentile	−1.67 (3.25)	−0.91 (2.94)	.15	−1.31 (2.93)	−0.83 (2.79)	.26
Change in values from baseline to 12 months						
Height, cm	4.37 (3.10)	3.82 (4.47)	.40	3.89 (2.94)	3.27 (4.06)	.24
Weight, kg	4.17 (5.55)	6.11 (4.63)	.03	4.05 (5.22)	4.77 (5.13)	.34
BMI	0.12 (1.99)	1.11 (2.19)	.01	0.25 (1.89)	0.78 (2.13)	.07
*z*BMI	−0.13 (0.26)	−0.01 (0.21)	.01	−0.10 (0.24)	−0.03 (0.21)	.02
BMI percentile	−1.86 (4.15)	−0.60 (3.09)	.05	−1.40 (3.80)	−0.88 (3.36)	.33

Abbreviations: BMI, body mass index; zBMI, standardized BMI.
[a] Participants with both 6-month and 12-month assessments.
[b] *P* values were determined by an independent samples *t* test between conditions.
[c] Students initially assigned to the 2 conditions who were unavailable for measurement assessments at 6 and 12 months. Analysis was conducted by using the last observation carried forward method. All participants who had been randomized to a study condition were included in this analysis.

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ORIGINAL RESEARCH

Early Onset Obesity and Risk of Metabolic Syndrome Among Chilean Adolescents

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PEER REVIEWED

Editor's Note: This article is 1 of 2 winners of the 2017 Student Research Paper Contest in the Doctoral category.

Abstract

Introduction
Obesity and metabolic syndrome (MetS) indicators have increased globally among the pediatric population. MetS indicators in the young elevate their risk of cardiovascular disease and metabolic disorders later in life. This study examined early onset obesity as a risk factor for MetS risk in adolescence.

Methods
A cohort of Chilean participants (N = 673) followed from infancy was assessed at age 5 years and in adolescence (mean age, 16.8 y). Adiposity was measured at both time points; blood pressure and fasting blood samples were assessed in adolescence only. Early onset obesity was defined as a World Health Organization *z* score of 2 standard deviations (SDs) or more for body mass index (BMI) at age 5 years. We used linear regression to examine the association between early onset obesity and adolescent MetS risk *z* score, adjusting for covariates.

Results
Eighteen percent of participants had early onset obesity, and 50% of these remained obese in adolescence. Mean MetS risk *z* score in adolescence was significantly higher among those with early onset obesity than among those without (1.0; SD, 0.8 vs 0.2; SD, 0.8 [$P < .001$]). In the multivariable model, early onset obesity independently contributed to a higher MetS risk score in adolescence ($\beta = 0.27$, $P < .001$), controlling for obesity status at adolescence and sex, and explained 39% of the variance in MetS risk.

Conclusion
Early onset obesity as young as age 5 years relates to higher MetS risk.

Introduction

Obesity among children is a global public health problem (1,2), and signs of metabolic syndrome (MetS) have increased among both children and adolescents over the past 25 years (3,4). MetS is defined as having at least 3 of 5 risk factors: a large waist circumference, high blood pressure, fasting hyperglycemia, hypertriglyceridemia, and low high-density lipoprotein (HDL) cholesterol levels (5). Although few children meet all 5 MetS criteria, up to 30% of obese children have at least one element of MetS (6). A recent systematic review showed a median prevalence of MetS of 3% (range 0%–19.2%) among all children and 29% (range 10%–66%) among obese children (3). In a sample of US adolescents aged 12 to 17 years, the overall MetS prevalence was 7%, with a range from 19% to 35% among obese adolescents (7). Additionally, Hispanic adolescents had a higher MetS prevalence (11%) than non-Hispanic white adolescents (9%) (8).

MetS increases a person's risk for developing chronic disease (9,10). Pediatric MetS is independently associated with type 2 diabetes and adult MetS and with subclinical atherosclerosis leading to cardiovascular disease (CVD) (11,12). Additionally, research shows that obesity tracks from childhood into adulthood (13) and

contributes to adverse consequences, including premature mortality and cardiometabolic disorders (14,15). However, the impact of the age of obesity onset in early childhood on adolescent MetS risk has not been documented, because research has largely focused on infant weight gain and catch-up growth as predictors of health outcomes later in life (16–18). This study examined early onset obesity as a risk factor for MetS risk in adolescence. We hypothesized that obesity onset early in life is associated with a higher MetS risk score in adolescence.

Methods

Study design and population

Participants were 677 Chilean infants who were part of an observational longitudinal study of biopsychosocial determinants of obesity and CVD risk. From 1991 through 1996, 1,933 infants were enrolled in either a preventive trial of iron supplementation to prevent iron-deficiency anemia or a neuromaturation study, a study that assessed neurodevelopment by using neurophysiological and electrophysiological techniques. The studies were conducted in Santiago, Chile, where infancy iron deficiency was widespread at the time and no national program existed for iron supplementation. Infants were from low-to-middle income, working-class communities. Inclusion criteria for the infancy studies were an uncomplicated, singleton, term, vaginal birth with birthweights of 3 kg or more, no major congenital abnormalities, and no prior iron therapy. Because of a successful national breastfeeding campaign, all but 8 infants in the cohort were initially breastfed.

Infants were recruited at age 4 to 6 months. Infants without iron-deficiency anemia were randomly assigned to high-iron supplementation, low-iron supplementation, or usual nutrition (no added iron). Further details about enrollment and trial specifications are described elsewhere (19). A total of 1,657 infants completed the preventive trial (high iron, n = 718; low iron, n = 405; usual nutrition, n = 534). Infants found to have iron-deficiency anemia, and the next nonanemic infant (the control), were treated with medicinal iron and participated the neuromaturation study (20). A total of 135 infants completed the neuromaturation study. At age 5 years, because of a cut in funding, only 2 of the 3 randomly selected preventive trial groups and neuromaturation trial participants could be evaluated. Thus, only 888 of 1,501 infants who were in the high-iron and no-added-iron groups or completed the neuromaturation study were assessed. At age 16 years, participants from the 5-year follow up were invited to participate in a study of obesity and CVD risk. A total of 677 of 888 (76%) participants agreed and were assessed from 2009 through 2012. Our analytic sample for the obesity and MetS study consisted of 673 participants from the obesity and CVD risk study who had complete data at 5 years and 16 years (Figure).

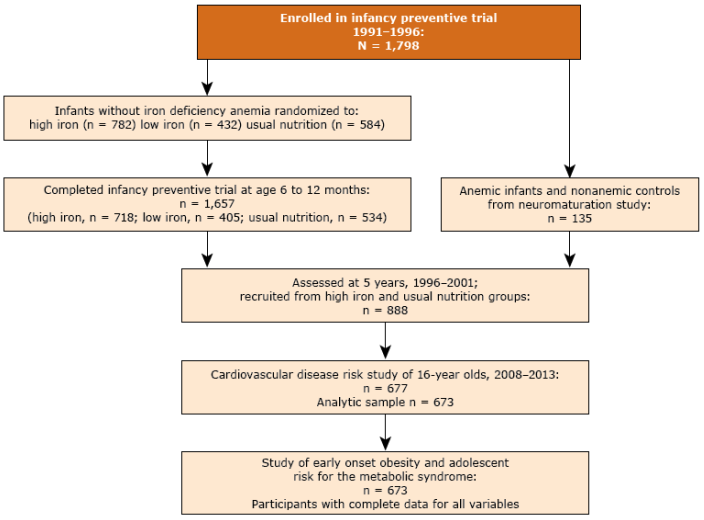

Figure. Flow of participants in study on relationship between early onset obesity and metabolic syndrome risk in adolescence, Santiago, Chile, 2009–2012. Participants were drawn from a larger study of infancy iron-deficiency anemia.

The sample was representative of the original cohort, with no differences in infant and family characteristics, including birthweight (3.5 kg in the original cohort vs 3.6 kg in the final analytic sample), breastfeeding for at least 6 months (63% in the original cohort vs 61% in the final analytic sample), socioeconomic status (SES) (27.3 on the Graffar index [21] for the original cohort vs 27.0 for the final analytic sample), and household environment (30.1 on the Home Observation for Measurement of the Environment [HOME] [22] scale for the original cohort vs 30.0 for the final analytic sample). The study was approved by the institutional review boards of the University of California, San Diego, the University of Michigan, and the University of Chile Institute of Nutrition and Food Technology (INTA).

Data collection and analysis

Participants were considered to have early onset obesity if obesity was present at age 5 years (defined as ≥2 standard deviations [SDs] for body mass index [BMI] *z* score) by using WHO growth standard indicators. BMI is a measure of weight relative to height (kg/m^2), with age-specific and sex-specific norms (23).

Adolescents were assessed at age 16 to 17 years. Height (cm), weight (kg), waist and hip circumference (cm), and blood pressure (mmHg) were measured by a physician-investigator at INTA. Standardized procedures were used to measure weight to the closest 0.1 kg by using a SECA scale (SECA), and height to the closest 0.1 cm by using a Holtain stadiometer (Holtain Ltd) (24). Each measurement was taken twice, and a third measurement was

taken if the difference between the first 2 exceeded 0.3 kg for weight, 0.5 cm for height, or 1.0 cm for waist. The WHO BMI *z* score indicator was used to dichotomize (yes/no) obesity status at adolescence, with obesity defined as an SD of 2 or more in the BMI *z* score. Fasting serum triglyceride, cholesterol, and glucose levels were assessed. Serum glucose concentration (mg/dL) was determined by using an enzymatic–colorimetric test (Química Clínica Aplicada S.A.). Triglyceride (mg/dL), and cholesterol (mg/dL) levels were determined with the Vitros dry analytical methodology (Ortho Clinical Diagnostics Johnson & Johnson Inc).

A continuous MetS risk *z* score was calculated by applying the equations developed by Gurka et al (25). The equations provide a sex-specific and race-specific *z* score measure for MetS risk based on standardized and log-transformed values for each component of the MetS.

Characteristics that may be associated with both the variable of interest and the outcome were considered covariates. For infancy, the following were considered: birthweight, SES, breastfeeding, emotional and material support provided in the home environment, iron status during infancy, and iron supplementation as part of the preventive trial. For adolescents, the following were potential covariates: age at menarche, age at the adolescent assessment, physical activity, and obesity status. Birthweight, measured in kilograms, was analyzed as a continuous measure. Iron status during infancy, coded as iron sufficient, iron deficient, or iron-deficient anemic, was dichotomized to iron sufficient (0) and iron deficient or iron-deficient anemic (1) for modeling purposes. Iron supplementation in infancy was dichotomized to iron supplementation (high or low) (1) and no iron supplementation (0). The SES variable, the Graffar index, is a pseudocontinuous variable based on a 13-item questionnaire that produces a composite score that comprises questions on mothers' and fathers' years of education, occupation, and income (21) the higher the Graffar index, the lower the SES. Questions were coded as absent (1) to plentiful (6), for a possible score range of 13 to 78. The quality of the home environment that supported the children's development was assessed with HOME, a 45-item, observer-rated checklist (22). A higher HOME score reflects a more supportive home environment for children's development. Scores range from 0 to 45. Physical activity at adolescence was measured by using a 5-item questionnaire, validated for use in young populations (26). The questionnaire addresses planned and unplanned physical and sedentary activities as a continuous score between 0 and 10. Age at menarche and age at adolescent measurement were analyzed as continuous variables.

Statistical analyses

SAS version 9.2 (SAS Institute) was used for all statistical analyses, with the exception of computed MetS risk score, for which SPSS version 22.0 (IBM Corp) was used.

For describing sample characteristics, continuous variables were expressed as mean and SD, and categorical variables were expressed as frequencies. All variables were assessed for normality. Unadjusted comparisons between early onset obesity groups were calculated by using *t* tests for continuous outcomes and χ^2 tests for categorical outcomes. Regression diagnostics, using tests and graphical methods, examined linear regression assumptions including linearity (residual vs predictor plot) normality (Shapiro–Wilk test), homogeneity of variance (Breusch–Pagan test) and independence (Durbin–Watson statistic). All of these assumptions were met, indicating linearity, uncorrelated and normally distributed estimated residuals with constant variance. Influence and collinearity were also examined, with no extreme deviations observed for studentized and jackknife residuals, and small leverage and Cook's distance values. Multivariable linear regression analysis was used to assess the relationship between early onset obesity and MetS risk score, adjusting for possible confounders. The full model was tested by using backward elimination. Variables that were not statistically associated with the dependent variable were manually removed. Because the study sample participated in a preventive trial, iron status during infancy and iron supplementation were initially included as covariates. Neither variable was significantly associated with the outcome, and thus both were removed from the final model. Age at menarche, which was tested in the multivariable model, was not significantly associated with outcome and therefore was dropped from the final model. Significance was set at a *P* value of less than .05. Multicollinearity between variables was assessed with tolerance level with a cut point of less than 0.10. There was no evidence of multicollinearity in the model.

Marginal structural models (MSMs) refine the adjustment made by traditional analytic approaches and predict an estimate that accounts for the bias that exists when time-dependent covariates might act as both confounders and intermediates in a linear association. We used an MSM as a sensitivity analysis to account for potential bias resulting from the inclusion of adolescent weight status in the final model; bias may arise because adolescent weight status both mediates and confounds the relationship between early-life obesity and adolescent MetS risk score. To carry out these ana-

lyses, we estimated stabilized inverse probability weights (27) and reweighted our sample to create a pseudopopulation in which the exposure, early onset obesity, is statistically independent of potential time-dependent confounders. Results from the pseudopopulation models supported initial findings, indicating limited bias resulting from the inclusion of adolescent weight status as a covariate in the multivariable linear regression model.

Results

Mean age of participants at adolescence was 16.8 years, and 52.9% were male (Table 1). The mean birthweight in the study population was 3.6 kg (SD, 0.4 kg). Early onset obesity was found in 18.1% of the participants, of which 41.0% were girls. We found no significant differences in birthweight, sex, SES, HOME scores, and physical activity in adolescence between participants with early onset obesity and participants without early onset obesity. Obesity status at adolescence was related to early onset obesity. Of those with early onset obesity, 50% were obese at adolescence, in contrast to 6% of the comparison group ($P < .001$).

The MetS risk score and all variables related to CVD risk were significantly higher in the early onset obesity group, compared with the group without early onset obesity, with the exception of HDL cholesterol, which was inversely related to CVD risk, and fasting blood glucose, which did not differ between groups (Table 2). Participants in the early onset obesity group had significantly higher mean total cholesterol levels (156.4 mg/dL; SD, 27.9 vs 151.1 mg/dL; SD 27.5, $P = .04$) and low-density lipoprotein cholesterol levels (98.9 mg/dL, SD 24.8 vs 93.3 mg/dL, SD 24.2, $P = .03$) compared with the group without early onset obesity. Additional analyses for MetS components by sex showed that adolescent boys had significantly lower mean total cholesterol and HDL cholesterol levels and significantly higher fasting blood glucose levels and blood pressure than adolescent girls.

The final model, controlling for sex and obesity status in adolescence, indicated that early onset obesity was associated with a higher MetS risk score in adolescence ($\beta = 0.27$; 95% confidence interval [CI] 0.13– 0.41, $P < .001$) (Table 3) and explained 39% of the variance in the MetS risk score. The adjusted mean and standard error (SE) MetS risk score was 1.0 (SE, 0.06) and 0.7 (SE, 0.04) for participants with and without early onset obesity, respectively. Additionally, female sex was associated with a lower MetS risk score in the model ($\beta = -0.26$; 95% CI, −0.35 to −0.17; $P < .001$), adjusting for other covariates.

Findings from the MSM, a sensitivity analysis, did not differ from findings of the multivariable regression analysis. This corroborated the effect size of early onset obesity and its relationship with MetS risk score in adolescence.

Discussion

This study showed that early onset obesity was associated with greater MetS risk in adolescence. Independent of adolescent obesity status and sex, a child who had obesity at age 5 years had a higher MetS risk score ($\beta = 0.27$) at age 16. These results support our initial hypothesis.

Our findings are consistent with those in a mid-childhood cohort (28). Using a similar analytic approach and focusing on metabolic profiles that included dyslipidemia, hypertension, and insulin resistance, Garnett et al. (28) concluded that children who were overweight or obese at age 8 years were almost 7 times as likely to have CVD risk-clustering at age 15 years as those who were not overweight or obese (odds ratio, 6.9; 95% CI, 2.5– 19.0; $P < .001$) (28).

Boys in our cohort had higher mean MetS risk scores than girls, independent of early onset obesity and obesity status at adolescence. These results are similar to our prior findings (29) and those of US national data, in which adolescent boys were more likely to have MetS risk factors than adolescent girls (9). A recent systematic review of the prevalence of MetS in children and adolescents from 12 countries in North America and South America also found a higher prevalence of MetS among boys (29). Adolescent boys also manifested higher fasting blood glucose, higher blood pressure, and lower HDL cholesterol levels than adolescent girls. These CVD risks were primarily observed in Mexico, Canada, Colombia, and the United States (30).

This research emphasizes the value of studying longitudinal cohorts and the relevance this study's cohort to obesity in early childhood and adolescent health outcomes among Chileans. In addition to the longitudinal study design, this study has several strengths, such as the uniqueness of a Chilean cohort of infants followed successfully to adolescence, inclusion of a relatively large group of healthy infants, and good participant retention. Another strength is that the evaluation was conducted at a nutrition research center by highly trained study personnel. Furthermore, the use of a sex-specific and race-specific continuous MetS risk score is a study strength. Although continuous scores were previously developed, the methodology followed by Gurka et al and applied in this study, acknowledges correlations between the MetS components, accounting for MetS component correlation differences by sex and race/ethnicity (25).

A limitation of this study is that it may not be generalizable to other populations. The participant sample was restricted to infants who weighed 3 kg or more at birth. Thus, we cannot infer whether these relationships translate to preterm or low-birthweight infants. Also, probably because data on birthweight were restricted, we probably did not observe a relationship between birthweight and obesity. Generalization to higher-income or poverty groups is also restricted. Another limitation is lack of anthropometric data between measurement waves, thus placing participants in a BMI category at time of measurement, which might have been different a year before or after measurement. Additionally, data were unavailable on maternal or paternal obesity status, diet intake, and direct physical activity measures. Although we attempted to minimize unmeasured confounding in our study by including measures on recognized potential confounders, such unmeasured risk factors could confound the relationship between early onset obesity and MetS risk.

Notwithstanding these limitations, our findings add to the literature on early life determinants, in particular determinants related to the long-term effects of early onset obesity on MetS or other CVD-related risk factors. Future research should be conducted in populations with various races and ethnicities to substantiate these findings and address a key public health problem.

Our results underscore the public health implications of early childhood obesity for health outcomes later in life. The findings provide evidence for a clinically meaningful and significant association between early onset obesity and MetS risk score in this Chilean cohort. The results of this study emphasize the importance and need for early detection of childhood obesity and effective public health interventions.

Notes

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Tables

Table 1. Characteristics of Participants (N = 673), Study of Relationship Between Early Onset Obesity and Risk of Metabolic Syndrome Among Adolescents[a], Santiago, Chile, 1991–1996 and 2009–2012

Characteristic	Total Sample (n = 673)	Early Onset Obesity (n = 122)	No Early Onset Obesity (n = 551)	*P* Value[b]
Infancy				
Birthweight, mean (SD), kg	3.6 (0.4)	3.6 (0.4)	3.5 (0.4)	.67
Male, %	52.9	59.0	51.5	.13
Breastfeed ≥6 months, %	63.4	63.6	63.3	.96
Iron status during infancy, %				
Iron sufficient	41.5	34.4	43.0	.06
Iron deficient	40.1	40.2	40.1	
Iron deficiency anemia	18.4	25.4	16.9	
Socioeconomic status, Graffar index[c], mean (SD)	27.0 (6.3)	27.0 (6.2)	27.0 (6.3)	.87
HOME score[d], mean (SD)	30.2 (4.7)	30.2 (4.8)	30.2 (4.7)	.90
Supplementation group, %				
High iron	47.2	45.9	47.6	.96
Low iron	2.7	3.3	2.5	
No added iron	42.1	42.6	41.9	
Neuromaturation study[e]	8.0	8.2	8.0	
Adolescence				
Age at menarche[f], mean (SD), y	12.5 (1.4)	12.0 (1.4)	12.5 (1.4)	.01
Age at adolescent measurement, y	16.8 (0.3)	16.8 (0.3)	16.8 (0.3)	.48
Physical activity score[g], mean (SD)	4.1 (1.6)	4.0 (1.5)	4.1 (1.7)	.38
Obesity at 16 y[h], %	14.1	50.0	6.2	<.001

Abbreviations: SD, standard deviation; HOME, home observation for measurement of the environment.
[a] Early onset obesity defined as obese at 5 years of age following World Health Organization *z* score cut-off ≥2 SD body mass index (kg/m^2).
[b] *P* value for χ^2 test for categorical variables and *t* test for continuous variables.
[c] Graffar index is a social stratification tool used to assess socioeconomic status (range 13-78); the higher the Graffar index, the lower the socioeconomic status (21).
[d] HOME score (range 0-45) is a home environment quality assessment tool; the higher the HOME score, the better the home environment for child development (22).
[e] Participants in the neuromaturation study were infants found to have iron-deficiency anemia at age 6 months, and the next nonanemic infant (control) whose neurodevelopment was evaluated with neurophysiological and electrophysiological techniques (20).
[f] Female participants only.
[g] Physical activity score (range 0-10) assessing planned and unplanned physical and sedentary activities (26).
[h] Obesity at 16 years defined as obese at 16-year follow-up according to the World Health Organization z score cut-off ≥2 SD for body mass index.

Table 2. Metabolic Syndrome Risk Score[a] and Cardiovascular Disease Risk Factors Among Participants (N = 673), Study of Relationship Between Early Onset Obesity[b] and Risk of Metabolic Syndrome Among Adolescents, Santiago, Chile 1991–1996 and 2009–2012[c]

Variable	Total Population (N = 673)	Early Onset Obesity (n = 122)	No Early Onset Obesity (n = 551)	*P* Value[d]
Metabolic syndrome risk *z* score	0.3 (0.8)	1.0 (0.8)	0.2 (0.8)	<.001
Waist circumference, cm	81.3 (11.4)	94.0 (12.5)	78.5 (9.0)	<.001
HDL cholesterol, mg/dL	40.2 (10.6)	37.1 (9.5)	40.9 (10.7)	<.001
Triglycerides, mg/dL	88.2 (50.0)	103.3 (57.2)	84.8 (47.7)	.001
Systolic blood pressure, mm Hg	111.7 (10.5)	117.5 (11.7)	110.4 (9.8)	<.001
Diastolic blood pressure, mm Hg	69.1 (7.1)	71.9 (7.2)	68.5 (6.9)	<.001
Fasting blood glucose, mg/dL	88.6 (9.5)	89.5 (12.2)	88.5 (8.8)	.36

Abbreviations: HDL, high-density lipoprotein.
[a] Metabolic syndrome risk *z* score calculated with sex-specific and race-specific equations with confirmatory factor analysis.
[b] Early onset obesity defined as obese at age 5 years according to World Health Organization z score cut-off ≥2 standard deviations for body mass index (kg/m^2).
[c] Values are unadjusted mean (standard deviation) unless otherwise indicated.
[d] *P* values calculated with *t* test for continuous variables for differences between the early onset obesity group and no early onset obesity group.

Table 3. Linear Regression Models to Determine Adjusted Associations With Participants' (N = 673) Metabolic Syndrome Risk Score[a], Study of Relationship Between Early Onset Obesity and Risk of Metabolic Syndrome Among Adolescents, Santiago, Chile 2009–2012

Variable	Full Model[b]		Final Model[b]	
	β (95% CI)	*P* Value[c]	β (95% CI)	*P* Value[c]
Early onset obesity[d]	0.29 (0.15 to 0.44)	<.001	0.27 (0.13 to 0.41)	<.001
Obesity at 16 y[e]	1.18 (1.02 to 1.34)	<.001	1.20 (1.04 to 1.35)	<.001
Female[f]	−0.29 (−0.40 to −0.18)	<.001	−0.26 (−0.35 to −0.17)	<.001
Birthweight, kg	0.08 (−0.05 to 0.21)	.23	—	—
Breastfed ≥6 months	0.01 (−0.09 to 0.11)	.83	—	—
Iron deficient during infancy[g]	−0.02 (−0.12 to 0.08)	.73	—	—
Iron supplementation[h]	0.05 (−0.05 to 0.15)	.35	—	—
Graffar index[i]	0.004 (−0.01 to 0.01)	.32	—	—
HOME score[j]	0.003 (−0.01 to 0.01)	.54	—	—
Age at menarche[k]	−0.01 (−0.06 to 0.05)	.83	—	—
Age at adolescent measurement	−0.02 (−0.20 to 0.18)	.86	—	—
Physical activity score[l]	−0.03 (−0.06 to 0.01)	.10	—	—

Abbreviations: —, not calculated for parsimony; CI, confidence interval; HOME, home observation for measurement of the environment.
[a] Metabolic syndrome risk score calculated with sex-specific and race-specific equations with confirmatory factor analysis.
[b] Linear regression modeling, presenting β estimate and 95% confidence interval.
[c] *P* values calculated by linear regression modeling, adjusted for all other listed variables in each of the models (full and final).
[d] Early onset obesity defined as obese at age 5 years according to World Health Organization *z* score cut-off ≥2 standard deviations for body mass index (kg/m^2). Reference: no early onset obesity.
[e] Obesity at age 16 years defined as obese at 16-year follow-up according to World Health Organization z score cut-off ≥2 standard deviations for body mass index. Reference: no obesity at age 16 years.
[f] Reference: male.
[g] Includes iron deficient and iron deficiency anemia. Reference: iron sufficient.
[h] Iron supplementation includes: high-iron and low-iron supplementation during trial. Reference: no iron supplementation.
[i] Graffar index is a social stratification tool used to assess socioeconomic status (range 13-78); the higher the Graffar index, the lower the socioeconomic status (21).
[j] HOME score (range 0-45) is a home environment quality assessment tool; the higher the HOME score, the better the home environment for child development (22).
[k] Age at menarche for female participants.
[l] Physical activity score (range 0-10) assessing planned and unplanned physical and sedentary activities (26).

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ORIGINAL RESEARCH

A Diabetic Retinopathy Screening Tool for Low-Income Adults in Mexico

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PEER REVIEWED

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Abstract

Introduction
A national diabetic retinopathy screening program does not exist in Mexico as of 2017. Our objective was to develop a screening tool based on a predictive model for early detection of diabetic retinopathy in a low-income population.

Methods
We analyzed biochemical, clinical, anthropometric, and sociodemographic information from 1,000 adults with diabetes in low-income communities in Mexico (from 11,468 adults recruited in 2014–2016). A comprehensive ophthalmologic evaluation was performed. We developed the screening tool through the following stages: 1) development of a theoretical predictive model, 2) performance assessment and validation of the model using cross-validation and the area under the receiver operating characteristic curve (AUC ROC), and 3) optimization of cut points for the classification of diabetic retinopathy. We identified points along the AUC ROC that minimized the misclassification cost function and considered various scenarios of misclassification costs and diabetic retinopathy prevalence.

Results
Time since diabetes diagnosis, high blood glucose levels, systolic hypertension, and physical inactivity were considered risk factors in our screening tool. The mean AUC ROC of our model was 0.780 (validation data set). The optimized cut point that best represented our study population ($z = -0.640$) had a sensitivity of 82.9% and a specificity of 61.9%.

Conclusion
We developed a low-cost and easy-to-apply screening tool to detect people at high risk of diabetic retinopathy in Mexico. Although classification performance of our tool was acceptable (AUC ROC > 0.75), error rates (precision) depend on false-negative and false-positive rates. Therefore, confirmatory assessment of all cases is mandatory.

Introduction

In 2016, diabetes was declared a national epidemiologic emergency in Mexico (1). In 2006, the estimated prevalence of diabetes in Mexican adults was 14.4% (2). Mortality rates attributable to this disease in Mexico are among the highest in the world (3). By 2012, 74.7% of Mexican adults with diagnosed diabetes had inadequate glycemic control (4). Diabetes is associated with the development and progression of diabetic retinopathy (5–8), a major cause of sight loss and blindness in Latin American countries (9). A population-based survey from 2010 in the state of Chiapas found that 38.9% of adults aged 50 or older with diabetes had diabetic retinopathy and 21.0% had proliferative diabetic retinopathy (10).

Long-term diabetes and hypertension are consistently associated with diabetic retinopathy (5–8,11–13). The Mexican National Nutrition Survey 2006 found that the mean time since diabetes diagnosis among adults was more than 8 years (2). In 2012, an estimated 65.6% of adults with diabetes had hypertension (14). In this

context, an epidemic of diabetes complications, including diabetic retinopathy, could worsen in Mexico, and the study of screening systems for diabetic retinopathy is important.

Diabetic retinopathy ranks third in direct costs generated by diabetes complications in Mexico (15); these costs result from specialized procedures for diagnosis and treatment. A cost-benefit analysis to identify optimal cut points for identifying people who are at risk for diabetic retinopathy and who need a comprehensive ophthalmologic evaluation is an approach to developing an adequate-performance screening tool (16); however, such an approach would be complex because of the detailed cost information required.

Our objective was to develop a practical screening tool based on a predictive model and a simplification of a cost-benefit analysis to optimize cut points for early detection of diabetic retinopathy in low-income communities in Mexico.

Methods

We conducted a screening protocol for eye-related complications of diabetes from May 1, 2014, to June 30, 2016, in 3 low-income municipalities in the state of Morelos. We recruited 11,468 adults (aged ≥20 y) for a screening of chronic diseases in our mobile unit and community health centers. From these participants, we invited those with a type 2 diabetes diagnosis (n = 1,768 [15.4%]) to a comprehensive ophthalmologic evaluation. Exclusion criteria for this evaluation were signs of ocular infection or pregnancy.

Of the 1,768 participants, 538 declined to participate in the ophthalmologic evaluation, 1 person was excluded because the quality of photographs was not adequate for grading, and 229 participants did not have a photographic assessment at the time of analysis. One thousand participants (56.6%) completed the procedure. We obtained informed consent from all participants, and the protocol was approved by the ethics, research, and biosecurity committees of the Mexican National Institute of Public Health.

Data collection and definition of variables

All participants had at least 1 glycemic assessment (fasting [≥8 h] capillary or random capillary glycemia [glucometer method] or fasting venous glycemia [glucose oxidase method]). Fasting serum triglycerides, total cholesterol, and high-density lipoprotein cholesterol were assessed by enzymatic method (n = 418) and serum insulin with radioimmunoassay method (n = 112) for a portion of the sample; because of logistical and budgetary constraints, the entire sample could not be assessed for these variables.

High blood glucose was defined as a fasting glucose of 126 mg/dL or more or, if fasting glucose was unavailable, as random glucose of 200 mg/dL or more (17). Insulin resistance was classified by using a homeostasis model assessment value of 3.8 or more (18).

Hypertriglyceridemia was defined as triglycerides of 150 mg/dL or more, hypercholesterolemia as total cholesterol of 200 mg/dL or more, and hypoalphalipoproteinemia as high-density lipoprotein cholesterol of less than 50 mg/dL for women and less than 40 mg/dL for men (19,20).

Blood pressure was measured twice (interval of 30 seconds). We diagnosed high systolic/diastolic blood pressure when the average of the assessments was ≥140/≥90 mm Hg. Likewise, we recorded whether participants reported a diagnosis of hypertension (21).

Weight, height, and waist circumference were measured by trained personnel using standard protocols. Body mass index (BMI; weight in kilograms divided by height in m^2 [kg/m^2]) was calculated: overweight was defined as a BMI of 25.0 to 29.9 and obesity as a BMI of 30.0 or more (22). Abdominal obesity was defined as a waist circumference of 80 cm or more for women and 90 cm or more for men (19).

Data on sociodemographic characteristics and clinical history were collected by trained interviewers through an adapted version of the questionnaires applied in the National Health and Nutrition Survey of Mexico (23). We used the time since diabetes diagnosis as a proxy of duration of type 2 diabetes and categorized it into 4 intervals (<5 y, 5 y to <10 y, 10 y to <15 y and ≥15 y). Participants reported whether they followed diet and physical activity recommendations to control their diabetes.

We conducted a principal component analysis of 15 characteristics related to household appliances and services (eg, ownership of car, telephone, computer, vacuum cleaner, washing machine, refrigerator, pay television, internet) as a proxy for socioeconomic status (SES). Similar methods have been used (14). These characteristics had a factorial loading of 0.30 or more. The first principal component was divided into tertiles and used as a proxy for low SES, medium SES, and high SES.

Ophthalmologic evaluation

All participants were interviewed by using a validated questionnaire for ocular assessment. The following data were collected by trained technicians: best-corrected visual acuity, refractometry (by using an automated refractor [Huvitz HRK-7000]), and intraocular pressure (by using a rebound tonometer [Icare TA01i]). Afterwards, all participants received a photographic evaluation of their posterior pole (45° nonmydriatic fundus camera [DRS-Centervue]). Participants were dilated with tropicamide only if the

quality of the photographs was not adequate for grading. We took 3 fields of the posterior pole using a standardized protocol. The first field centered on the optic nerve, the second field centered on the fovea, and third field was temporal to the macula but included the fovea. This protocol has an adequate level of sensitivity and specificity for grading referable stages of diabetic retinopathy (24).

All photographs were sent to Eye Knowledge Network (www.eyeknowledge.net). All cases were masked and reviewed by trained graders from the Hospital Luis Sánchez Bulnes of the Association for the Prevention of Blindness in Mexico. The cases were graded by using the Revised English Diabetic Eye Screening Program Grading System (25), which allows prompt referral of proliferative stages of diabetic retinopathy and macular edema. Diabetic retinopathy was recorded when a participant had background diabetic retinopathy, preproliferative diabetic retinopathy, or proliferative diabetic retinopathy.

Statistical analysis

We tabulated categorical variables as frequency and proportion distributions and quantitative variables as measures of central tendency (mean or median) and dispersion (standard deviation [SD] or interquartile range). We set statistical significance at an α of .05. We compared measures of central tendency according to diabetic retinopathy status of participants (has diabetic retinopathy or does not have diabetic retinopathy) by using the Student *t* test or Mann–Whitney *U* test, depending on the distribution of the quantitative variables. We used a χ^2 test or Fisher exact test to compare the prevalence of diabetic retinopathy across categories of nonquantitative variables. We conducted a descriptive analysis to compare sociodemographic and clinical characteristics and diabetic retinopathy risk factors between participants and nonparticipants.

We developed the screening tool in 3 stages: 1) we developed the theoretical predictive model, 2) we assessed the performance of the model and conducted a validation analysis, and 3) we optimized risk-score cut points for diabetic retinopathy classification.

Development of the theoretical predictive model

For multivariate analysis, we included only participants who had complete information on diabetic retinopathy status (the dependent variable), and we determined whether at least 95% of the participants provided information for each of the independent variables. If 5% or more of the participants did not provide information for an independent variable (theoretical risk factors of diabetic retinopathy), we used multiple imputation through a logistic regression model, where diabetic retinopathy, sex, age, and self-reported diabetes screening were the independent variables, to complete the information.

We generated a predictive probit model based on theoretical risk factors of diabetic retinopathy (5–8,11–13). We decided to use this model to develop our tool because of its easy interpretability as a *z* score from its linear equation and because it provides a predicted probability for the linear predictor (applying the standard normal cumulative function). Familiarity with this distribution provides a better understanding of coefficients and predicted *z* scores. The dependent variable was diabetic retinopathy, and the 4 predictors were time since diabetes diagnosis, high blood glucose, high systolic blood pressure, and physical inactivity. We estimated probabilities adjusted by covariables of having diabetic retinopathy given each risk factor category though predictive margins.

Performance assessment and validation

We used the *k*-fold cross-validation method ($k = 10$ partitions) and the area under the receiver operating characteristic curve (AUC ROC). To assess the performance of the model in training and validation data sets, we randomly divided the sample into 10 partitions. In each partition, one segment was reserved for model validation (validation data set, n ~ 10%), while the rest of the sample in this partition was used as a training subsample (training data set, n ~ 90%). We calculated the AUC ROC for each iteration and its mean for the 10 iterations.

Optimization of risk-score cut points for diabetic retinopathy classification

We developed a risk score for diabetic retinopathy based on the *z* predictor of our statistical model. In this way, the attributable score of each risk factor was equivalent to its probit coefficient.

The use of a cost-benefit analysis to select cut points implies knowledge of true and false classification costs; however, it is difficult to have such complete information. To select the optimal cut points of the *z* predictor to classify diabetic retinopathy, we decided to focus on misclassification costs only through the misclassification cost term (16). We identified points along the ROC curve that minimized the misclassification cost function for various scenarios of misclassification costs and diabetic retinopathy prevalence. The costs of true classification were assumed as null, and the examples of the variations of misclassification ratios were set according to consequences in health costs of screening for diabetic retinopathy.

We estimated sensitivity and specificity across AUC ROC and isocost curves, which minimized the costs of misclassification. Likewise, we estimated positive predictive values and negative predictive values.

We considered the following scenarios for the optimization of the cut points: diabetic retinopathy prevalence of 35.0%, 40.0%, and 45.0%, and the observed prevalence in our sample. We examined various ratios of cost misclassification (classification costs of false negatives divided by classification costs of false positives). We examined ratios of 1, 4, and 10, assuming that classification of a false negative would generate higher health care costs than would classification of a false positive.

The statistical analysis was conducted by using Stata version 13.1 (StataCorp LLC) and RStudio version 1.0.136 with the OptimalCutpoints package.

Results

The mean age of our sample was 57.2 y (SD, 11.0 y), and 73.0% were women. The prevalence of diabetic retinopathy was 31.7% (Table 1); 18.9% had background diabetic retinopathy, 5.7% had preproliferative diabetic retinopathy, and 7.1% of participants had active proliferative diabetic retinopathy.

The prevalence of diabetic retinopathy was significantly higher among participants with insulin resistance, high blood glucose, and hypertension than among participants without those conditions. Participants with diabetic retinopathy had significantly longer times since diabetes diagnosis, higher blood glucose levels, and higher systolic blood pressure than those without diabetic retinopathy. In contrast, the prevalence of diabetic retinopathy was lower among participants who were overweight or obese, had abdominal obesity, or used physical activity to control their diabetes than among participants without these characteristics. The prevalence of diabetic retinopathy was highest, by SES, in the lowest tertile of SES and highest, by marital status, among divorced adults (Table 1).

We found no significant differences in the distribution of sociodemographic characteristics, clinical characteristics, or diabetic retinopathy risk factors between participants and nonparticipants.

Development and cross-validation of predictive model

From all independent variables included in our model, except physical activity (data were missing for 17.0% of participants), had at least 95.0% of information. After multiple imputation analysis for physical activity, we obtained a probit model with 939 observations.

According to our multivariate analysis (Table 2), time since diabetes diagnosis was positively associated with the estimated probability of diabetic retinopathy. For example, the probability of diabetic retinopathy was 11.4% (95% confidence interval [CI], 7.9%–14.9%) when time since diabetes diagnosis was less than 5 years, whereas the probability was 56.0% (95% CI, 49.5%–62.6%) when time since diabetes diagnosis was 15 years or more. Similarly, the probability of diabetic retinopathy was higher among those with high blood glucose (35.6%) and high systolic blood pressure (37.4%) than among those without those conditions (23.9% and 29.3%, respectively). On the other hand, participants who reported using physical activity to control diabetes had a lower predicted probability of diabetic retinopathy (25.4%) than those who reported not using physical activity (34.8%).

According to the cross-validation analysis (Table 3), the diagnostic performance of our model was similar between training data sets (mean AUC ROC = 0.780) and validation data sets (mean AUC ROC = 0.778).

Risk-score cut points for diabetic retinopathy classification

According to the prevalence of diabetic retinopathy observed with misclassification ratios of 1, 4, and 10, the optimal cut points were −0.046, −0.640, and −1.209, respectively (Table 4).

Four points minimized the misclassification costs given the ROC curve of our model (Figure). The optimized cut point according to a misclassification ratio of 4 and the diabetic retinopathy prevalence observed in our sample (31.7%) was $z = -0.640$, with a sensitivity of 82.9%, a specificity of 61.9%, a positive predictive value of 50.3%, and a negative predictive value of 88.6% (Table 4).

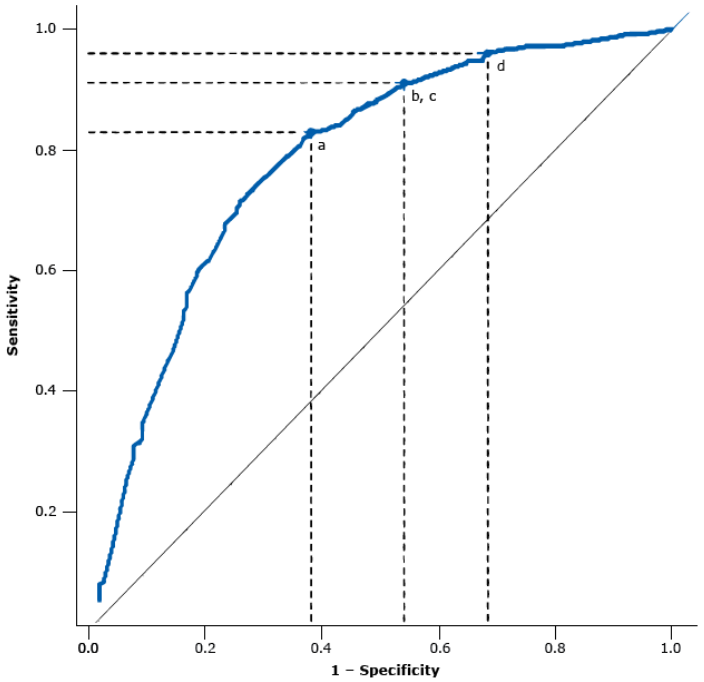

Figure. Area under the receiver operating characteristic (ROC) curve and points along the ROC curve corresponding to optimized cut points given a cost ratio (classification costs of false negatives divided by classification costs of false positives) equal to 4 and various scenarios of diabetic retinopathy prevalence: a) 31.7%, the observed prevalence in the study population; b) and c) prevalence of 35.0% and 40.0%; and d) prevalence of 45.0%.

On the basis of our data, we propose a risk-score screening tool (Box): A health care provider (can be a nonspecialized provider) asks the patient 2 questions (on time since diabetes diagnosis and use of physical activity to control diabetes) and obtains 2 measurements (blood glucose and systolic blood pressure). Each response is scored, the scores are summed, and a final score is calculated. The health care provider consults a simple chart that shows 4 levels of diabetic retinopathy prevalence, chooses the prevalence that most closely matches the prevalence of the community in which the patient resides, and then identifies the cut point that corresponds with the prevalence. If the patient has a score equal to or greater than the cut point, the patient should be directed to receive a comprehensive ophthalmologic evaluation.

Box. Proposed Screening Tool for Diabetic Retinopathy in Mexican Adults Aged ≥20 With Type 2 Diabetes, Given a Cost Ratio (Classification Costs of False Negatives Divided by Classification Costs of False Positives) of 4

Application Instructions:

1. Check one box per question.
2. Sum the corresponding scores of each checked box and then subtract 1.48.
3. Use the cut point closest to the diabetic retinopathy prevalence of the population in which you are applying this tool.
4. If the patient obtained a higher or equal score to the cut point used, the patient must be referred to specialized health services for a comprehensive ophthalmologic evaluation.

Risk Factors for Diabetic Retinopathy	Score
The information of the following 2 questions must be obtained by direct interview:	
1. How long have you been diagnosed with type 2 diabetes?	
<5 years □	0
5 to 9 years □	0.55
10 to 14 years □	1.16
≥15 years □	1.41
2. Do you use physical activity to control blood sugar?	
No □	0
Yes □ (If you checked yes for this question, you must subtract 0.33)	−0.33
The information of the following 2 questions must be obtained from measurements carried out by the interviewer:	
3. The patient had fasting capillary or venous glucose higher or equal to 126 mg/dL or random capillary glucose higher or equal to 200 mg/dL?	
No □	0
Yes □	0.41
4. The patient presented systolic blood pressure higher or equal to 140 mm Hg?	
No □	0
Yes □	0.27
Sum of scores	
Subtract	1.48
Final score	

- If prevalence of diabetic retinopathy is close to 31.7%, then cut point is −0.640
- If prevalence of diabetic retinopathy is close to 35.0%, then cut point is −1.017
- If prevalence of diabetic retinopathy is close to 40.0%, then cut point is −1.017
- If prevalence of diabetic retinopathy is close to 45.0%, then cut point is −1.190

Discussion

We developed a practical screening tool for diabetic retinopathy that could be used by nonspecialized health care personnel in low-income settings. The tool requires information on 4 risk factors. Other risk scores exist (26,27); unlike these, we optimized various cut points according to misclassification costs and diabetic retinopathy prevalence. This optimization allows the application of this tool in various contexts.

We assumed that classifying people as not having diabetic retinopathy when they actually have the condition (false negative) would result in higher long-term health care costs than would classifying them with the disease when they do not have it (false positive), because without timely diagnosis and treatment, these people are likely to progress to advanced stages of the condition. We recommend using the cut points for misclassification ratios of 4 and 10, which gives greater importance to sensitivity than to specificity. Although this recommendation substantially decreases specificity, it does not imply negative health effects, because all people with type 2 diabetes should receive an ophthalmologic evaluation when diabetes is diagnosed (17).

Although the rate of false positives generated by our tool could increase health care costs (as a result of comprehensive ophthalmologic evaluations), the application of our tool could help improve compliance with recommendations for obtaining these evaluations. In addition, the benefits of timely diagnosis and treatment could compensate for any increases in health care costs.

Although we did not have complete information for a cost-benefit analysis, we showed how results changed when the relative importance of the cost of false negatives (type 2 error) to the cost of false positives (type 1 error) varied. We set false-negative rates to be higher than false-positive rates because the health care costs resulting from delays in diagnosis and treatment of false negatives may be high in the context of the screening of diabetic retinopathy. Although the classification performance of our tool was acceptable (AUC ROC > 0.75), the precision of classification depends on the false-negative rate and false-positive rate. Therefore, confirmatory assessment of all cases is mandatory. Additionally, the negative cases identified by this tool also are at some risk of diabetic retinopathy, so periodic exploratory evaluations should be performed in all patients with diabetes.

We presented misclassification ratios only as examples: different ratios could be assumed for future research or in different contexts. Our study demonstrated a simplified approach for developing a screening tool based on a misclassification-cost criterion. Future research should focus on the assignment of costs for the 4 classification types (true positives, true negatives, false positives, and false negatives) on diabetic retinopathy screening context.

We found that systolic blood pressure and the lack of physical activity were associated with diabetic retinopathy; some studies showed that high systolic blood pressure is a potentially modifiable risk factor for diabetic retinopathy (7,12). Physical inactivity could be another important modifiable risk factor for diabetic retinopathy because it is associated with poor glycemic control (28). Our study showed that a simple question about physical activity can predict a significantly lower probability of diabetic retinopathy. Although the question cannot determine whether a person is implementing this lifestyle recommendation, it may reflect awareness and knowledge of self-care practices.

Consistent with other researchers (29,30), we observed a negative effect of obesity on diabetic retinopathy. Participants with overweight and obesity had lower levels of blood glucose and less time since diabetes diagnosis than did underweight and normal-weight participants (data not shown). We believe that the negative effect of obesity on diabetic retinopathy may be attributed to the fact that people with excess weight are experiencing an earlier stage of diabetes than people with normal or low weight.

We found a higher proportion of women (73.0%) than men in our study sample possibly because women engage in self-care practices and informal unpaid activities more than men do; this engagement may have facilitated their attendance to the recruitment process. We found a lower systolic blood pressure among women than among men (data not shown), which, given the higher proportion of women, could have underestimated the effect of systolic blood pressure in our analysis.

Our study has limitations. We did not measure HbA1c, which prevented us from adjusting our model by a variable of long-term glycemic control. However, our model adequately predicted diabetic retinopathy using parameters that are easier to measure and less expensive than an HbA1c test, which is not available at all primary health care service locations in Mexico.

An important portion of the population with type 2 diabetes may not receive a diagnosis for years (17). In Mexico, almost half of the population with diabetes is not diagnosed during routine health care, and many of them have complications that indicate many years of living with the disease (2). However, it was not possible to assess how long our study participants had been living with diabetes. Because the onset of type 2 diabetes can occur at any point during adulthood (random error), age is not the best indicator of diabetes duration. Instead of age, we used time since diagnosis as a variable for diabetes duration. Self-report of time since diabetes

diagnosis may underestimate duration, but we considered it to be a nondifferential systematic error that did not affect our results. People with type 2 diabetes may recall onset of their disease inaccurately, but the inaccuracy is the same across the population of people with diabetes, and recall of onset is independent of the diabetic retinopathy condition.

The high health cost of diabetic retinopathy in Mexico is due in part to the lack of a program designed to prevent diabetes complications (15). A challenge for our team will be to develop pilot studies that evaluate the feasibility, functionality, and costs of offering our screening tool at primary health care service locations as a strategy for strengthening the system for ophthalmologic evaluation of people with diabetes.

Early detection strategies must be implemented to reduce the burden of diabetic retinopathy. Our new screening tool is a promising approach and a practical strategy with an adequate performance to detect risk of diabetic retinopathy in adults with type 2 diabetes in low-income communities in Mexico.

Notes

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Tables

Table 1. Prevalence of Diabetic Retinopathy[a] by Sociodemographic and Clinical Characteristics, and Means/Medians for Other Clinical Characteristics by Diabetic Retinopathy[a] Status of Study Population in 3 Low-Income Municipalities, Mexico, 2014–2016

Characteristics	Total (N = 1,000)	Has Diabetic Retinopathy, % (n = 317)	Does Not Have Diabetic Retinopathy, % (n = 683)	*P* Value[b]
Overall	1,000	31.7	68.3	
Sex[c]				
Female	730	30.6	69.4	.20
Male	270	34.8	65.2	
Socioeconomic status[c,d]				
Low	332	35.5	64.5	.04
Middle	332	32.8	67.2	
High	331	26.6	73.4	
Marital status[c]				
Single	100	20.0	80.0	.01
Married	675	31.6	68.4	
Divorced	77	41.6	58.4	
Widowed	133	35.3	64.7	
Can speak an indigenous language[c]				
Yes	47	34.0	66.0	.71
No	949	31.5	68.5	
Education[c]				
None	162	34.6	65.4	.06
Some elementary school	454	33.5	66.5	
Some junior high school	237	32.9	67.1	
Some high school	82	23.2	76.8	
Some bachelor's degree or more	63	19.1	80.9	
Health system affiliation[c]				
None	83	30.1	69.9	.26

Abbreviations: HOMA, homeostasis model assessment; IMSS, the Mexican Social Security Institute (Spanish: Instituto Mexicano del Seguro Social); IQR, interquartile range; ISSSTE, the Institute for Social Security and Services for State Workers (Spanish: Instituto de Seguridad y Servicios Sociales de los Trabajadores del Estado).

[a] Diabetic retinopathy classification according to Revised English Diabetic Eye Screening Program Grading System (grade 1, grade 2, or grade 3) (25).

[b] χ^2 test (contingency tables for more than 2 categories or proportion comparison), Student *t* test, or Mann–Whitney *U* test.

[c] The percentage of participants with missing data was <5.0% or with complete information.

[d] Socioeconomic index developed by using first principal component methodology.

[e] Prevalence of diabetic retinopathy was 32.5% among those measured for triglycerides, total cholesterol, and high-density lipoprotein cholesterol (n = 418).

[f] Prevalence of diabetic retinopathy was 25.9% among those measured for insulin (n = 112).

[g] The percentage of participants with missing data ≥5.0%.

[h] Determined by answer to question "Do you have any other treatment for sugar control?" Exercise (no/yes) and diet (yes/no) were provided as possible responses.

[i] Prevalence of diabetic retinopathy was 30.7% among those measured for fasting capillary glucose (n = 423).

[j] Prevalence of diabetic retinopathy was 31.6% among those measured for random capillary glucose (n = 402).

[k] Prevalence of diabetic retinopathy was 32.5% among those measured for fasting venous glucose (n = 418).

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Table 1. Prevalence of Diabetic Retinopathy[a] by Sociodemographic and Clinical Characteristics, and Means/Medians for Other Clinical Characteristics by Diabetic Retinopathy[a] Status of Study Population in 3 Low-Income Municipalities, Mexico, 2014–2016

Characteristics	Total (N = 1,000)	Has Diabetic Retinopathy, % (n = 317)	Does Not Have Diabetic Retinopathy, % (n = 683)	*P* Value[b]
IMSS	150	27.3	72.7	
ISSSTE	72	23.6	76.4	
Seguro Popular	681	33.5	66.5	
Private	13	46.2	53.8	
Other	1	0.0	100.0	
Body mass index,[c] kg/m^2				
<25.0	247	44.9	55.1	<.001
25.0–29.9	416	30.8	69.2	
≥30.0	321	23.1	76.9	
Abdominal obesity (waist circumference ≥80 cm for women and ≥90 cm for men)[c]				
Yes	869	30.4	69.6	.008
No	115	42.6	57.4	
Triglycerides ≥150 mg/dL[e]				
Yes	294	34.0	66.0	.32
No	124	29.0	70.1	
Cholesterol ≥200 mg/dL[e]				
Yes	168	37.5	62.5	.08
No	250	29.2	70.8	
High-density lipoprotein cholesterol <50 mg/dL for women and <40 mg/dL for men[e]				
Yes	329	31.3	68.7	.30
No	89	37.1	62.9	
Insulin resistance HOMA index ≥3.8[f]				
Yes	48	39.6	60.4	.004
No	64	15.6	84.4	
High blood glucose[c] (fasting glucose ≥126 mg/dL or random glucose ≥200 mg/dL)				
Yes	603	38.1	61.9	<.001

Abbreviations: HOMA, homeostasis model assessment; IMSS, the Mexican Social Security Institute (Spanish: Instituto Mexicano del Seguro Social); IQR, interquartile range; ISSSTE, the Institute for Social Security and Services for State Workers (Spanish: Instituto de Seguridad y Servicios Sociales de los Trabajadores del Estado).

[a] Diabetic retinopathy classification according to Revised English Diabetic Eye Screening Program Grading System (grade 1, grade 2, or grade 3) (25).

[b] χ^2 test (contingency tables for more than 2 categories or proportion comparison), Student *t* test, or Mann–Whitney *U* test.

[c] The percentage of participants with missing data was <5.0% or with complete information.

[d] Socioeconomic index developed by using first principal component methodology.

[e] Prevalence of diabetic retinopathy was 32.5% among those measured for triglycerides, total cholesterol, and high-density lipoprotein cholesterol (n = 418).

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Table 1. Prevalence of Diabetic Retinopathy[a] by Sociodemographic and Clinical Characteristics, and Means/Medians for Other Clinical Characteristics by Diabetic Retinopathy[a] Status of Study Population in 3 Low-Income Municipalities, Mexico, 2014–2016

Characteristics	Total (N = 1,000)	Has Diabetic Retinopathy, % (n = 317)	Does Not Have Diabetic Retinopathy, % (n = 683)	*P* Value[b]
No	345	20.0	80.0	
General hypertension[c] (previous diagnosis or measurement of blood pressure ≥140/≥90 mm Hg)				
Yes	524	35.5	64.5	.006
No	469	27.3	72.7	
Physical activity used to control diabetes[g, h]				
Yes	272	26.8	73.2	.01
No	554	35.6	64.4	
Diet used to control diabetes[g, h]				
Yes	345	30.4	69.6	.23
No	483	34.4	65.6	
Age, mean (SD), y[c]	57.2 (11.0)	57.9 (9.3)	56.9 (11.7)	.16
Time since diabetes diagnosis, median (IQR), y[c]	7.0 (3.0–14.0)	13.0 (8.0–18.0)	5.0 (2.0–10.0)	<.001
Fasting capillary glucose, median (IQR), mg/dL[i]	149.0 (118.0–221.0)	194.5 (140.0–243.0)	137.0 (113.0–195.0)	<.001
Random capillary glucose, median (IQR), mg/dL[j]	214.5 (155.0- 295.0)	240.0 (182.0–325.0)	196.0 (148.0–273.0)	<.001
Fasting venous glucose, median (IQR), mg/dL[k]	153.0 (117.0–219.0)	198.0 (146.0–252.0)	135.5 (110.0–197.0)	<.001
Insulin, median (IQR), μIU/mL[f]	9.75 (6.7–13.8)	10.4 (7.3–15.6)	9.5 (6.6–13.7)	.48
Systolic blood pressure, median (IQR), mm Hg[c]	127.5 (115.5–142.0)	131.5 (118.5–147.5)	126.5 (114.0–140.0)	<.001
Diastolic blood pressure, median (IQR), mm Hg[c]	72.0 (64.0–79.5)	72.5 (65.0–80.5)	71.5 (63.5–79.5)	.19

Abbreviations: HOMA, homeostasis model assessment; IMSS, the Mexican Social Security Institute (Spanish: Instituto Mexicano del Seguro Social); IQR, interquartile range; ISSSTE, the Institute for Social Security and Services for State Workers (Spanish: Instituto de Seguridad y Servicios Sociales de los Trabajadores del Estado).

[a] Diabetic retinopathy classification according to Revised English Diabetic Eye Screening Program Grading System (grade 1, grade 2, or grade 3) (25).

[b] χ^2 test (contingency tables for more than 2 categories or proportion comparison), Student *t* test, or Mann–Whitney *U* test.

[c] The percentage of participants with missing data was <5.0% or with complete information.

[d] Socioeconomic index developed by using first principal component methodology.

[e] Prevalence of diabetic retinopathy was 32.5% among those measured for triglycerides, total cholesterol, and high-density lipoprotein cholesterol (n = 418).

[f] Prevalence of diabetic retinopathy was 25.9% among those measured for insulin (n = 112).

[g] The percentage of participants with missing data ≥5.0%.

[h] Determined by answer to question "Do you have any other treatment for sugar control?" Exercise (no/yes) and diet (yes/no) were provided as possible responses.

[i] Prevalence of diabetic retinopathy was 30.7% among those measured for fasting capillary glucose (n = 423).

[j] Prevalence of diabetic retinopathy was 31.6% among those measured for random capillary glucose (n = 402).

[k] Prevalence of diabetic retinopathy was 32.5% among those measured for fasting venous glucose (n = 418).

Table 2. Predictive Multivariate Model in the Development of a Screening Tool for Diabetic Retinopathy for Use in Low-Income Communities, Mexico, 2014–2016

Risk Factors for Diabetic Retinopathy	Predictive Probit Model (n = 939)[a]			
	Coefficient (SE)	*P* Value[b]	Estimated Probability[c], % (95% CI)	*P* Value[b]
Time since diabetes diagnosis, y				
<5	—[d]	—[d]	11.4 (7.9–14.9)	—[d]
5 to <10	0.55 (0.13)	<.001	24.9 (19.2–30.6)	<.001
10 to <15	1.16 (0.14)	<.001	46.6 (39.4–53.9)	<.001
≥15	1.41 (0.13)	<.001	56.0 (49.5–62.6)	<.001
High blood glucose (fasting venous or capillary glucose ≥126 mg/dL or random capillary glucose ≥200 mg/dL)				
No	—[d]	—[d]	23.9 (19.5–28.3)	—[d]
Yes	0.41 (0.10)	<.001	35.6 (32.2–39.0)	<.001
High systolic blood pressure (≥140 mm Hg)				
No	—[d]	—[d]	29.3 (26.2–32.4)	—[d]
Yes	0.27 (0.10)	.007	37.4 (32.3–42.5)	.007
Physical activity used to control diabetes[e]				
No	—[d]	—[d]	34.8 (31.4–38.2)	—[d]
Yes	−0.33 (0.11)	.002	25.4 (20.9–30.0)	.002
Constant	−1.48 (0.12)	<.001	—[d]	—[d]

Abbreviations: CI, confidence interval; SE, standard error.
[a] Multivariate probit model with any grade of diabetic retinopathy (grade 1, grade 2, or grade 3) as dependent variable according to Revised English Diabetic Eye Screening Program Grading System (25).
[b] *P* value for probit coefficients or for comparison of estimated probabilities among categories and lowest category of different variables.
[c] Obtained by predictive margins.
[d] Lowest category or estimated probability of constant.
[e] Determined by answer to question "Do you have any other treatment for sugar control?" Exercise (no/yes) was provided as a possible response.

Table 3. Cross-Validation Analysis (k = 10) of Predictive Probit Model (n = 939) in the Development of a Screening Tool for Diabetic Retinopathy for Use in Low-Income Communities, Mexico, 2014–2016

Iteration	Training Data Set (n ~ 90%), AUC ROC (95% CI)	Validation Data Set (n ~ 10%), AUC ROC (95% CI)
1	0.775 (0.742–0.809)	0.806 (0.720–0.891)
2	0.780 (0.747–0.813)	0.784 (0.690–0.877)
3	0.783 (0.751–0.815)	0.756 (0.642–0.870)
4	0.782 (0.750–0.814)	0.764 (0.659–0.869)
5	0.777 (0.744–0.810)	0.806 (0.712–0.899)
6	0.779 (0.747–0.811)	0.780 (0.664–0.896)
7	0.786 (0.754–0.818)	0.723 (0.603–0.842)
8	0.783 (0.750–0.815)	0.754 (0.653–0.855)
9	0.774 (0.740–0.807)	0.830 (0.746–0.914)
10	0.778 (0.746–0.811)	0.776 (0.672–0.881)
Average	0.780	0.778

Abbreviations: AUC ROC, area under the receiver operating characteristic curve; CI, confidence interval.

Table 4. Diagnostic Tests for Cut Points of a Screening Tool for Diabetic Retinopathy for Use in Low-Income Communities, by Misclassification-Cost Ratio and Various Scenarios of Diabetic Retinopathy Prevalence, Mexico, 2014–2016

Misclassification Cost Ratio[b]	Predictive Probit Model (n = 939)[a]				
	Sensitivity, %	Specificity, %	Positive Predictive Value, %	Negative Predictive Value, %	*z* Cut Point
Diabetic retinopathy prevalence of 31.7% (observed)					
1	56.4	83.0	60.7	80.4	−0.046
4	82.9	61.9	50.3	88.6	−0.640
10	96.6	28.7	38.7	94.9	−1.209
Diabetic retinopathy prevalence of 35.0%					
1	60.1	81.1	63.2	79.1	−0.121
4	90.9	45.9	47.5	90.4	−1.017
10	96.6	28.7	42.2	94.1	−1.209
Diabetic retinopathy prevalence of 40.0%					
1	67.8	76.4	65.7	78.1	−0.305
4	90.9	45.9	52.8	88.4	−1.017
10	96.6	28.7	47.5	92.8	−1.209
Diabetic retinopathy prevalence of 45.0%					
1	71.5	74.0	69.2	76.0	−0.374
4	96.0	31.7	53.5	90.6	−1.190
10	96.6	28.7	52.6	91.3	−1.209

[a] Multivariate probit model with any grade of diabetic retinopathy (grade 1, grade 2, or grade 3) as dependent variable according to Revised English Diabetic Eye Screening Program Grading System (25). Estimated coefficients from the multivariate probit model are shown in Table 2.
[b] Misclassification-cost ratio = cost of classification of false negatives divided by cost of classification of false positives. Ratios of 1, 4, and 10 were used, assuming that false-negative classification of a person receiving diabetic retinopathy screening would generate greater health costs than would a false-positive classification.

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ORIGINAL RESEARCH

Using Geographical Convergence of Obesity, Cardiovascular Disease, and Type 2 Diabetes at the Neighborhood Level to Inform Policy and Practice

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PEER REVIEWED

Editor's Note: This article is the winner of the 2017 Student Research Paper Contest in the Undergraduate category.

Abstract

Introduction
Chronic diseases are increasing across the world. Examination of local geographic variation in chronic disease patterns can enable policy makers to identify inequalities in health outcomes and tailor effective interventions to communities at higher risk. Our study aimed to determine the geographic variation of obesity, cardiovascular disease (CVD), and type 2 diabetes, using general practice clinical data. Further objectives included identifying regions of significantly high and low clusters of these conditions and assessing their association with sociodemographic characteristics.

Methods
A cross-sectional approach was used to determine the prevalence of obesity, CVD, and type 2 diabetes in western Adelaide, Australia. The Getis-Ord Gi* method was used to identify significant hot spots of the conditions. Additionally, we used the Pearson correlation test to determine the association between disease clusters and risk factors, including socioeconomic status (SES), smoking history, and alcohol consumption.

Results
The spatial distribution of obesity, CVD, and type 2 diabetes varied across communities. Hot spots of these conditions converged in 3 locations across western Adelaide. An inverse relationship was observed between area-level prevalence of CVD, obesity, and type 2 diabetes with SES.

Conclusion
Identification of significant disease clusters can help policy makers to target prevention strategies at the right people, in the right location. The approach taken in our study can be applied to identify clusters of other chronic diseases across the world, wherever researchers have access to clinical data.

Introduction

The global prevalence of obesity is a major threat to public health because of its steep increase in recent years (1,2). This trend is of international concern, with over 13% of men and 21% of women in the world classified as obese according to their body mass index (BMI) (1). Although the financial burden of high BMI raises concerns about the effectiveness of intervention strategies (3–5), increasingly more attention is placed on the role of obesity in the development of other chronic diseases (1). The relationship between obesity, cardiovascular disease (CVD), and type 2 diabetes mellitus is well documented, with high BMI associated with the development of atherosclerosis, hypertension, and insulin resistance (6–9). Because obesity is a clear risk factor of chronic disease, questions are raised about whether obese populations have higher rates of CVD and type 2 diabetes.

The reported interplay of sociodemographic characteristics and lifestyle factors in the development of adulthood obesity supports the notion that high BMI is not randomly distributed within a population (3,10). Therefore, the implementation of intervention programs that target all individuals within a population are limited in

their capacity to create change. Intervention strategies need to be tailored to communities where clusters of obesity, CVD, and type 2 diabetes exist. Examination of local geographic variation and the identification of the hot spots is a novel approach to inform policy and practice about inequalities in health outcomes.

The primary objective of our study was to determine the geographic variation of obesity, CVD, and type 2 diabetes in an Australian community, using general practice clinical data. Secondary objectives included the identification of regions of significantly high and low clusters of these conditions and the determination of their relationship with sociodemographic characteristics.

Methods

A clinical data set of de-identified patient records (n = 84,387) from 2010 through 2014 was acquired from 16 general practices across western Adelaide, South Australia. Obesity was defined as a BMI of 30.0 or higher, as calculated by clinical measurements of an individual's weight and height (kg/m^2). CVD was defined as having at least 1 of the following 5 CVD events: carotid stenosis, chronic heart disease, heart failure (chronic and acute), myocardial infarction, or peripheral vascular disease. Active type 2 diabetes was defined by prior diagnosis from a medical practitioner. The study obtained ethics approval from the Australian National University Human Ethics Committee (protocol 2014/174).

Data analysis was restricted to individuals aged 35 to 74 years. Active patients (individuals who had visited their general practitioner at least 3 times between 2012 and 2014) with complete data on sociodemographic characteristics and geographic information were included in the individual-level analysis (n = 20,594). After exclusion of individuals residing outside of western Adelaide, patients' medical records were geo-linked to Australian Bureau of Statistics (ABS) Statistical Area Level 1 (SA1) regions (mean, 400 individuals per SA1) (11). Active patients across 490 SA1 regions (n = 17,716; mean, 36 patients per SA1) were included in the population-level analysis. Only SA1 regions with 5 or more patients were included to preserve patient privacy.

Descriptive analysis

Mean BMI and frequency of CVD and type 2 diabetes diagnosis were determined for sex, age category, and SES through use of the Stata software (version 14; StataCorp LP). SES was classified into tertiles based on ABS Socioeconomic Indexes for Areas (SEIFA) data, including low socioeconomic, moderate socioeconomic, and high socioeconomic regions (12). Mean BMI and disease frequency was further calculated for each discrete BMI category, including the underweight class (<18.5), normal class (18.5–24.9), overweight class (25.0–29.9) and obese class (≥30.0). Additionally, mean BMI and disease frequency was determined for tobacco smoking status, frequency of alcohol consumption, and total cholesterol level. Using definitions from the Metadata Online Registry (13), individuals were classified as having smoked tobacco throughout their life or as not having smoked. Individuals who consumed alcohol at least once in the past year were identified as alcohol consumers and those who had not consumed alcohol in the past year were identified as not alcohol consumers (13). Cholesterol levels were classified as either normal or high: normal cholesterol was defined as less than 5.5 mol/L and high cholesterol was defined 5.5 mol/L or higher (14). For all risk factors, individuals with incomplete records were excluded from the descriptive analysis. The percentage of individuals with CVD and type 2 diabetes in each subpopulation was calculated by direct standardization to allow for within-group and between-group comparisons. The statistical significance of the difference in BMI and disease prevalence between each subpopulation was further calculated using the non-parametric Kruskal–Wallis test.

Spatial analysis

Mean BMI and percentage of individuals diagnosed with CVD and type 2 diabetes were aggregated at the SA1 level for western Adelaide. The regional variation was mapped across western Adelaide communities for continuous values of BMI, CVD, and type 2 diabetes diagnosis. Values were categorized into 4 groups using the Jenks natural breaks classification method (separation of data based on naturally occurring groups, determined to be the best arrangement of data) (15). A similar technique was used to map the geospatial variation of SES in western Adelaide, although SA1 regions were instead categorized into 3 groups based on the ABS SEIFA tertiles.

Local spatial clusters at the SA1 level with obesity, CVD, and type 2 diabetes were examined using the Getis-Ord Gi* technique (16,17). This tool compares the local sum of, for example, obesity values (the sum of obesity values of the targeted SA1 area and its neighboring SA1s) to the sum of obesity values of all SA1s within the study area. A significant, positive *z* score indicates a local high-rate cluster (hot spot). Hot spots are detected when an SA1 with high rates of disease is surrounded by SA1s that also have high rates of disease; the observed local sum of disease is higher than the expected local sum, and the difference is too large to be the result of chance alone. Similarly, a significant, negative *z* score indicates a local low-rate cluster (cold spot), where an SA1 with low rates is surrounded by SA1s with low rates (16,17). Significant hot spot and cold spot clusters were visualized in the western Adelaide area to highlight communities with high rates and low rates of obesity, CVD, and type 2 diabetes.

Resulting visual representations of the spatial distribution of obesity, CVD, and type 2 diabetes promoted comparison of disease hot spots and cold spots, allowing conclusions to be made about the convergence of the 3 conditions. Pearson correlation statistics were used to determine the global relationship between SES and the 3 conditions, with further comparisons made between the prevalence of CVD and type 2 diabetes. For the spatial analysis, we used ArcGIS software (version 10.4, Esri).

Results

Descriptive statistics

The prevalence of obesity in the sample population was 43.2% (Table 1). Mean BMI across sex, age category, and SES was constant, with total variation at most 1.4 kg/m^2 between high SES and low SES. Men had a significantly higher BMI than women ($P <$ .001) and increasing age had a significant, positive relationship with increasing BMI ($P <$ .001). This trend was further seen for CVD and type 2 diabetes diagnosis, with men reporting a significantly higher diagnosis rate than women ($P <$ .001 for each). CVD prevalence was 3 times higher in men than in women, where 9.1% of men reported at least 1 cardiovascular event throughout their life. Type 2 diabetes diagnosis rates were 3 percentage points higher in men than in women.

The prevalence of CVD events and type 2 diabetes also had a significant, positive association with increasing age ($P <$ .001 for each), with adults aged 65 to 74 years reporting the highest rate of diagnosis. In comparisons between the age groups of 35 to 44 and 65 to 74 years, the prevalence of CVD events among older adults was 40 times higher than that in younger adults, and the occurrence of type 2 diabetes diagnosis was 5 times higher in adults aged 65 to 74 years (Table 1).

Differences in disease prevalence related to SES were smaller than those associated with sex and age (Table 1). Individuals with high SES had lower diagnosis rates of CVD or type 2 diabetes than did individuals with a low or moderate SES. This inverse relationship indicates that even individuals with a moderate SES have a lower prevalence of all conditions than those in the lowest tertile. However, differences were only at most 1.4% lower across the sample population for CVD events.

The percentage of individuals diagnosed with type 2 diabetes and CVD had a significant, positive association with increasing BMI ($P <$ .001 for each). Obese individuals had a higher rate of type 2 diabetes (4.4 times higher) and CVD events (2.1 times higher) than those in the normal BMI range (Table 2).

Individuals with high total cholesterol levels did not have a higher prevalence of type 2 diabetes or CVD events than individuals with normal cholesterol levels (Table 2). We found an inverse relationship between cholesterol level and obesity, CVD, and type 2 diabetes. The highest percentage-point difference was for type 2 diabetes diagnosis, where individuals with normal cholesterol levels had a 10 percentage-point higher prevalence of type 2 diabetes than those with high cholesterol levels. However, data on cholesterol level were missing for 1,193 individuals, which may have changed the associations between cholesterol level and disease prevalence.

Individuals who reported a history of smoking had a higher prevalence of type 2 diabetes or CVD ($P <$ .001 for each). In contrast to the results on smoking, we found an overall inverse relationship between alcohol consumption and disease occurrence. However, this relationship was not significant for CVD ($P =$ .50) or type 2 diabetes diagnosis ($P =$ .62). Although the association was not significant, 67.5% of the total sample population did not have complete reports of their alcohol consumption. This could have changed the relationship between alcohol use and type 2 diabetes and CVD prevalence.

Spatial analysis

The regional distribution of BMI, CVD diagnosis (%), and type 2 diabetes (%) across western Adelaide indicated that the prevalence of the conditions varied across SA1 regions (Figure 1). Thematic maps (choropleth maps) show that the mean BMI of SA1 regions in western Adelaide was largely skewed toward the obese BMI class. Across the 490 SA1 regions, the lowest and highest reported mean BMIs were 24.0 and 36.0, respectively. The population-level rate of CVD was higher than that of type 2 diabetes.

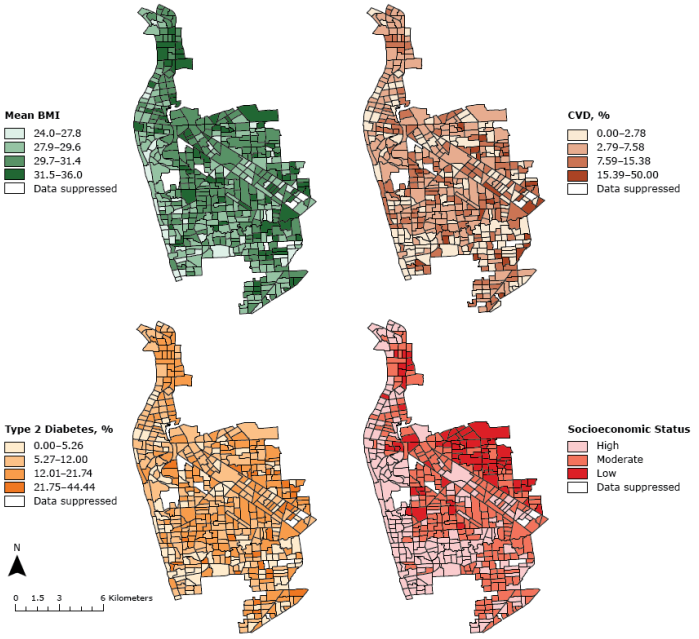

Figure 1. Regional variation of mean body mass index (BMI) (as calculated by clinical measurements of an individual's weight and height [kg/m^2]), cardiovascular disease event (CVD) diagnosis (%), type 2 diabetes diagnosis (%), and socioeconomic status, by Australian Bureau of Statistics Statistical Area Level 1 region, in western Adelaide, South Australia.

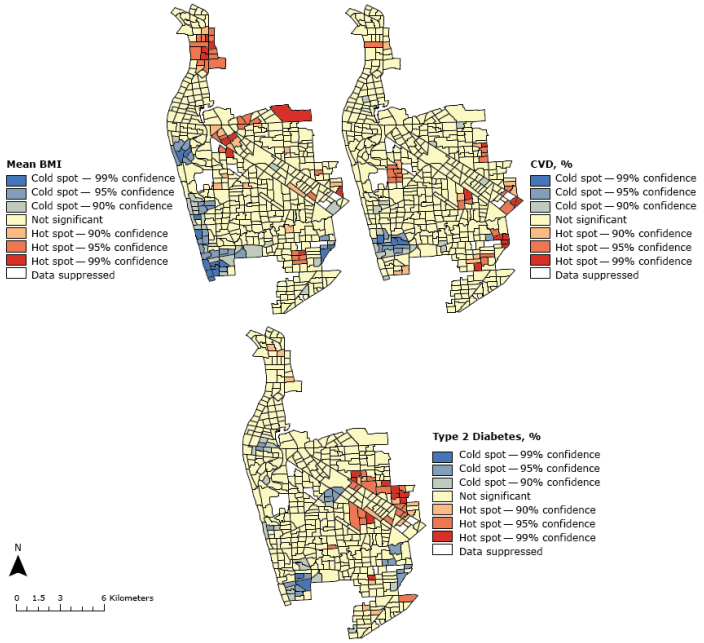

Figure 2. Hot spots and cold spots of mean body mass index (BMI) (as calculated by clinical measurements of an individual's weight and height [kg/m^2]), cardiovascular disease (CVD) event diagnosis (%), and type 2 diabetes diagnosis (%), by Australian Bureau of Statistics Statistical Area Level 1 regions, western Adelaide, South Australia.

The western coastline of western Adelaide has the lowest levels of obesity. This area is similar to the high-SES SA1 regions. We found a significant, inverse correlation between SES and mean BMI (−0.278) through Pearson correlation statistics. A similar relationship was shown for SES and CVD (−0.126), and SES and type 2 diabetes (−0.187). Disease patterns of CVD and type 2 diabetes had a significant, positive relationship (0.224).

Getis-Ord Gi* calculations determined regions across western Adelaide where the prevalence of mean BMI, CVD, and type 2 diabetes was significantly higher than other regions (Figure 2). We found 48 hot spots for BMI; they were primarily in the northern and eastern regions of western Adelaide. High-BMI cold spots were on the western coastline (Figure 2) and were associated with higher SES SA1 regions (Figure 1).

The spatial distribution of CVD events and type 2 diabetes also related to northern and central-eastern SA1 regions in western Adelaide. For CVD, 2 hot spots were found in the northern region and 26 hot spots toward the eastern region (Figure 2). For type 2 diabetes, we found a clustering of 32 hot spots in the central-eastern part of the study area. Furthermore, we observed geographical convergence for cold spots of high BMI, CVD, and type 2 diabetes in the southwestern region of western Adelaide (Figure 2), where SES is high (Figure 1).

Discussion

Through combining geospatial analysis and general practice clinical data, our study aimed to determine the spatial variation of obesity, CVD, and type 2 diabetes in western Adelaide communities. Descriptive analysis of the study population revealed a positive association between high BMI and diagnosed CVD and type 2 diabetes. Identification of disease hot spots further showed geographic convergence of the 3 chronic diseases.

As supported by data from the Australian Institute of Health and Welfare (18,19), increasing age was positively associated with the increasing proportion of CVD and type 2 diabetes diagnoses.

Mapping of mean BMI across demographic characteristics also aligned with trends found in literature (14,20), indicating that the sample used for the analysis was representative of other Australian communities. This is further established in the relationship between physiologic and lifestyle risk factors determined throughout the individual-level study, where increased BMI was associated with higher disease prevalence.

To date, population health researchers in Australia have not investigated the geographic variation of obesity, CVD, and type 2 diabetes at the neighborhood level. However, a study by Paquet et al (21) determined the clustering of biological risk factors related to the development of cardiometabolic diseases. The research emphasized the importance of using medical data collected by trained clinicians in determining the geographic spread of cardiometabolic outcomes and further outlined how clustering differs in relation to the geographic level analyzed (21). The level of spatial analysis completed by Paquet et al (21) was limited relative to our study. The intra-class correlation analysis was insufficient to determine the geographic hot spots and cold spots of cardiometabolic outcomes, investigating only the difference in the level of clustering of the risk factors (21). Thus, our study responds to a gap in the research of the spatial distribution of obesity, CVD, and type 2 diabetes across communities in Australia.

The overall aims of our study related to the population level and centered on using methods that would result in information that could be used to guide health policy and program implementation in the community. We found obesity, CVD, and type 2 diabetes hot spots in the northern and central-eastern SA1 regions. These hot spots could be a priority for policy interventions. Because these hot spots were further associated with populations of a low SES, there are further implications for the equality of health care access in the western Adelaide community. The problem of health care disparities may need to be more effectively monitored through longitudinal surveillance and related health care policies.

Our study has limitations. Use of clinical data is favored by Australian guidelines in assessing the prevalence of diseases in communities (20). Despite this, selection of study participants from local general practice records creates questions of bias. Although Australian data indicate that 85% of individuals visit their local general practitioner annually (22), the generalizability of our study is limited because individuals who visit their doctor are those who are sick and require medical attention. This selection bias may account for the larger prevalence of obesity, CVD, and type 2 diabetes shown in our study, in comparison to findings reported by the ABS (14). A further limitation in the generalizability of our study is its cross-sectional design. Because the analysis did not longitudinally follow participants, if individuals move to a different location, the identified disease hot spots and cold spots may not continue to represent the frequency of obesity, CVD, and type 2 diabetes in the SA1 regions.

In line with emerging recommendations from the World Health Organization, waist circumference, in addition to BMI, should be used to diagnose obesity in individuals (23). Therefore, we could improve our study approach by changing how we measure obesity. Because waist circumference measurements were not accurately reported in the general practice data used for our study, we could not use these data. Areas of future research could also include a qualitative study to determine the sociodemographic characteristics and lifestyle risk factors related to obesity, CVD, and type 2 diabetes. Through use of the South Australian Monitoring and Surveillance System (24), our approach could be extended to analyze the differences between identified hot spots and cold spots within the community, providing further evidence for changes to government policies and programs. In addition, a quantitative investigation into the access and use of primary care in western Adelaide could be developed to determine the effect of health care disparities on the spatial distribution of obesity, CVD, and type 2 diabetes. Further analysis of community disease profiles at the small-area level would allow more conclusions to be made about the most effective aspects of prevention and intervention programs and could be seen as an improvement to the new approach presented here.

Combining geospatial analysis and general practice data allows researchers and policy makers to identify chronic disease profiles at both the individual and community levels. This method of analysis further applies to the general practice level, where health care professionals in disease hot spots can increase the use of screening measures and related health education. Recognition of individuals and communities that require this increased surveillance would encourage the implementation of primary and secondary prevention techniques in general practices and related health services.

Notes

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Tables

Table 1. Distribution of Mean Body Mass Index (BMI)[a], Type 2 Diabetes Diagnosis, and Cardiovascular Disease (CVD) Event Diagnosis[b] in Individuals Across Demographic Characteristics in General Practice Clinical Data (N = 20,594), Western Adelaide, South Australia

Demographic Characteristic	No. (%)	Mean BMI	Type 2 Diabetes Diagnosis, No. (%)	CVD Event, No. (%)
Sex				
Male	9,190 (44.6)	30.0	1,154 (12.6)	839 (9.1)
Female	11,404 (55.4)	29.9	1,054 (9.2)	366 (3.2)
Age, y				
35–44	3,884 (18.9)	29.5	105 (2.7)	21 (0.5)
45–54	6,183 (30.0)	29.9	359 (5.8)	133 (2.2)
55–64	5,531 (26.9)	30.2	732 (13.2)	474 (8.6)
65–74	4,996 (24.3)	30.1	696 (13.9)	1,013 (20.3)
Socioeconomic status[c]				
Low	7,065 (34.3)	30.6	843 (11.9)	495 (7.0)
Moderate	6,710 (32.6)	30.1	750 (11.2)	373 (5.6)
High	6,819 (33.1)	29.2	616 (9.0)	377 (5.5)

[a] Calculated by clinical measurements of an individual's weight in kilograms and height in meters squared.
[b] At least 1 of 5 CVD events: carotid stenosis, chronic heart disease, heart failure (chronic and acute), myocardial infarction, and peripheral vascular disease.
[c] Classified into tertiles based on Australian Bureau of Statistics Socioeconomic Indexes for Areas data (12).

Table 2. Distribution of Mean Body Mass Index (BMI)[a], Type 2 Diabetes Diagnosis, and Cardiovascular Disease (CVD) Event Diagnosis[b] in Individuals Across Related Risk Factors in General Practice Clinical Data (N = 20,594), Western Adelaide, South Australia

Risk Factor	No.[c] (%)	Mean BMI	Type 2 Diabetes Diagnosis, No. (%)	CVD Event, No. (%)
BMI category				
Underweight (<18.5)	226 (1.1)	17.4	5 (2.2)	6 (2.7)
Normal (18.5–24.9)	4,275 (20.8)	22.6	155 (3.6)	148 (3.5)
Overweight (25.0–29.9)	7,198 (34.4)	27.5	639 (8.9)	419 (5.8)
Obese (≥30.0)	8,895 (43.2)	35.8	1,410 (15.9)	633 (7.1)
Cholesterol level				
Normal (<5.5 mol/L)	12,639 (61.4)	30.2	1,882 (14.9)	1,063 (8.4)
High (≥5.5 mol/L)	6,762 (32.8)	29.5	312 (4.6)	127 (1.9)
Smoking status				
Has smoked throughout life	9,001 (43.7)	30.1	1,028 (11.4)	753 (8.4)
Never smoked	9,913 (48.1)	29.9	1,061 (10.7)	399 (4.0)
Alcohol consumption				
Consumes alcohol[d]	5,180 (25.2)	29.6	571 (11.0)	170 (3.3)
Never consumes alcohol	1,514 (7.4)	30.8	274 (18.1)	126 (8.3)

[a] Calculated by clinical measurements of an individual's weight in kilograms and height in meters squared.
[b] At least 1 of 5 CVD events: carotid stenosis, chronic heart disease, heart failure (chronic and acute), myocardial infarction, and peripheral vascular disease.
[c] Numbers may not add to total N because of missing data.
[d] Consumed alcohol at least once in the past year.

PREVENTING CHRONIC DISEASE
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ORIGINAL RESEARCH

Marketing Strategies to Encourage Rural Residents of High-Obesity Counties to Buy Fruits and Vegetables in Grocery Stores

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PEER REVIEWED

Editor's Note: This article is the winner of the 2017 Student Research Paper Contest in the High School category.

Abstract

Introduction
Obesity rates in Appalachia are among the highest in the United States, and knowledge of upstream approaches to decrease prevalence among this vulnerable population is limited. The primary aim of this study was to examine the association between healthy, diet-based, social marketing interventions in grocery stores and frequency of fruit and vegetable intake.

Methods
A social marketing campaign was conducted among 17 grocery stores (N = 240 participant surveys) over 4 months in 5 rural Kentucky counties. Interventions included providing food samples, recipe cards, and promotional discounts on fruits and vegetables and moving high-calorie foods to side aisles.

Results
Most survey participants reported that recipe cards influenced their desire to purchase ingredients as well as fruits and vegetables in general. Results indicated a significant association between the influence of recipe cards and frequency of fruit and vegetable consumption.

Conclusion
Small-scale interventions in grocery stores influenced purchasing choices among Appalachian residents. Working with various store managers and food venues in rural high-obesity communities is a promising way to encourage purchasing of fruits and vegetables.

Introduction

Rural residents of the United States have higher levels of adult obesity than do other US residents (1), and Appalachia residents are at a 33% higher risk of diabetes (2). In part because of concern about these health disparities in the region, community-based studies have started focusing on different facets to combat the problems, with diet and shopping behavior being a major area of focus (3).

Given the high percentage of people who report shopping at supermarkets or grocery stores as their primary food stores (60%–85%) (4), grocery stores can provide an avenue for improving shopping choices, such as purchasing more fruits and vegetables, low-fat dairy products, and other healthy items. However, grocery stores, supermarkets, and supercenters also provide avenues for purchasing non–nutrient dense items, such as sugar-sweetened beverages, chips, baked goods, and other processed foods (5). However, provided that shoppers are encouraged to purchase healthy items in a store, stores have potential for improving the nutritional quality of what shoppers purchase and consume (6), thereby improving dietary intake.

Policies have been established to reduce prices on fruits and vegetables and relocating food in stores, and they are correlated with more fruit and vegetable purchases (7). Studies have been conducted on the efficacy of grocery store marketing features on food purchases, with varying degrees of apparent success. One study showed that of the many grocery store features, recipe samples and discount promotions resulted in frequent shoppers being more motivated to purchase healthier foods (8). Another study showed that increasing the perceived access of fruits and vegetables, spe-

cifically by focusing on display space, price, variety, and freshness, was associated with an increase in shoppers' consumption of fresh produce (9). It remains unclear what strategy may be most cost-effective and effective at promoting behavior change; perhaps a combination of all these strategies would be most effective.

The aims of this study were to test the effectiveness of marketing strategies (price reductions, recipe cards and samples, and product placements) on awareness of strategies and in increasing purchasing of fruits and vegetables. This study used a cross-sectional survey of neighborhood grocery stores in 5 counties in rural Appalachian Kentucky with high prevalence of obesity.

Methods

Grocery stores from the 5 counties participating in this project agreed to take part in the social marketing campaign strategies in stores as a way to improve food-purchasing choices among residents. The 5 counties met eligibility criteria for funding from the Centers for Disease Control and Prevention Obesity Prevention program: having a 40% or higher obesity rates among adults, being a rural geographic area, and being demographically composed primarily of white or Caucasian residents (97%). The reason behind these criteria was to study the rural high-prevalence obese population of Appalachian Kentucky.

Cooperative Extension agents in all 5 counties contacted all grocery store managers in each of their counties and managers of large supercenters in adjacent counties. Grocery store managers were given a letter explaining the social marketing campaign and were offered $100 per store event to offset any costs they might incur by moving food and displays to other locations in the store. Of the 30 stores contacted, 17 agreed to participate in the program. The grocery stores agreed to promote the campaign to their patrons, move merchandise around to promote the foods being sampled, display fruits and vegetables at the front of the store, display Plate It Up Kentucky Proud (PIUKP) materials, and offer a discount on the fruit or vegetable being tasted during the recipe sample.

The PIUKP program was conducted in 17 grocery stores (midsize grocery store with 5–7 checkout counters) or supercenters (large grocery store selling multiple produces and 15 or more checkout counters) during April and May of 2016 and then again in September and October of 2016. PIUKP is a partnership project between the University of Kentucky Cooperative Extension Service, the Kentucky Department of Agriculture, and the University of Kentucky School of Human Environmental Sciences. This project uses undergraduate students to develop and test new recipes using local and seasonal fruits and vegetables. After recipes have been tested, Cooperative Extension agents provide recipe cards, samples, and food demonstrations in their communities as a way to promote consumption. The events were held on various days of the week and various hours to capture a variety of store shoppers. The campaign consisted of displays with the PIUKP banner and recipe samples with recipe cards. Additionally, storeowners moved food that is typically higher in calories away from the front of the store and showcased the fruit or vegetable that was in the recipe. They also moved sugar-sweetened beverages or other "grab and go" items such as chips to a side aisle. Lastly, the storeowner agreed to offer a discount on the fruit or vegetable being sampled with the discount varying from 10% to 15% less than the original price. Each shopper was given a tote bag or gel-pack with the logo if they sampled a recipe. During these 2 months, the program was promoted through advertisements in local newspapers, flyers distributed in schools, and radio announcements.

A customer intercept survey was developed to capture the effectiveness of the in-store marketing events. The survey questions were previously tested for test–re-test among farmers market patrons in rural towns (10). During the marketing campaign, the Cooperative Extension agent or an assistant gave the survey to store patrons who took a recipe card or a recipe sample. A total of 240 surveys were collected from all 5 counties. The survey was conducted at the beginning of the social marketing campaign in April and again in September and October.

STATA version 12 (StataCorp LP) was used to perform statistical analyses. Descriptive statistics and multiple logistic regressions were used to assess the association between the influence of recipe cards and samples with the consumption of fruits and vegetables. All models were adjusted for age, education, and participation in the Supplemental Nutrition Assistance Program (SNAP).

Results

Mean age of participants was 51 years, and most participants (N = 240) were white (97%) and female (88%) (Table 1). Fifty-eight percent of participants reported a yearly income of less than $40,000, and 19% of participants reported receiving SNAP benefits.

Only 44% of participants had previously heard of the PIUKP Program. Forty-nine percent reported that the recipe cards influenced the purchasing of ingredients from the recipe, and 39% indicated that recipe cards influenced purchasing fruits and vegetables in general.

When assessing the intervention effectiveness on dietary intake (Table 2), results indicated a significant association between the influence of recipe cards and frequency of fruit and vegetable consumption. Participants who reported that a recipe card influenced

the purchase of ingredients related to the fruit and vegetable sample were 2.86 times ($P = .04$; 95% confidence interval [CI], 1.03–7.94) as likely to consume fruit 2 to 3 times per week than were those who reported that the cards had no influence. Participants who reported that the recipe card influenced fruit and vegetable purchases in general were 11.06 times as likely (95% CI; 3.35–36.51; $P < .001$) to consume fruit 2 to 3 times per week and 3.89 times as likely ($P = .006$; 95% CI, 1.46–10.33) to consume fruit at least once per day or more than were those that reported a recipe card not influencing fruit and vegetable purchases.

Discussion

Results of PIUKP grocery store marketing efforts suggest that there is a notable association between consumers' use of recipe cards and their dietary habits in geographically isolated rural areas of Appalachian Kentucky. Other research indicates that many grocery store features, such as recipe samples and discount promotions, resulted in frequent shoppers being more motivated to purchase healthier foods (8). Our results support these findings, particularly with regard to recipe cards. Our results also indicate how community-based efforts with cooperation from grocery store managers can influence patrons' purchasing habits. A strength of this study was that these efforts were conducted across various store types. Working with managers from different types of food stores operating in rural communities is a promising strategy for improving purchasing of fruits and vegetables (11).

Fruit and vegetable consumption can reduce a person's risk of becoming obese (12), and findings from this study can promote healthy shopping behaviors and improve personal diet. Providing opportunities for shoppers to sample different recipes as well as improving the consumer food environment may be a sustainable program approach year-round (13). Store managers who are willing to improve their stores in rural communities can make changes in their stores and thus help to improve fruit and vegetable intake among their customers (14).

Limitations of our study were the cross-sectional survey design, the small sample size, and the lack of causality. More research and different types of interventions, including those that are multipronged or not diet-focused (15), may be needed for more conclusive results on the effects of a social marketing campaign and on an overall look at dietary and shopping behavior among rural residents. Nonetheless, our study results suggest that the implementation of social marketing strategies in rural grocery stores may increase healthy food consumption habits among community residents and should be continued.

Notes

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Tables

Table 1. Characteristics of Participants (N = 240) in Plate It Up Social Marketing Campaign at Grocery Stores in Rural Appalachian Kentucky, 2016

Characteristic	Value[a]
Language is English	100
Female sex	88
Mean age, y	51
Own car	91
Highest grade completed (high school/GED)	34
SNAP recipient	19
White race	97
Income <$40,000	58
Answered yes to the question, "Does having recipe cards available at the market influence your buying of fruits and vegetables while at the market?"	39
Answered yes to the question, "Did the recipe sample available contribute to your buying the ingredients for the recipe you sampled?"	49
Heard of Plate it Up Kentucky Proud	44
Answered yes to the question, "If you took a food sample from the Plate It Up Kentucky Proud Program, did that sample make you want to prepare the food item at home?"	69
Consumption of fruit once per week or less	32
Consumption of vegetables once per week or less	29

Abbreviations: GED, general equivalency diploma; SNAP, Supplemental Nutrition Assistance Program.
[a] Values are percentages unless otherwise noted.

Table 2. Efficacy of Recipe Cards Intervention on Reported Frequency of Fruit and Vegetable Consumption, Rural Appalachian Kentucky, 2016

Characteristic	Recipe Cards Influenced Purchase of Included Ingredients		Recipe Cards Influenced Fruit and Vegetable Purchases in General	
	OR (95% CI)	*P* Value	OR (95% CI)	*P* Value
Fruit frequency				
2 or 3 times per week	2.86 (1.03–7.94)	.04	11.06 (3.35–36.51)	<.001
Once per day or more	1.48 (0.62–3.49)	.38	3.89 (1.46–10.33)	.006
Vegetable frequency				
2 or 3 times per week	2.8 (1.08–7.27)	.03	1.65 (0.61–4.45)	.32
Once per day or more	2.32 (0.99–1.04)	.07	2.63 (0.97–7.16)	.06

Abbreviations: CI, confidence interval; OR, odds ratio.

ADDITIONAL PUBLISHED STUDENT PAPERS

DOCTORAL CATEGORY

PREVENTING CHRONIC DISEASE
PUBLIC HEALTH RESEARCH, PRACTICE, AND POLICY
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ORIGINAL RESEARCH

Do Black Women's Religious Beliefs About Body Image Influence Their Confidence in Their Ability to Lose Weight?

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PEER REVIEWED

Abstract

Introduction
Black women are disproportionately burdened by obesity but maintain body satisfaction and strong religious commitment. Although faith-based weight-loss interventions have been effective at promoting weight loss among blacks, little is known about how body image and religious views contribute to weight-related beliefs among religious black women. The purpose of this study was to examine whether demographic and health history factors, religious involvement, and beliefs about body image could explain motivation and confidence to lose weight among a church-affiliated sample of black women.

Methods
We recruited 240 church-affiliated black women aged 18 to 80 years (average age, 55 y; SD, 12.3) in 2014 from 6 black churches that participated in a larger study, Project FIT (Faith Influencing Transformation), a clustered, diabetes/heart disease/stroke intervention among black women and men. We used baseline data from Project FIT to conduct a cross-sectional study consisting of a survey. Variables approaching significance in preliminary correlation and χ^2 analyses were included in 2 multiple linear regression models examining motivation and confidence in ability to lose weight.

Results
In final regression models, body mass index was associated with motivation to lose weight ($\beta = 0.283$, $P < .001$), and beliefs about body image in relation to God predicted confidence to lose weight ($\beta = 0.180$, $P = .01$).

Conclusion
Faith-based, weight-loss interventions targeting black women should emphasize physical well-being and highlight the health benefits of weight management rather than the benefits of altering physical appearance and should promote positive beliefs about body image, particularly relating to God.

Introduction

Black women are disproportionately burdened with obesity. An estimated 80% are overweight or obese (body mass index [BMI] ≥25) (1,2), and cultural beliefs may contribute to high rates of obesity among black women (3,4). Black women's beliefs regarding an ideal body shape (ie, being shapely and curvy; having large breasts, hips, and buttocks) are perceived to be more attractive in the black community but tend to differ from those of mainstream archetypes (3).

Many studies report that black women are less concerned about weight than women in other racial/ethnic groups (4), that they prefer large body shapes (5), that they have high levels of body satisfaction and self-esteem while overweight or obese, and that they tend not to believe that losing weight will improve quality of

life (4,6–9). Furthermore, studies showed that black women who lost weight were concerned that they appeared too thin or unwell (10) and worried that a petite body frame might be viewed negatively (eg, as scrawny) (3). Conversely, some studies found that overweight and obese black women have weight-related concerns and would like to lose weight (11,12), particularly because of the effect of their weight on their health (13). In one study, obese black women reported that a larger body size could be healthy and attractive but expressed interest in losing weight and were self-conscious about their body size (14). Still, cultural norms that promote body acceptance, inaccurate perceptions of body size, and limited knowledge of weight-related health problems (12) may reduce motivation and confidence to lose weight. Little is known about what influences motivation and confidence to lose weight among black women, especially in settings that could extend the reach and effect of black female-focused, culturally tailored, weight-loss interventions.

Black churches have the potential to shift cultural body image norms and provide support for weight loss among black women. In national studies, more than 80% of black women described religion as very important, and almost 60% reported attending church services weekly (15). Most black churches have health or outreach ministries (eg, food and clothing pantries, day care) that can be tapped by health promotion programs to reach women in the communities they serve (16–18). Additionally, most churches promote the scripture that the body is made in the image of God and is the temple of God, encouraging members to take care of their bodies (19).

Despite the growing number of obesity studies in black churches (17), virtually no studies have examined potential cultural and health contributors to weight-related beliefs among black women church-goers. Improving understanding of these beliefs could inform the design of tailored weight-loss interventions. The objective of this study was to explore whether demographic and health history factors, religious involvement, and body image beliefs would predict motivation and confidence to lose weight in a church-affiliated sample of black women.

Methods

We used a cross-sectional design to examine baseline data that were collected over a 6-week period in October and November 2014 as part of larger intervention, Project FIT (Faith Influencing Transformation), a religiously tailored intervention for diabetes/heart disease/stroke education, screening, and linkage to care conducted in urban areas of Kansas City, Missouri, among black women and men. Analyses for Project FIT were performed in November 2016 (results have not been published). Participants for our study were recruited from 6 black churches that participated in Project FIT through announcements from pastors and other church leaders during church services and through church outreach events (eg, food pantry).

We recruited 240 black women from Project FIT. The response rate was 94% across all predictor variables and 98% for outcome variables. Participants met the following eligibility criteria: self-identified as black and female, were aged 18 to 80 years, did not have sickle cell anemia, were not pregnant or planning to become pregnant, and were willing to participate in a survey. Surveys were paper and pencil and assessed health-related beliefs and behaviors. Surveys took approximately 30 to 45 minutes to complete, and participants received $20 in cash for completing the survey. Participants provided written informed consent, and the University of Missouri–Kansas City institutional review board approved the study.

Survey measures

Participants were asked to provide information on age, education level, income, marital status, and whether they had children. Income and marital status were dummy-coded to compare married women with all other groups (eg, single, widowed, divorced women) and to compare women with a monthly household income of more than $3,000 to women with a household income of $3,000 or less. Having children was measured as a dichotomous (yes/no) variable.

Health history variables collected were health insurance coverage, body mass index (BMI; kg/m^2), health care visits, diagnosed health conditions, and perceived stress. To calculate BMI, a member of the research team used a SECA stadiometer and scale (SECA) to measure height and weight without shoes.

Three survey questions developed for this study assessed health care visits over the past 12 months (ie, physician visits, emergency department visits, and hospitalizations; Cronbach $\alpha = 0.46$) with responses ranging from none, once, twice, or 3 or more. Responses were summed, with total scores ranging from 0 (no health care visits) to 12 (nine or more health care visits). Fifteen dichotomous (yes/no) questions assessed diagnosed health conditions (eg, high blood pressure, diabetes, depression; Cronbach $\alpha = 0.50$). Responses were summed, with total scores ranging from 0 (no diagnoses) to 15 (maximum number of conditions). Perceived stress was measured by using questions adapted from the Perceived Stress Scale, which was designed for ease of use with community-member participants (Cronbach $\alpha = 0.84$–0.86 in previous studies)

(20). Fourteen questions asked participants to rate their experiences with stress (eg, "Felt that you were unable to control the important things in your life"; 1 = never to 5 = very often; Cronbach α = 0.95). Questions with positive answers (eg, "Dealt successfully with irritating life hassles") were reverse-scored. Summed scores ranged from 14 (low stress) to 70 (high stress).

To assess religiosity, one question asked how many years participants had been church members. Seven questions, adapted from the Religious Background and Behavior Scale (21) and used in previous studies among faith-based black populations (Cronbach α = 0.77) (22), assessed participants' religiosity (Cronbach α = 0.74 for this study). The first question asked participants to describe their religious identity (ie, 1 = atheist, 2 = agnostic, 3 = unsure, 4 = spiritual, 5 = religious). Six additional questions asked participants about frequency of religious behaviors (eg, thought of God, prayed, attended a worship service) and were ranked on a scale of 0 (never) to 8 (more than once a day). Summed scores for the 7 religious identity and behavior items ranged from 7 (low religiosity) to 53 (high religiosity).

Participants were asked to rate satisfaction with their overall appearance and with their arms, waist, thighs, and buttocks on a scale of 1 (highly not satisfied) to 7 (highly satisfied) (Cronbach α = 0.92 for this study). Responses were summed, so that total scores ranged from 5 (low body satisfaction) to 35 (high body satisfaction).

Five questions assessed participants' beliefs about their body in relation to God (eg, belief that "My body is a temple of God" and that "My body is a gift from God."). Responses were rated on a scale of 1 (strongly disagree) to 7 (strongly agree) (Cronbach α = 0.74 for this study). Responses were summed, and scores ranged from 5 (no body image beliefs in relation to God) to 35 (strong body image beliefs in relation to God).

Two questions ranked how motivated participants were to lose weight and how confident they were that they could do so, both on a scale of 0 (not at all confident or motivated) to 10 (very confident or motivated).

Data analysis

Descriptive statistics were used to examine all variables. Preliminary analyses (ie, correlation, χ^2) were performed to examine associations between predictor variables (ie, demographics, health history, religious involvement, body image beliefs) and motivation and confidence to lose weight. We used SPSS version 22.0 (IBM Corp) to enter variables that were significantly associated or approached significance (ie, $P \leq .10$) with motivation or confidence to lose weight into 2 separate multiple linear regression models with the first model examining motivation to lose weight and the second model examining confidence to lose weight. Significance levels were set a priori for both regression models at $P < .05$. Categorical variables (eg, marital status, income) were dummy-coded. All variables included in each of the linear regression models were entered in a single step. For the purposes of this cross-sectional study, explanatory variables are referred to as predictor variables with motivation and confidence to lose weight as outcomes (23).

Results

Participants' average age was 55 years (standard deviation [SD], 12.3; range, 18–80 y). Most participants reported being married and having children, a college degree or higher, health insurance, and a monthly household income less than $3,000 (Table 1). Average motivation to lose weight was 7.8 on a scale of 0 to 10 (SD, 2.7) and average confidence in ability to lose weight was slightly higher (mean, 8.0; SD, 2.5; scale 0–10). Age and having children were not related to motivation to lose weight (Table 2) or confidence in ability to lose weight (Table 3). Income and marital status were both positively related to motivation to lose weight in preliminary analyses. Income also was positively related to confidence in ability to lose weight in preliminary analyses; however, neither income nor marital status predicted motivation or confidence in ability to lose weight in final regression models.

Participants' average BMI was 32.8 (SD, 8.5; range, 18–54). In preliminary analyses BMI was significantly associated with motivation but not with confidence. BMI significantly predicted motivation to lose weight in the regression model.

Most participants (87%) had visited their physician for a regular checkup in the past year, and 44% had visited their physician 3 or more times (overall scores for health care visits ranged from 3 to 10, scale 0–12). The most common place for routine medical care was a physician's office or health maintenance organization (73%). More than half (52%) had visited an emergency department, and 39% had been hospitalized in the past year.

Participants reported an average of 1 or 2 diagnosed health conditions (mean, 1.7; SD, 1.5; scale 1–15; range, 0–6 conditions), most commonly high blood pressure (57%), high cholesterol (39%), or diabetes (24%). Diagnosed health conditions and health care visits were not associated with motivation or confidence in preliminary analyses.

Participants reported an average perceived stress score of 36.7 (SD, 7.0; range, 20–55 on the Perceived Stress Scale). The association between perceived stress and motivation to lose weight ap-

proached significance in preliminary analyses, but stress did not predict motivation to lose weight in the regression model. Perceived stress was not associated with confidence in ability to lose weight in preliminary analyses.

The average length of time the woman had been a church member was 23 years (SD, 18.6; range, 1–72 y). The average religiosity score was 46.4 (SD, 5.7; range, 21–53; scale 7–53). Most participants described themselves as religious (84%) and attended church at least weekly (93%). More than once per day, many participants thought of God (85%), prayed (75%), meditated (43%), or had direct experiences with God (43%); 38% read scriptures or holy writings almost daily. Religiosity and years as a church member were not significantly associated with motivation or confidence in ability to lose weight in preliminary analyses.

Average combined body satisfaction was 21.8 (SD, 7.9; range, 5–35; scale 5–35). Body satisfaction was not associated with motivation or confidence to lose weight in preliminary analyses.

Participants had very strong body image beliefs about their bodies in relation to God (mean, 32.4; SD, 6.8; range, 5–35, scale 5–35). In preliminary analyses, body image beliefs in relation to God approached significance for motivation to lose weight and were significantly associated with confidence to lose weight. In the regression model, body image beliefs in relation to God predicted confidence to lose weight.

Discussion

To our knowledge, this study is among the first to examine body image and religiosity, demographics, and health history as predictors of motivation and confidence in ability to lose weight among church-affiliated black women. We found that women in this study were highly motivated and confident in their ability to lose weight. Moreover, BMI significantly predicted motivation to lose weight, which was an important finding considering the high levels of overweight and obesity among this study's church-affiliated participants and among similar populations in other church-based studies (16,17,24).

Slightly more than one-fourth of participants had been diagnosed with at least one health condition, most commonly high blood pressure, high cholesterol, or diabetes, which is consistent with previous estimates (1). Although overall poor health has been shown to motivate weight loss among black people (10,11,13), diagnosed health conditions among black women in our sample were not related to motivation or confidence in ability to lose weight. Previous research indicated that concerns about developing a chronic illness drove interest in weight-loss among black women (11,13) and that preventing or managing chronic illnesses was a primary reason to lose weight (10). Still, other studies showed that people living with chronic diseases tend to have little interest in weight loss (25), particularly because chronic illnesses can result in financial problems, pain, fatigue, limited physical functioning, or depression (26), which can inhibit weight loss. Moreover, most participants visited their physician for a regular checkup in the past year, and nearly half saw their physician multiple times. Slightly more than half of participants had visited an emergency department, and more than one-third had been hospitalized in the past year. Given the growing focus on patient-centered medicine and the high rates of contact with health care services among women in our sample, consideration should be given to how culturally tailored messages can be incorporated into physician visits or hospitalizations to increase motivation and confidence in ability to lose weight among black women at risk for, or living with, chronic diseases. Additionally, opportunities may exist for pastors and other church leaders to encourage weight loss when making hospital visits with their members.

Perceived stress did not predict motivation or confidence in ability to lose weight. Previous studies of black women demonstrated a direct relationship between stress and consumption of larger portions of unhealthy foods (13). It is likely that the perception of stress is related to behaviors that can immediately mitigate its effects (eg, emotional eating) (27) and may dampen resolve to lose weight. Black women are also particularly susceptible to stressors (eg, racism, discrimination, low pay) that can exacerbate weight gain (28). Future studies should continue to explore the influence of perceived stress on weight management attitudes and behaviors.

Participants were highly religious, and consistent with other church-based studies, they attended church frequently (15,18). However, religiosity was not associated with motivation or confidence in ability to lose weight, which is likely due to a ceiling effect (ie, very high religiosity across the sample). Similarly, time as a church member was not associated with motivation or confidence in ability to lose weight. It has been suggested that the black church environment can influence weight-related health beliefs and behaviors, including exerting pressure to consume large portions or unhealthy foods at church events (24). Recommendations for weight-loss interventions designed for black people include faith-based changes to the church culture and environment (17,19), including incorporation of church policies to limit high-fat, high-calorie, and sodium-rich foods at church events. Faith-based programs may also benefit from efforts to reshape the health-related climate in church settings by increasing social support for healthy behavior change and promoting acceptability of weight-loss behaviors.

Despite the high levels of overweight and obesity in our study sample, participants reported moderate levels of body satisfaction, which is consistent with previous studies that found positive body image perceptions among obese black women (6,7,9,). Yet, body satisfaction was not related to motivation or confidence in ability to lose weight. This finding is somewhat inconsistent with a previous study of overweight and obese women from a diverse sample that found that body satisfaction was the strongest predictor of current weight-loss efforts (29). Also, participants demonstrated equal body satisfaction across different body areas, which contrasts with the literature that suggests black women are not consistently satisfied with their bodies across all areas (11). These conflicting findings suggest that much remains to be learned about body image and motivation and confidence in ability to lose weight among church-affiliated black women.

Participants had strong beliefs about body image in relation to God, which were associated with motivation and confidence and significantly predicted confidence in ability to lose weight. Qualitative studies of church-affiliated black people have shown that believing that one's body is a temple of God was related to engagement in healthy behaviors (eg, abstaining from alcohol, tobacco, and drugs) (19). Faith-based weight-loss interventions for black women could be tailored to promote positive, faith-based attitudes about the body while encouraging preventive health behaviors (eg, physical activity, healthy eating).

This study had limitations. It was not guided by hypothesis or theory. Instead, we took an exploratory, stepwise approach for the inclusion of variables to be analyzed. Additionally, this study was cross-sectional, which limits causal inferences. Still, this study had several strengths, including a comprehensive list of demographic, health history, religious, and body image variables of a diverse church-affiliated sample of black women with representation across age, income, and marital status. This study also contributes to the literature on motivation and confidence in ability to lose weight among church-affiliated black women, a population with high rates of overweight and obesity. Recognition of the influence of BMI and body image beliefs in relation to God on motivation and confidence in ability to lose weight presents opportunities for black faith communities to tap this inherent cultural aspect of religiosity and church tenets to reduce the burden of obesity among black church-affiliated black women.

Acknowledgments

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Tables

Table 1. Demographic and Psychosocial Characteristics of a Sample of Church-Affiliated Black Women (N = 240) in Kansas City, Missouri, 2014

Characteristic	No. (%)[a]
Age, mean (SD), y	55 (12.3)
Education	
11th grade or below	10 (4)
High school diploma or general equivalency degree	29 (12)
Some college or post-high school technical training	5 (2)
Associates degree or technical school certificate	71 (30)
College degree or higher	125 (40)
Monthly household income, $	
0–1,000	24 (10)
1,001–2,000	36 (15)
2,001–3,000	55 (23)
>3,000	76 (32)
Don't know	11 (5)
Refused to answer	14 (6)
Marital status	
Single, never married	60 (25)
Living with partner, not married	3 (1)
Married	83 (35)
Separated	13 (5)
Divorced	59 (25)
Widowed	22 (9)
Children	
Yes	201 (85)
No	37 (15)
Years as a church member	
0 to <2	5 (3)
2 to <5	21 (14)
5 to <10	22 (14)
10 to <20	31 (20)
≥20	74 (49)
Health insurance coverage[b]	
Medicare	60 (25)
Medicaid	19 (8)
Private insurance	129 (54)

Abbreviations: —, not assessed; SD, standard deviation.
[a] Unless otherwise indicated, values are numbers (percentages). Percentages may total less than 100 because of rounding or missing responses.
[b] Percentages total more than 100 because categories were not mutually exclusive.

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(continued)

Table 1. Demographic and Psychosocial Characteristics of a Sample of Church-Affiliated Black Women (N = 240) in Kansas City, Missouri, 2014

Characteristic	No. (%)[a]
Other insurance	28 (12)
No insurance	32 (13)
Body mass index (kg/m^2)	
Underweight (<18.5)	5 (2)
Normal weight (18.5–24.9)	24 (10)
Overweight (25.0–29.9)	56 (24)
Obese class I (30.0–34.9)	56 (24)
Obese class II (35.0–39.9)	43 (19)
Obese class III (≥40.0)	48 (21)
Number of health care visits in past 12 months	
1	0
2	0
3	23 (10)
4	25 (10)
5	29 (12)
≥6	92 (38)
Number of diagnosed health conditions	
0	53 (22)
1	63 (26)
2	53 (22)
3	41 (17)
4	16 (7)
5	10 (4)
≥6	4 (2)

Abbreviations: —, not assessed; SD, standard deviation.
[a] Unless otherwise indicated, values are numbers (percentages). Percentages may total less than 100 because of rounding or missing responses.
[b] Percentages total more than 100 because categories were not mutually exclusive.

Table 2. Preliminary Associations and Linear Regression for Motivation to Lose Weight Among Church-Affiliated Black Women in Kansas City, Missouri, 2014

Variable	Preliminary Analyses			Linear Regression		
	r	χ^2	*P*	β (95% CI)	SE	*P*
Demographic characteristic						
Age	0.052	—[a]	.43	—[b]	—[b]	—[b]
Income	—[a]	75.7	.08	−0.003 (−0.824 to 0.792)	0.410	.97
Marital status	—[a]	67.9	.046	0.133 (−0.044 to 1.54)	0.401	.06
Children	—[a]	14.1	.83	—[b]	—[b]	—[b]
Health history						
Body mass index (kg/m^2)	0.218	—[a]	<.001	0.283 (0.046 to 0.135)	0.022	<.001
Health care visits	−0.018	—[a]	.82	—[b]	—[b]	—[b]
Diagnosed health conditions	−0.012	—[a]	.86	—[b]	—[b]	—[b]
Perceived stress	−0.127	—[a]	.07	−0.117 (−0.099 to 0.008)	0.027	.10
Religious involvement						
Years as church member	−0.076	—[a]	.25	—[b]	—[b]	—[b]
Religiosity[c]	0.037	—[a]	.59	—[b]	—[b]	—[b]
Body image						
Body satisfaction	−0.077	—[a]	.28	—[b]	—[b]	—[b]
Body in relation to God	0.111	—[a]	.09	0.049 (−0.038 to 0.081)	0.030	.48

Abbreviations: CI, confidence interval; SE, standard error.
[a] Preliminary associations were either correlation (continuous variable) or χ^2 (categorical variable), as appropriate.
[b] Excluded from regression because of nonsignificant preliminary associations.
[c] Religious attitudes, beliefs, and behaviors.

Table 3. Preliminary Associations and Linear Regression for Confidence to Lose Weight Among Church-Affiliated Black Women in Kansas City, Missouri, 2014

Variable	Preliminary Analyses			Linear Regression		
	r	χ^2	*P*	β (95% CI)	SE	*P*
Demographic characteristic						
Age	−0.003	—[a]	.96	—[b]	—[b]	—[b]
Income	—[a]	78.7	.02	0.068 (−0.320 to 1.045)	0.346	.30
Marital status	—[a]	47.8	.36	—[b]	—[b]	—[b]
Children	—[a]	6.3	>.99	—[b]	—[b]	—[b]
Health history						
Body mass index	0.095	—[a]	.15	—[b]	—[b]	—[b]
Health care visits	−0.114	—[a]	.14	—[b]	—[b]	—[b]
Diagnosed health conditions	−0.085	—[a]	.20	—[b]	—[b]	—[b]
Perceived stress	−.029	—[a]	.66	—[b]	—[b]	—[b]
Religious involvement						
Years as a church member	−0.029	—[a]	.66	—[b]	—[b]	—[b]
Religiosity[c]	0.090	—[a]	.20	—[b]	—[b]	—[b]
Body image						
Body satisfaction	0.097	—[a]	.17	—[b]	—[b]	—[b]
Body in relation to God	0.179	—[a]	.01	0.180 (0.019 to 0.113)	0.024	.01

Abbreviations: CI, confidence interval; SE, standard error.
[a] Preliminary associations were either correlation (continuous variable) or χ^2 (categorical variable), as appropriate.
[b] Excluded from regression because of nonsignificant preliminary associations.
[c] Religious attitudes, beliefs, and behaviors.

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ORIGINAL RESEARCH

Disparities in Preventive Dental Care Among Children in Georgia

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PEER REVIEWED

Abstract

Introduction
We compared access to preventive dental care among low-income children eligible for public dental insurance to access among children with private dental insurance and/or high family income (>400% of the federal poverty level) in Georgia, and the effect of policies toward increasing access to dental care for low-income children.

Methods
We used multiple sources of data (eg, US Census, Georgia Board of Dentistry) to estimate, by census tract, measures of preventive dental care access in 2015 for children aged 0 to 18 years. Measures were percentage of met need, 1-way travel distance to a dentist, and scarcity of dentists. We used an optimization model to estimate access, quantify disparities, and evaluate policies.

Results
About 1.5 million children were eligible for public insurance; 600,000 had private insurance and/or high family income. Across census tracts, average met need was 59% for low-income children and 96% for high-income children; for rural census tracts, these values were 33% and 84%, respectively. The average 1-way travel distance for all census tracts was 3.7 miles for high-income and/or privately insured children and 17.2 miles for low-income children; for rural census tracts, these values were 11.6 and 32.9 miles, respectively. Increasing dentists' acceptance of public insurance–eligible children increased met need more in rural areas than in urban areas. To achieve 100% met need in rural tracts, however, an 80% participation rate among dentists would be required.

Conclusion
Across census tracts, high-income children had better access to preventive dental care than low-income children had. Identifying tracts with disparities in access could result in more efficient allocation of public health dental resources.

Introduction

Children living in poverty are more than twice as likely to have untreated tooth decay as children with family incomes greater than 200% of the federal poverty level (FPL) (25% vs 12%) (1). Tooth decay, if left untreated, can lead to problems in eating, speaking, and learning (2). Strong evidence demonstrates the effectiveness of preventive dental care services (3), and increasing low-income children's access to these services is a national health goal (4). A major barrier to poor children not receiving dental care is difficulty in finding a dentist who accepts Medicaid (5). Policies and programs aimed at increasing access to preventive dental care (eg, increasing the number of dental care providers or providing services in schools) are typically implemented locally.

The objective of this study was to estimate 3 measures of local access to preventive dental care services – percentage of met need for preventive dental services, 1-way travel distance to a dentist, and dentist scarcity – by census tract among children in Georgia. We compared local access for 2 groups: children eligible for public dental insurance and children with private dental insurance and/or high family income. We also estimated these measures separately for rural and urban tracts. Finally, we examined the effect of increasing dentists' participation in public insurance programs (Medicaid and Children's Health Insurance Program [CHIP]) on preventive dental care access in both groups.

Methods

We used data from the US Census and the American Community Survey (6) to compare access to preventive dental services for Georgia children aged 0 to 18 years in 2 groups: children living in households with family incomes less than or equal to 247% of the FPL (the income threshold for Medicaid/CHIP eligibility [7]), hereinafter referred to as publicly insured children, and 2) children in families with an income greater than 400% of the FPL, hereinafter referred to as privately insured children. We assumed the latter group would have private insurance or be able to afford out-of-pocket expenses.

We calculated 3 measures of access for each census tract. We calculated percentage of met need as the total met need divided by pediatric need for preventive dental care services. Met need refers to the need served within state access standards (8), which specify the maximum distance to be traveled in rural or urban areas to reach a provider for people using a private vehicle or using public transportation. The state access standards are 30 miles or 30 minutes for urban communities and 45 miles or 45 minutes for rural communities. Higher values indicate smaller proportions of children who need to travel longer distances than the distances specified by state access standards to reach an available provider. We calculated travel distance as the average distance in miles a child must travel from his or her residence 1 way to visit the dentist. Higher values indicate larger travel distances. We computed travel distance by using street networks indicated by Esri's ArcMap GIS (geographic information system) version 10.3.1 software. We calculated provider scarcity as the patient caseload served by dentists divided by maximum patient caseload capacity. Higher values indicate greater scarcity of dentists.

We also designated census tracts as served, underserved, or unserved according to the proportion of children with unmet need within the state access standards or the proportion of uninsured children in households that cannot afford dental care: 10% or less (served), 10% to 50% (underserved), and more than 50% (unserved).

We estimated these measures across all census tracts in Georgia and separately across rural census tracts only (located in counties with population <35,000) and urban tracts only (population ≥35,000) (9). To estimate need for pediatric preventive dental services, we used a published methodology (10) to estimate the number of dental care provider hours required to provide preventive dental services at a frequency recommended by the American Academy of Pediatric Dentistry (11) and the American Dental Association (12). Recommended services and frequency of delivery depend on a child's age and risk for caries.

We obtained a list of Georgia dentists and their practice addresses from the 2015 Georgia Board of Dentistry. We used their taxonomy code (2015 National Plan and Provider Enumeration System) to identify providers of preventive dental services to children. We geocoded the addresses of individual dentists and computed street-network distances between dentists' addresses and census tract centroids by using Texas A&M Geocoding Services (13). Maximum capacity for preventive dental care for children per dentist was estimated according to existing estimation procedures (10). The proportion of provider capacity allocated to prevention was based on the distribution of services as defined in the Medical Expenditure Panel Survey in units of time (14).

To estimate the number of dentists accepting public insurance in each census tract, we used data from InsureKidsNow.gov (IKN). By using an approach similar to that used by the American Dental Association (15), we matched dentists recorded as accepting public insurance in the IKN database with all dentists in the Georgia Board of Dentistry list by using fuzzy logic, after removing repeats in the IKN data and accounting for both individual dentists and dental care offices. For dental care offices, we assumed all dentists who were identified in an office that was recorded in the IKN database accepted public insurance.

We used 2012 Medicaid Analytic Extract claims data obtained from the Centers for Medicare & Medicaid Services to estimate the distribution of caseload capacity allocated by each dentist for publicly insured children; these data accounted for excess capacity attributable to no-shows and potential underutilization. This study was approved by Centers for Medicare & Medicaid Services data use agreement no. 23621 and by the institutional review board of the Georgia Institute of Technology (protocol no. H11287).

To estimate access, we used an optimization model (16) that matched dental care supply and dental care need under the following set of constraints:

- Supply: the number of patients assigned to each dentist does not exceed the maximum caseload capacity for pediatric preventive care (ie, provider scarcity ≤1);
- Public insurance acceptance: the number of assigned publicly insured patients does not exceed the provider's public insurance caseload;

- Patient's travel mobility: the patient's travel distance does not exceed Georgia guidelines on access standards (17). The maximum distance for patients with personal vehicles is 30 miles in urban areas and 45 miles in rural areas (17). For patients without a private vehicle who must use an alternative means of transportation, we set a maximum distance threshold of 15 miles (45 minutes of travel time) for rural census tracts and 8 miles (30 minutes of travel time) for urban tracts.

The optimization model was based on the assumption that patients prefer providers who are nearer rather than farther to their residence, so the model's objective was to minimize the total distance traveled to reach dentists by publicly insured and privately insured children. We did not include uninsured children from families with incomes between 247% and 400% of the FPL directly in the optimization model because they were assumed not to have access to public insurance or to have the money necessary to pay for dental care out of pocket.

The model determined the number of children in the 2 study populations for each census tract assigned to a dentist's location according to the aforementioned constraints. Need within a census tract could be assigned to different dentists; unmet need within a census tract occurs when the total provider capacity in the census tract is not enough to satisfy all the need. Because many dentists do not accept patients using public insurance, our model assigned privately insured and publicly insured children separately. To account for uncertainty in the estimates of provider caseload and in the proportion of children with a greater need for preventive dental care (ie, high-risk children), we ran 65 microsimulations that simultaneously sampled from these parameters.

We defined a disparity as the absolute difference in access between publicly insured children (low family income) and privately insured children (insured and/or high family income). Using a simultaneous inference approach (18), we identified census tracts with poorer access than various disparity thresholds at the significance level of .05. For travel distance, we tested the disparity thresholds of 2, 6, 8, and 10 miles. For provider scarcity, we tested the disparity thresholds of 0, 0.1, 0.2, and 0.3. We selected these thresholds because we believed they were reasonable.

We examined the effect of various acceptance rates (ranging from 20% to 80%) of public insurance for children among dentists on our 3 access measures. To do this, we first set the acceptance rate to a given value and then sampled the public insurance caseload separately for dentists in urban tracts (caseload ranged from 35% to 50%) and dentists in rural tracts (caseload ranged from 55% to 65%). Similarly, we varied the caseload capacity of dentists accepting public insurance patients from 20% to 75% and set the maximum allowed travel distance to dentists for families owning a vehicle from 30 miles to 60 miles (for both rural and urban census tracts). Further details on all methods are available at https://healthanalytics.gatech.edu/publications/journal-papers.

Results

Among the 4,123 dentists who provided preventive dental care to children, 27.9% accepted public insurance. Among Georgia's approximately 2.6 million children, the estimated number of publicly insured children was 1.5 million, and the number of privately insured children was 600,000. The state has 1,969 census tracts (1,527 urban) in 159 counties (50 urban). The number of publicly insured children was 1,183,470 in urban census tracts and 309,813 in census tracts. The number of privately insured children was 536,043 in urban census tracts and 68,194 in rural census tracts. Both rural and urban census tracts had low percentages of children with financial access to preventive dental care; few census tracts had a percentage greater than 90% (Figure 1).

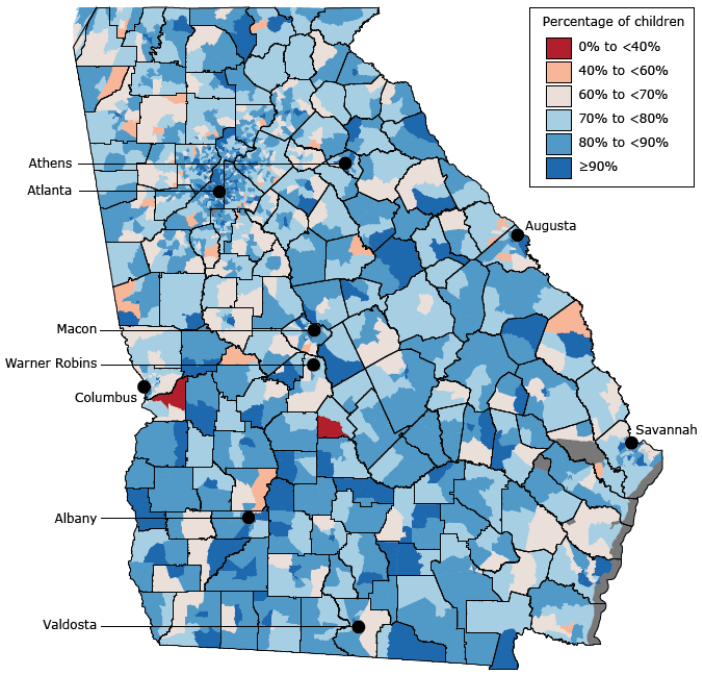

Figure 1. Percentage of children with financial access to preventive dental care in each census tract. Financial access is the percentage of children who either are eligible for public insurance or have the ability to afford dental care through commercial insurance or ability to pay out-of-pocket.

The state average (10th–90th percentile) met need for publicly insured children was 0.59 (0–1.00) and for privately insured children was 0.96 (0.90–1.00) (Table 1). In rural areas, these values were 0.33 for publicly insured and 0.84 for privately insured children, and in urban areas, 0.67 for publicly insured and 0.99 for privately insured children. The average travel distance for publicly insured children was 17.2 miles and for privately insured children 3.7 miles. In rural areas, the average travel distance was 32.9 miles and 11.6 miles, and in urban areas 12.6 miles and 1.5 miles for publicly and privately insured children, respectively. The average provider scarcity for publicly and privately insured children was 0.70 and 0.45, respectively. In rural areas, the average provider scarcity was 0.88 and 0.50 and in urban areas 0.65 and 0.43 for publicly and privately insured children, respectively.

Assuming a caseload capacity ranging from 35% to 50% in urban census tracts and from 55% to 65% in rural census tracts, we found that 6% of the census tracts were served, 57% were underserved, and 37% were unserved (Table 2).

The difference in travel distance between publicly insured children and privately insured children was greater than 2 miles for 72% of the census tracts and greater than 10 miles for 38% of the census tracts (Table 3). The difference in provider scarcity between publicly insured children and privately insured children was greater than 0 in 68% of census tracts and greater than 0.3 in 16% of census tracts.

Access to preventive dental care increased among publicly insured children as dentists' participation in public insurance increased (Figure 2). For a provider participation rate of 20%, the median met need was 30.5%, provider scarcity was 0.86, and the median travel distance was 23.4 miles. To achieve 100% median met need, a provider participation rate of 80% would be required. This increase from 20% to 80% would also result in a decrease in median travel distance to 5.6 miles and a provider scarcity of 0.52. For an increase in provider participation rate from 20% to 80% in rural tracts, the median met need increased from 21.7% to 100%, provider scarcity decreased from 0.94 to 0.65, and the median travel distance decreased from 38.9 miles to 20.2 miles. In urban tracts, the median met need increased from 46.7% to 100%, provider scarcity decreased from 0.83 to 0.47, and the median travel distance decreased from 19.2 miles to 3.8 miles.

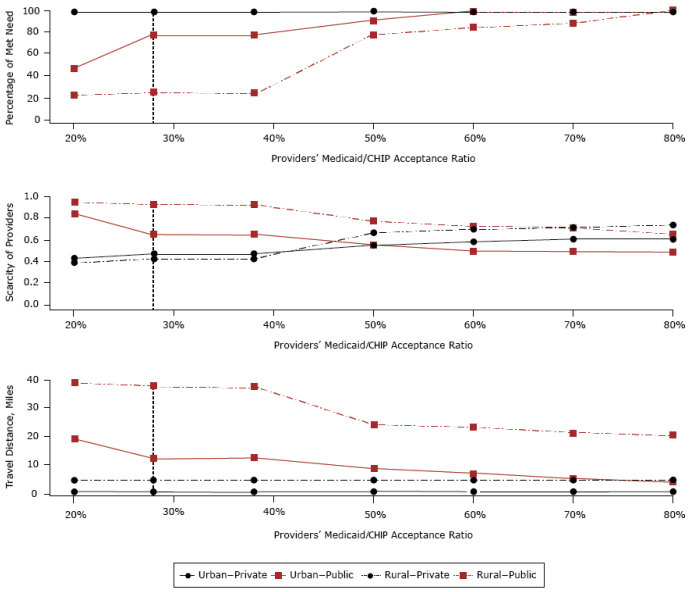

Figure 2. Median values of the percentage of met need, travel distance, and scarcity of dentists in rural and urban census tracts, by dentists' Medicaid/CHIP acceptance ratio. Scarcity was calculated as the patient caseload served by dentists divided by maximum patient caseload capacity; higher values indicate greater scarcity of dentists. The vertical dashed line at 28% represents the current rate of providers participating in public insurance programs. Abbreviation: CHIP, Children's Health Insurance Program.

Access to preventive dental care among privately insured children was negligibly affected by increases in dentists' participation in public insurance: overall, median met need was 100% at all levels of participation in public insurance. An increase of participation in public insurance from 20% to 80% would result in an increase of the median travel distance from 0.71 to 0.74 miles, and an increase of provider scarcity from 0.42 to 0.65.

When we held other variables constant in the optimization model, an increase from 20% to 75% in the public insurance caseload of dentists currently accepting public insurance patients also increased access to preventive dental care among publicly insured children. Met need increased from 24.0% to 98.1% overall, from 17.4% to 79.6% in rural census tracts, and from 26.2% to 100% in urban census tracts. Overall, travel distance decreased from 24.8 to 10.4 miles, and provider scarcity decreased from 0.85 to 0.70. For privately insured children, the effect of an increase in the public insurance caseload from 20% to 75% was again negligible: median met need was 100%, median travel distance increased from 0.71 to 0.77 miles; and provider scarcity increased from 0.36 to 0.54.

Access measures varied overall and for urban and rural census tracts when maximum allowed travel distance for people with a personal vehicle was varied from 30 miles to 60 miles. Overall, at the state level, the percentage of met need was 76.4% for publicly insured children and 100% for privately insured children for all levels of the maximum allowed travel distance. An increase of the parameter from 30 miles to 60 miles would result in an increase of the median travel distance from 15.1 miles to 25.51 miles for publicly insured children; an increase in this parameter would not affect the median travel distance for privately insured children (0.71 miles for every value of the parameter). Median provider scarcity was equal to 0.73 for public insured children and varied from 0.46 and 0.47 for privately insured children.

Discussion

Approximately 60% of the 2.6 million children living in Georgia are eligible for public dental insurance. We found that these children had significantly less access to preventive dental care than privately insured children and that disparities in access were most pronounced in rural areas. Our model predicted that publicly insured children would travel at least 20 miles more to a dentist's office than would higher-income or privately insured children in 40% of all census tracts in Georgia, in 50% of rural census tracts, and in 35% of urban census tracts.

Increasing dentists' participation rate in public insurance from its current level of 27.9% to 50% could decrease the 1-way travel distance for a dental visit for publicly insured children from 40 to 25 miles in rural census tracts and from 12 to 10 miles in urban census tracts. The finding that almost doubling dentists' participation in public insurance would negligibly affect the access of privately insured children suggests that dentists' patient caseload capacity could increase if the public insurance program in Georgia were to provide incentives (eg, increased reimbursement rates) for dentists to participate. Although an analysis of national data found that increasing Medicaid dental care reimbursement rates had only a modest effect on use of dental care among Medicaid-enrolled children (19,20), another study in Connecticut found that increasing Medicaid reimbursement rates from roughly 35% of the private insurance reimbursement rate to 70% during a 4-year period increased dental care use from 42% to 76% (21). The larger effect of increased reimbursement on Medicaid use in Connecticut may have been due to the state's simplification of Medicaid administrative procedures and the raising of reimbursement rates during a recession, which could have lowered private demand and opened dental care capacity.

However, incentivizing public insurance participation by increasing dental fees may not be feasible in the current economic environment. We found that only at a public insurance participation rate of 80%, which is challenging to attain, would all need be met for preventive dental care among publicly insured children. Another potential way to increase capacity for preventive dental care is to allow dental hygienists to provide preventive dental care in school settings (22). This approach could also lead to a decrease in costs, because the marginal rate for a hygienist is less than the rate for a dentist. Because of long travel distances in rural census tracts regardless of the participation rates of dentists in public insurance, the provision of preventive dental care in schools might be an attractive solution (23). Recently, Georgia passed legislation (HB-154) to allow dental hygienists to provide this care (24).

Our estimates are more conservative than estimates produced in a recent study (25), which found that 94% of children live within 15 minutes of a dentist that accepts Medicaid. The main reasons for this difference are that we 1) accounted for the fact that dentists who accept public insurance do not devote 100% of their capacity to public insurance–enrolled children, 2) assumed that not all dentists take new public insurance–enrolled patients, and 3) focused only on access to preventive care. Optimization models such as ours have been compared with the classic catchment area method (26); although the optimization model is more complex, it has several advantages in providing more accurate access estimates (27).

Limitations of this study pertain to assumptions made to estimate access and to the limited availability of detailed data. Limitations exist in estimating need and supply for preventive dental care (10). First, we used household income thresholds for public insurance programs to estimate the numbers of children who are eligible for public insurance. Second, we relied on Georgia Board of Dentistry data to identify practice locations of dentists. Although many dentists practice from various offices, only the business address is provided by the Georgia Board of Dentistry. Third, we used the IKN database to identify dentists accepting public insurance, assuming capacity for public insurance to be within a given range. The IKN database can be inconsistent in that it includes duplicate entries, and it names many providers not found in the Georgia Board of Dentistry data. We assumed all dentists in an office accepting public insurance took publicly insured children. We also assumed that dentists accepting public insurance took all types of public insurance. Fourth, we estimated matches between patients and dentists assuming a centralized framework; we showed elsewhere (18) how the model could be modified to incorporate decentralized decision making with patients maximizing their own welfare. Finally, travel distances do not account for potential differences in the associated travel time that may arise from population density or road shape.

The methods used in this study could help decision makers identify areas where disparities in access to preventive dental care are largest and implement strategies to increase dental care capacity for public insurance patients accordingly. Without access to preventive dental care it is likely that many of these children would develop dental caries. Dental caries is one of the most common diseases of childhood (28), and effective interventions exist to prevent it (29,30). Furthermore, evidence suggests that increasing access to effective preventive dental services could be cost saving to the Centers for Medicare & Medicaid Services (31).

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Tables

Table 1. Average Values (10th–90th Percentile) for 3 Measures of Access to Preventive Dental Care Across 65 Microsimulations, by Type of Insurance and Type of Census Tract (Rural or Urban), Georgia, 2015

Measure of Access/Type of Census Tract	Entire State Population[a]	Type of Insurance	
		Public	Private
Percentage of met need[b]			
All	0.67 (0.14–1.00)	0.59 (0–1.00)	0.96 (0.90–1.00)
Rural	0.42 (0–0.92)	0.33 (0–0.89)	0.84 (0–1.00)
Urban	0.74 (0.26–1.00)	0.67 (0–1.00)	0.99 (0.99–1.00)
Travel distance,[c] mi			
All	14.4 (0.52–36.43)	17.2 (1.1–45.0)	3.7 (0.02–7.3)
Rural	29.26 (7.95–45.00)	32.9 (10.3–45.0)	11.6 (0.6–45.0)
Urban	10.12 (0.34–23.50)	12.62 (0.74–30.00)	1.46 (0.01–3.56)
Scarcity of providers[d]			
All	0.67 (0.38–0.95)	0.70 (0.39–1.00)	0.45 (0.05–0.91)
Rural	0.82 (0.57–1.00)	0.88 (0.65–1.00)	0.50 (0.09–1.00)
Urban	0.63 (0.35–0.91)	0.65 (0.38–1.00)	0.43 (0.04–0.89)

[a] Entire population in Georgia is represented by 1,969 census tracts (1,527 urban and 442 rural).
[b] Calculated as the total met need (the need served within state access standards [8]) divided by pediatric need for preventive dental care services. Higher values indicate smaller proportions of children who need to travel longer distances than the distances specified by state access standards to reach an available provider.
[c] Calculated as the average distance in miles a child must travel from his or her residence 1-way to visit the dentist. Higher values indicate larger travel distances.
[d] Calculated as the patient caseload served by dentists divided by maximum patient caseload capacity; higher values indicate greater scarcity of dentists.

Table 2. Mean Percentage (Range) of Census Tracts[a], by Level of Preventive Dental Care Service and by Type of Census Tract (Urban or Rural), Across 65 Microsimulations[b], Georgia, 2015

Type of Census Tract	Level of Preventive Dental Care		
	Served[c]	Underserved[d]	Unserved[e]
All	6 (2–8)	57 (56–60)	37 (36–38)
Urban	8 (3–10)	64 (62–68)	29 (27–31)
Rural	1 (0–2)	35 (32–38)	64 (61–67)

[a] Entire population of Georgia is represented 1,969 census tracts (1,527 urban and 442 rural).
[b] In microsimulations, capacity ranged between 35% and 50% for urban communities and between 55% and 65% for rural communities.
[c] Met need ≥90%.
[d] Met need from 50% to 90%.
[e] Met need <50%.

Table 3. Absolute Difference[a] in Access Measure of Preventive Dental Care Between Publicly Insured Children and Privately Insured Children at Multiple Thresholds of Met Need, Georgia, 2015[b]

Type of Census Tract	Travel Distance, mile				Scarcity of Providers[c]			
	2	6	8	10	>0	>0.1	>0.2	>0.3
All	1,399 (72)	1,104 (56)	934 (48)	749 (38)	1,321 (68)	919 (47)	612 (31)	307 (16)
Urban	1,095 (78)	842 (76)	691 (74)	530 (71)	1,009 (76)	684 (74)	451 (74)	200 (65)
Rural	304 (22)	262 (24)	243 (26)	219 (29)	312 (24)	235 (26)	161 (26)	107 (35)

[a] For example, the difference in travel distance between publicly insured children and privately insured children was greater than 2 miles for 72% of the census tracts and greater than 10 miles for 38% of the census tracts.
[b] All values are number (percentage).
[c] The difference in provider scarcity was greater than 0 in 68% of census tracts and greater than 0.3 in 16% of census tracts. Scarcity was calculated as the patient caseload served by dentists divided by maximum patient caseload capacity; higher values indicate greater scarcity of dentists.

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ORIGINAL RESEARCH

Individual-Level Fitness and Absenteeism in New York City Middle School Youths, 2006–2013

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PEER REVIEWED

Abstract

Introduction
Youth health-related fitness positively affects academic outcomes, although limited research has focused on the relationship between fitness and school absenteeism. We examined the longitudinal association between individual children's fitness and lagged school absenteeism over 4 years in urban middle schools.

Methods
Six cohorts of New York City public school students were followed from grades 5 through 8 (school years 2006–2007 through 2012–2013; n = 349,381). A 3-level longitudinal generalized linear mixed model was used to test the association of change in fitness composite percentile scores and 1-year lagged child-specific days absent.

Results
Adjusted 3-level negative binomial models showed that students with a more than 20% increase, 10% to 20% increase, less than 10% increase or decrease, and 10% to 20% decrease in fitness from the year prior had 11.9% (95% confidence interval [CI], 7.2–16.8), 6.1% (95% CI, 1.0–11.4), 2.6% (95% CI, −1.1 to 6.5), and 0.4% (95% CI, −4.3 to 5.4) lower absenteeism compared with students with a more than 20% fitness decrease.

Conclusion
Cumulative effects of fitness improvement could have a significant impact on child absenteeism over time, particularly in high-need subgroups. Future research should examine the potential for school-based fitness interventions to reduce absenteeism rates, particularly for youths who have fitness drop-offs in adolescence.

Introduction

Youth physical activity and health-related fitness (henceforth fitness) positively affects academic outcomes (1,2), potentially acting through pathways involving enhanced cognition and memory (3) or improvements in both physical and psychosocial wellness (4,5). Fitness and physical activity are strongly associated, and frequent vigorous physical activities are likely to improve fitness (6). For example, daily physical activity of at least moderate intensity is associated with reduced clustering of cardiovascular risk factors in youths, including high blood pressure, insulin level, lipids, and adiposity (7). However, accelerometry data show that only 42% of children aged 6 to 11 years meet international physical activity recommendations for at least 60 minutes per day of moderate to vigorous physical activity (8). Although these rates are similar to rates in European countries (9), declines in physical activity are steeper from childhood to adolescence in the United States compared with declines in other nations (10). This national trend is also evident in New York City (NYC), where 40% and 20% of youths aged 6 to 12 and 14 to 18, respectively, meet physical activity recommendations (11,12).

Another established predictor of academic performance is school absenteeism (1,13), which may mediate the observed fitness–academic achievement association. Maintaining regular attendance, defined as missing fewer than 6 excused or unexcused days per year, predicts academic success (14). School absenteeism, regardless of reason, predicts poor academic achievement and is associated with poor school adjustment; alcohol, tobacco, and substance

use; increased rates of teen pregnancy; juvenile delinquency; and both family and home–school disengagement (4,15,16). Fitness improvements may both directly and indirectly reduce absenteeism, working potentially through pathways involving self-esteem, physical health, mental health, and cognitive processing (3,4).

Limited research has examined the fitness–absenteeism relationship (4,5,17), demonstrating consistent inverse associations between fitness and school absenteeism. For example, Blom et al demonstrated that students with greater fitness had lower odds of more than 8 absences per year (odds ratio [OR], 3.31; 95% confidence interval [CI], 1.51–7.28 for students with 6 compared with less than 5 healthy fitness zones achieved) (5). Two other articles found significant crude associations between student physical activity and absenteeism (4,17). These studies drew predominantly from cross-sectional data and did not account for a range of potential confounders, including contextual factors that contribute to absenteeism and fitness. For example, neighborhood poverty contributes to parent–school engagement and youth fitness (18,19). Similarly, school size affects programs and policy toward school attendance and physical activity (20,21). The bulk of research on fitness and absenteeism is unable to support causal hypotheses given that temporality of exposure and outcome are not known. Nuanced research in this area that draws from individual-level measures collected over multiple years and includes school-level factors is necessary to better inform policy in support of increased school-based fitness programs.

We analyzed the longitudinal association between change in fitness and 1-year lagged absenteeism in 6 cohorts of NYC public school students based on year of initiating middle school and followed consecutively over 4 years (fitness change from grades 5 to 6, 6 to 7, and 7 to 8 paired with days absent per year for grades 6, 7, and 8, respectively) during a 7-year study period (2006–2007 through 2012–2013). We hypothesized that improvements in fitness (cardiorespiratory, muscular endurance, and muscular strength fitness composite percentile scores) would predict lower subsequent absenteeism.

Methods

Study population

Data were drawn from the NYC FITNESSGRAM (Fitnessgram) data set jointly managed by the NYC Department of Education (DOE) and Department of Health and Mental Hygiene (DOHMH) (22). It comprises annual fitness assessments collected by DOE for approximately 870,000 NYC public school students per year (grades K–12) starting in 2006–2007. This study was approved by the City University of New York and DOHMH institutional review boards.

The Fitnessgram is based on the Cooper Institute's Fitnessgram, which has both strong reliability and validity (23). Fitnessgram performance tests provide a health assessment related to present and future health outcomes. NYC schools are mandated to have 85% or more of eligible students complete the test each year. Inclusion criteria for this study included enrollment in a NYC public school that collected Fitnessgram measurements for 2 or more consecutive years while in grades 6 through 8 during the study period (2006–2007 through 2012–2013) (see Figure 1 for sample selection flowchart). Student cohorts were defined based on year of initiating grade 6. Students were excluded (n = 6,225) if they were enrolled for less than n − 5 days per school year (where n is the maximum number of days enrolled across all students in each given year [n range: 292–297 days]) to ensure a consistent period of observation across school years with different total instructional days per year. Next, students were excluded if they did not take the Fitnessgram test for 2 or more consecutive years (n = 56,464), attended schools with poor-quality fitness data (n = 350), or changed schools during 6th through 8th grade (to be able to account for school clustering in the analysis; n = 44,977). After the above exclusions, the final sample of 6th through 8th graders included 349,381 unique students (51% male, 83% born in the United States, 38% Hispanic, 28% non-Hispanic black, and 16% non-Hispanic white; mean [standard deviation (SD)] school population = 541 [632]). Students in 6th, 7th, and 8th grades contributed 177,281, 220,769, and 186,135 student-years, respectively, across 624 schools.

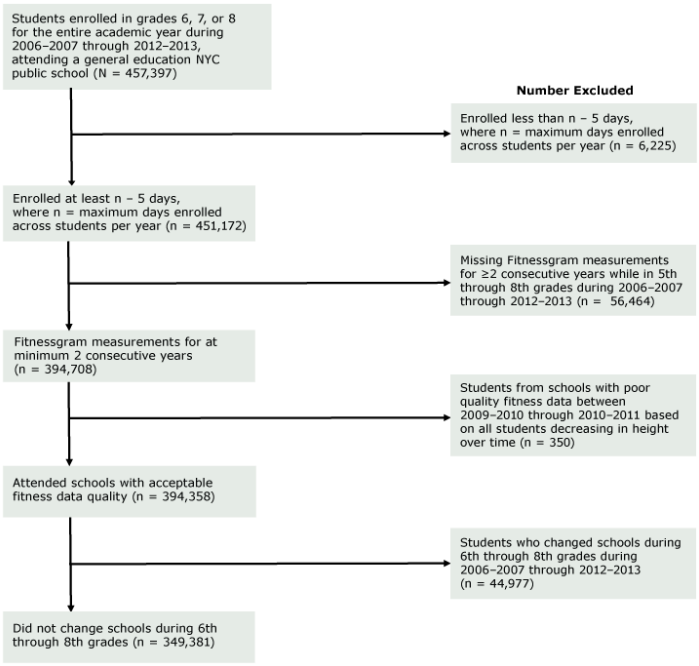

Figure 1. Sample selection flowchart for the association of fitness and absenteeism in New York City (NYC) public middle school students, 2006–2007 through 2012–2013.

Measures

The primary exposure was a categorical variable representing age- and sex-specific percentage change in fitness composite percentile scores based on the sum of percentile scores for the Progressive Aerobic Cardiovascular Endurance Run (PACER), muscle strength and endurance (curl-up and push-up) tests (23). Scores were converted to percentiles to account for expected improvements in performance with increasing age and by sex. The fitness variable was categorized as more than 20% decrease, 10% to 20% decrease, less than 10% change, 10% to 20% increase, and greater than 20% increase in performance from the year prior, consistent with longitudinal research on fitness and academic outcomes drawing from the Fitnessgram data set (24).

The primary outcome variable for this analysis was student-level number of days absent per year. Annual enrollment and attendance records were matched to Fitnessgram results by a unique student identifier.

Adjusted models included sex, age, race/ethnicity, place of birth, socioeconomic status (SES), and school size. These covariates predict both fitness and absenteeism (4,20,21,24). Age at the time of height and weight measurement was treated as a continuous variable. Race/ethnicity was based on school enrollment forms completed by parents and grouped into 5 categories: Hispanic, non-Hispanic black, non-Hispanic white, Asian/Pacific Islander, and other. Place of birth (United States vs foreign country) was included as a covariate based on literature demonstrating that immigration status is predictive of physical activity (25) and school attendance (26). SES was defined as the percentage of households in the students' school zip code living below the federal poverty threshold (low [<10%], medium [10%–20%], high [>20%–30%], and very high [>30%] poverty area) according to American Community Survey 2007–2012 data (27). School size classified schools, as per the literature, as small (<400 students) or nonsmall (≥400 students) (20).

Change in obesity status from the year prior (obese to not obese, consistently not obese, consistently obese, not obese to obese) was also included as a potential confounder based on the literature (4). Body mass index (BMI) is collected annually as a part of the Fitnessgram curriculum. Obesity was defined as having a BMI in the 95th percentile or higher for the same sex and age group using 2000 Centers for Disease Control and Prevention guidelines (28). Change in obesity status category was used in lieu of changes in BMI percentile to capture meaningful shifts in body composition associated with school outcomes (29).

Statistical analysis

Descriptive statistics were computed to summarize sample characteristics. Next, trends in absenteeism (days absent) by fitness, grade, and demographics were examined.

Because observations were nested within students, nested within schools, mixed-model methods were used. Specifically, a series of crude and adjusted 3-level longitudinal generalized linear mixed models with random intercepts for student and school effects were fit to assess the fitness–absenteeism association while accounting for clustering and individual- and school-level confounders.

First, to determine the extent of variation in absenteeism at the school level, an unconditional model with random intercepts was fit to the data (model 1). The school-level intraclass correlation (ICC) was calculated as the ratio of the variance for the school divided by the sum of the 3 variance parameter estimates, represented as $\sigma^2_{school} / (\sigma^2_{student} + \sigma^2_{school} + \sigma^2_{\varepsilon})$. Although univariate distributions for days absent demonstrated a long right-tailed Poisson distribution, the ICC was calculated based on a linear model given that the ICC definition is not well defined for Poisson models (30).

Next, the longitudinal association of change in fitness and lagged number of days absent per year was assessed by using a 3-level crude longitudinal negative binomial mixed model with random intercepts and the exposure, child-specific change in fitness from

the year prior, as well as an offset term representing total instructional days per school year included in the model (model 2). Negative binomial models were used because data were overdispersed. β Coefficients represented the effects of the exposure, change in fitness on outcome, 1-year lagged number of days absent per year. Absenteeism rates were computed by calculating the incidence rate ratio, represented as exp(β).

Finally, potential individual- and group-level confounders were added to the model (model 3). Confounding variables included level-1 time-varying covariates for grade, year (to control for potential cohort effects), and change in obesity status from the year prior, level-2 covariates for individual sociodemographic factors (sex, race/ethnicity, place of birth), level-3 covariates for school size and SES, and interactions (grade*race/ethnicity, grade*sex, grade*place of birth, and SES*race/ethnicity).

In these analyses, students contributed fitness-change data for 5th to 6th, 6th to 7th, and/or 7th to 8th grades (n = 349,381 unique students; 675,318 observations). A 2-sided *P* value of less than .05 was considered significant. Analyses were performed using SAS version 9.4 software (SAS Institute, Inc).

Results

Just under 40% of students had less than 10% change in fitness from the year prior, followed by greater than 20% increase (20%), greater than 20% decrease (19%), 10% to 20% increase (12%), and 10% to 20% decrease (12%) (Table 1). The mean (SD) number of days absent per year were highest among boys (11.0 [11.7]) and Hispanic (12.6 [12.9]) and non-Hispanic black (12.3 [13.1]) racial/ethnic groups (Table 2). Mean days absent were also highest among students who were born in the United States (11.3 [12.1]) compared with those who were born in a foreign country (11.1 [13.8]).

Overall, the mean number of days absent per year decreased with improvements in fitness scores from the year prior. The mean (SD) days absent per year for students with the lowest (>20% decrease) to highest (>20% increase) improvements in fitness were 11.9 (12.8), 11.1 (12.2), 10.7 (11.9), 10.3 (11.3), and 10.3 (11.2). Also, fitness decreased and absenteeism increased with increasing grade (Table 2). Moreover, for students in the same grade, the difference in mean days absent for those with improved versus diminished fitness became larger with increasing grade level (Figure 2). For example, mean (SD) days absent for students with the greatest increase (>20%) in fitness were 9.6 (10.1), 9.8 (10.8), and 11.9 (12.7), for students in 6th, 7th, and 8th grades, respectively. In contrast, mean (SD) days absent for students with the greatest decrease (>20%) in fitness were 10.6 (11.3), 11.6 (12.6), and 13.9 (14.3), for students in 6th, 7th, and 8th grades, respectively.

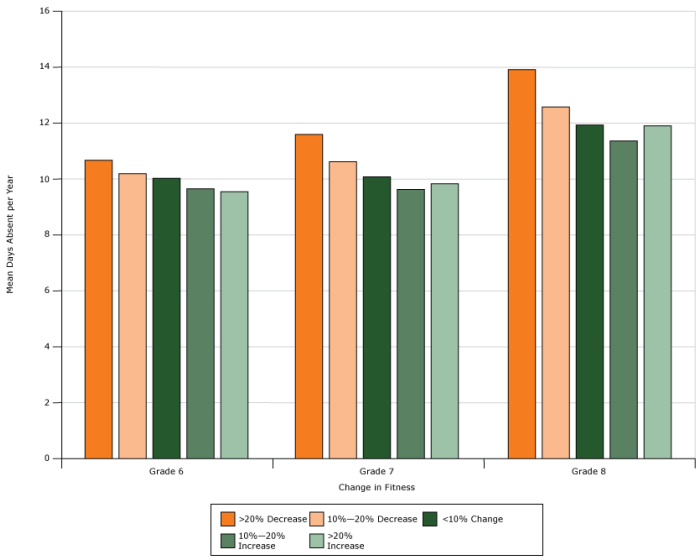

Figure 2. Mean days absent per year by grade across fitness-change categories in New York City public middle school students (N = 349,381), 2006–2007 through 2012–2013. Change in fitness composite percentile scores based on Progressive Aerobic Cardiovascular Endurance Run (PACER) Push-up and Curl-up Fitnessgram tests from the year prior. Categories are based on tabulated mean estimates.

The ICC (model 1) demonstrated a sizable degree of variance in student absenteeism explained by schools (9%). Results from model 2 showed all levels of change in fitness were significantly associated with absenteeism ($P < .001$). Compared with the reference category (>20% decrease in fitness), the absenteeism rate decreased 13.3% (95% CI, 8.3–16.6), 8.3% (95% CI, 3.3–12.7), 5.6% (95% CI, 1.9–9.0), and 1.6% (95% CI, −3.0 to 6.2) for those who had a greater than 20% increase, 10% to 20% increase, less than 10% change, and 10% to 20% decrease in fitness composite percentile scores from the year prior, respectively.

After adjusting for covariates (sex, race/ethnicity, change in obesity status from the year prior, place of birth, SES, and school size), and including interactions (grade*race/ethnicity, grade*sex, grade*place of birth, and SES*race/ethnicity), β estimates for the association of fitness change and lagged number of days absent per year diminished but remained significant ($P < .005$). Relative to the reference category (>20% decrease in fitness), the absenteeism rate decreased 11.9% (95% CI, 7.2–16.8), 6.1% (95% CI, 1.0–11.4), 2.6% (95% CI, −1.1 to 6.5), and 0.4% (95% CI, −4.3 to 5.4) for those who had a greater than 20% increase, 10% to 20% increase, less than 10% change, and 10% to 20% decrease in fitness composite percentile scores from the year prior, respectively (model 3, Table 3).

Sensitivity analyses were run to determine the effect of days of enrollment exclusions, BMI categorization specification, and total years of consecutive fitness change data on findings. Results showed slightly more conservative estimates for the magnitude of effects, although the inverse dose–response association remained consistent and significant ($P < .001$, $P = .004$, and $P = .01$ for enrollment, BMI, and fitness data sensitivity models, respectively).

Discussion

We found that all levels of 1-year change in fitness were significantly associated with absenteeism ($P < .001$) in both crude and adjusted models. Furthermore, consistent levels of fitness improvement each year at the greater than 20% level (vs >20% decrease) were found to have the potential to reduce a student's number of days absent substantially. For example, a child with a mean 10 days absent in 6th grade would have 6.5 days absent per year in 8th grade and 1.5 days absent per year in 12th grade. This change in days absent represents a shift well within the range of regular attendance (≤5 days absent per year). Findings here are consistent with the existing cross-sectional literature on fitness and absenteeism (4,5,17), lending strong support for future research on the effects of youth fitness interventions on school absenteeism. NYC programs unrelated to fitness promotion have shown a 15% reduction in chronic absenteeism in 100 high-need schools over 2 years (13), through implementing "early warning" flags to identify at-risk students, family and student "success mentors," progress monitoring systems, and community collaborations. However, despite gains and similar programs nationally, high absenteeism rates remain widespread, including 5 million to 7.5 million chronically absent US students each year (13,14).

Strengths of this study were being the first article to the authors' knowledge to examine the association of change in fitness and lagged absenteeism, drawing from multiple years of multilevel data. Also, this analysis included a large and diverse study sample of approximately 349,000 students comprised of 6 cohorts.

Findings from this study may not be generalized to other cities or nationally, given a high minority and low-income population in NYC. Future work should examine potential differences in the fitness–attendance relationship by race/ethnicity and poverty status, given higher absenteeism observed in this study among both non-Hispanic black and Hispanic students and those attending schools in high poverty areas. Furthermore, although DOE protocols promote retesting students who are absent on the original testing dates, a large number of students were excluded because of missing Fitnessgram tests for 2 or more consecutive years, insufficient enrollment period, or moving schools. Not all students are required to take the Fitnessgram, including those with chronic health conditions such as severe asthma. These students, however, would be more likely to have higher absenteeism given psychosocial, family, and health factors associated with moving and long-term absences (31). These effects potentially would move the association farther from the null.

Although we offer evidence in support of a causal association between fitness change and absenteeism, a bidirectional relationship may exist between exposure and outcome. For example, it is possible that children who have higher absenteeism are more sedentary, particularly if they are ill or occupied in nonactive ways (eg, video-game playing, watching television). Domestic factors may also persist over time. In this sense, although this analysis lagged absenteeism to fitness, the temporality of exposure and outcome could be reversed. Future research should explore the directionality of fitness and absenteeism in more detail, in addition to the role of chronic conditions in this association.

In our study, systematic bias and differential measurement error are possible, given that the Fitnessgram data are not collected for research purposes. Data were not available on many student- and school-level factors, including self-esteem, drug and alcohol use, family structure, and individual household poverty (such as income or eligibility for free or reduced-price lunch). These factors may influence not only absenteeism but also motivation to perform well on fitness tests. Absence of this data makes it difficult to disentangle these relationships. Future work should research whether mental, social, or emotional health and peer or parent influence are antecedents to fitness on the hypothesized fitness–attendance causal pathway. This research may shed light on why some adolescents have fitness performance drop-offs and may garner particular attendance benefits from these interventions.

Although testing protocols are designed to promote consistency across administers, Fitnessgram testing sites may vary in their implementation of the protocol. However, in NYC the Fitnessgram is administered by physical education teachers who receive formal training on conducting the test, including manuals, video-based training, and site visits, as well as calibrated scales (22,23).

Fitness levels in US youths decline with increasing age at rates faster than in other nations. Diminished fitness is shown in longitudinal studies to be associated with lower academic performance, and cross-sectionally to be associated with higher absenteeism. We present evidence for a longitudinal inverse dose–response association between fitness and absenteeism in NYC middle school youths. Cumulative effects of consistent fitness improvements from 6th through 12th grades may shift a child from chronic absenteeism to regular attendance. Future research should examine the effectiveness of school-based fitness interventions to reduce absenteeism rates, particularly within subgroups that have fitness

drop-offs in adolescence. Findings may inform policy mandating increases in school fitness time, including increased classroom-based physical activity and both stricter school physical education and recess policies.

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Tables

Table 1. Demographic and Fitness-Change Characteristics of New York City Public Middle School Students (N = 349,381), 2006–2007 Through 2012–2013

Characteristic	n[a,b] (%)
Sex	
Male	177,355 (51)
Female	172,026 (49)
Race/ethnicity	
Asian or Pacific Islander	58,295 (17)
Hispanic	134,453 (38)
Non-Hispanic black	99,363 (28)
Non-Hispanic white	55,857 (16)
Language spoken at home	
English	197,727 (57)
Spanish	86,052 (25)
Other language	65,602 (19)
Place of birth	
United States	289,160 (83)
Foreign country	60,149 (17)
Change in fitness[c] (all years)	
>20% Decrease	126,115 (19)
10%–20% Decrease	79,172 (12)
<10% Change	253,161 (37)
10%–20% Increase	82,117 (12)
>20% Increase	134,753 (20)
Change in obesity status[d] (all years)	
Obese to not obese	36,029 (5)
Consistently not obese	504,762 (73)
Consistently obese	119,235 (17)
Not obese to obese	27,273 (4)
School-area poverty[e]	
Low poverty	62,238 (18)
Medium poverty	119,219 (34)
High poverty	89,407 (26)

[a] N for missing place of birth = 72; N for missing area poverty = 7; N for missing or having >1 race/ethnicity = 177.
[b] Students in 6th, 7th, and 8th grades contributed 177,281, 220,769, and 186,135 student-years, respectively, across 624 schools.
[c] Based on change in change in fitness composite percentile scores based on Progressive Aerobic Cardiovascular Endurance Run (PACER) Push-up and Curl-up Fitnessgram tests from the year prior.
[d] Obesity status was defined according to Centers for Disease Control and Prevention growth chart–derived norms for sex and age (in months), based on a historical reference population, and used to compute the body mass index (BMI) percentile for each child. Obesity was defined as having a BMI ≥95th percentile for youths in the same sex and age (in months) group.
[e] Based on percentage of households in the school zip code living below the federal poverty threshold (low [<10%], medium [10%–20%], high [>20%–30%], and very high [>30%] area poverty) drawing from the American Community Survey 2007–2012 (27).

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(continued)

Table 1. Demographic and Fitness-Change Characteristics of New York City Public Middle School Students (N = 349,381), 2006–2007 Through 2012–2013

Characteristic	n[a,b] (%)
Very high poverty	78,510 (22)
School size	
Attending small schools (<400 students)	59,856 (17)
Attending nonsmall schools (≥400 students)	289,525 (83)

[a] N for missing place of birth = 72; N for missing area poverty = 7; N for missing or having >1 race/ethnicity = 177.
[b] Students in 6th, 7th, and 8th grades contributed 177,281, 220,769, and 186,135 student-years, respectively, across 624 schools.
[c] Based on change in change in fitness composite percentile scores based on Progressive Aerobic Cardiovascular Endurance Run (PACER) Push-up and Curl-up Fitnessgram tests from the year prior.
[d] Obesity status was defined according to Centers for Disease Control and Prevention growth chart–derived norms for sex and age (in months), based on a historical reference population, and used to compute the body mass index (BMI) percentile for each child. Obesity was defined as having a BMI ≥95th percentile for youths in the same sex and age (in months) group.
[e] Based on percentage of households in the school zip code living below the federal poverty threshold (low [<10%], medium [10%–20%], high [>20%–30%], and very high [>30%] area poverty) drawing from the American Community Survey 2007–2012 (27).

Table 2. Mean Days Absent per Year Across Student- and School-Level Demographic and Fitness-Change Characteristics in New York City Public Middle School Students (N = 349,381)[a], 2006–2007 Through 2012–2013

Characteristic	Student-Level[b], Mean (SD)	School-Level[c], Mean (SD)
Sex		
Male	11.0 (11.7)	11.2 (11.5)
Female	10.1 (11.0)	10.4 (10.8)
Race/ethnicity		
Asian or Pacific Islander	5.5 (7.7)	6.4 (8.3)
Hispanic	12.6 (12.9)	13.3 (13.2)
Non-Hispanic black	12.3 (13.1)	12.8 (13.3)
Non-Hispanic white	10.0 (9.7)	10.7 (10.2)
Language spoken at home		
English	11.9 (12.1)	12.0 (11.9)
Spanish	10.9 (11.1)	11.0 (10.9)
Other language	6.0 (7.4)	6.5 (7.5)
Place of birth		
United States	11.3 (12.1)	11.7 (11.5)
Foreign country	11.1 (13.8)	8.1 (8.8)
Change in fitness (all years)[d]		
>20% Increase	10.3 (11.2)	11.0 (11.6)
10%–20% Increase	10.3 (11.3)	10.8 (11.5)
<10% Change	10.7 (11.9)	11.8 (12.6)
10%–20% Decrease	11.1 (12.2)	11.6 (12.4)
>20% Decrease	11.9 (12.8)	12.7 (13.2)
Grade[e]		
Grade 6	10.2 (11.0)	10.8 (11.1)
Grade 7	10.9 (12.5)	11.2 (12.2)
Grade 8	13.1 (14.5)	13.1 (13.6)
School-area poverty[f]		
Low poverty	8.5 (9.2)	8.9 (9.3)
Medium poverty	9.5 (10.3)	9.8 (10.2)
High poverty	11.1 (11.7)	11.4 (11.6)
Very high poverty	13.1 (13.3)	13.1 (12.9)
School size		
Small schools (<400 students)	12.0 (12.3)	11.8 (11.9)
Non-small schools (≥400 students)	10.3 (11.1)	11.8 (11.0)

[a] N for missing place of birth = 72; N for missing area poverty = 7; N for missing or having >1 race/ethnicity = 177.
[b] Student-level columns do not account for school clustering.
[c] School-level columns account for school clustering.
[d] Based on change in change in fitness composite percentile scores based on Progressive Aerobic Cardiovascular Endurance Run (PACER) Push-up and Curl-up Fitnessgram tests from the year prior.
[e] Students in 6th, 7th, and 8th grades contributed 177,281, 220,769, and 186,135 student-years, respectively.
[f] Based on percentage of households in the school zip code living below the federal poverty threshold (low [<10%], medium [10%–20%], high [>20%–30%], and very high [>30%] area poverty) drawing from the American Community Survey 2007–2012 (27).

Table 3. Association of Fitness Change and Attendance in New York City Public Middle School Students[a], 2006–2007 Through 2012–2013

Fitness Change[b]	Unadjusted (Model 2)[c], IRR[d] (95% CI)	Adjusted (Model 3)[c,e], IRR[d] (95% CI)
>20% Increase	1.13 (1.09–1.18)	1.12 (1.07–1.17)
10%–20% Increase	1.08 (1.03–1.14)	1.06 (1.01–1.11)
<10% Change	1.06 (1.02–1.09)	1.03 (0.989–1.07)
10%–20% Decrease	1.02 (0.97–1.06)	1.00 (0.96–1.05)
>20% Decrease		1 [Reference]

Abbreviations: CI, confidence interval; IRR, incidence rate ratio.
[a] N = 349,381 students in 6th, 7th, and 8th grades; 675,318 observations across 624 schools.
[b] Change in fitness composite percentile scores based on Progressive Aerobic Cardiovascular Endurance Run (PACER) Push-up and Curl-up Fitnessgram tests from the year prior.
[c] Based on 3-level longitudinal negative binomial mixed models.
[d] All estimates, $P < .001$.
[e] Adjusted for sex, race/ethnicity, change in obesity status from the year prior, place of birth (United States or foreign country), school size, and school-area poverty, and including interactions grade*race/ethnicity, grade*sex, grade*place of birth, and school-area poverty*race/ethnicity.

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ORIGINAL RESEARCH

Tobacco Use Cessation Among Quitline Callers Who Implemented Complete Home Smoking Bans During the Quitting Process

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PEER REVIEWED

Abstract

Introduction
The implementation of a home smoking ban (HSB) is associated with tobacco use cessation. We identified which quitline callers were most likely to report 30-day cessation among those who implemented complete HSBs after enrollment.

Methods
Our sample consisted of callers to the Arizona Smokers' Helpline who enrolled from January 1, 2011, through July 26, 2015, and who reported no HSB at enrollment and a complete HSB by 7-month follow-up. We used logistic regression to estimate associations between no use of tobacco in the previous 30 days (30-day quit) at 7-month follow-up and demographic characteristics, health conditions, tobacco use, and cessation strategies.

Results
At 7-month follow-up, 65.4% of 399 callers who implemented a complete HSB reported 30-day quit. Lower odds of tobacco use cessation were associated with having a chronic health condition (odds ratio [OR], 0.31; 95% confidence interval [CI], 0.18–0.56) and living with other smokers (OR, 0.46; 95% CI, 0.29–0.73). Higher odds of tobacco cessation were associated with completing 5 or more telephone coaching sessions (OR, 2.48; 95% CI, 1.54–3.98) and having confidence to quit (OR, 2.05; 95% CI, 1.05–3.99). However, confidence to quit was not significant in the sensitivity analysis.

Conclusion
Implementing an HSB after enrolling in quitline services increases the likelihood of cessation among some tobacco users. Individuals with complete HSBs were more likely to quit if they did not have a chronic health condition, did not live with another smoker, and were actively engaged in coaching services. These findings may be used by quitlines to develop HSB intervention protocols primarily targeting tobacco users most likely to benefit from them.

Introduction

Home smoking bans (HSBs) are household rules that restrict smoking from certain areas (partial HSB) or all areas (complete HSB) (1). Implementing HSBs may facilitate changes in smoking behavior by limiting exposure to smoking cues from household members and visitors who smoke (2). Implementing any type of HSB is associated with tobacco use cessation (2–4). However, complete HSBs are a more effective cessation strategy than partial HSBs (5), which present challenges in enforcing smoking restrictions (6).

In the United States, quitlines provide evidence-based cessation services to residents of all 50 states, the District of Columbia, and Puerto Rico, reaching diverse populations, including those from underserved and vulnerable communities (7,8). Because success rates of cessation strategies vary among individuals (9), quitlines seek to expand the diversity of cessation services and tailor them to specific groups of smokers to optimize service delivery and improve quit rates (10). One area that has received little attention is the use of HSB interventions by quitlines. Identifying callers who are most likely to benefit from HSB interventions and quit tobacco use may inform the development of quitline protocols for HSB interventions for specific groups of tobacco users. The ob-

jective of our study was to describe predictors of tobacco use cessation among a sample of adults who implemented a complete HSB after enrolling in services from the Arizona Smokers' Helpline (ASHLine).

Methods

This retrospective cohort study was based on data from ASHLine, which is a state-funded quitline that supports cessation among tobacco users who live in Arizona (www.ashline.org). Callers who complete telephone assessments at enrollment are given the opportunity to work with a trained cessation coach who assists them through the process of quitting. Informed by motivational interviewing and evidence-based cognitive behavioral strategies, coaches provide up to 3 months of weekly telephone counseling. Callers are provided information and guidance on self-regulation, identification of triggers, stimulus-management and urge-management strategies, positive reinforcement, quit smoking tips, preparation for setting a quit day, and relapse prevention. Eligible callers are also provided with up to 4 weeks of free nicotine replacement therapy. Because the study used de-identified caller data, the study protocol was deemed exempt by the University of Arizona's institutional review board.

Eligible participants

Participants were male and female adult callers (aged 18 y or older) who enrolled in ASHLine from January 1, 2011, through July 26, 2015. Assessments were conducted at enrollment and 7-month follow-up by using telephone surveys administered by ASHLine staff members. To focus the study on the most effective type of HSB, a complete (rather than a partial) HSB, we included participants in the analysis only if they implemented a complete HSB between enrollment and 7-month follow-up. HSB status was determined by asking, "Is smoking allowed in your home?" Responses included "smoking not allowed," "smoking allowed in some places," or "smoking allowed anywhere." Implementation of a complete HSB was defined as having a response of "smoking allowed anywhere" at enrollment to indicate that no HSB was in place and a response of "smoking not allowed" at the 7-month follow-up assessment. Callers were excluded from the study if they did not report implementing a complete HSB by the 7-month follow-up.

Outcome and other variables

The study outcome was smoking cessation, which was determined at the 7-month follow-up assessment. Participants were asked the question "Have you used tobacco products in the last 30 days?" (30-day quit). Callers who responded no to the question at 7-month follow-up were categorized as quitters, and callers who responded yes were categorized as nonquitters. Smoking cessation was chosen as the study outcome because it is one of the primary measures of quitline effectiveness (11). Callers missing a response to this question were excluded from analysis. Several variables were assessed during enrollment, including demographic characteristics, health conditions, and tobacco use. Demographic characteristics were caller's age (years); sex (male, female); race (white, black, Asian, American Indian, or multiracial/other); Hispanic or Latino ethnicity; insurance type (private insurance, Arizona's Medicaid [Arizona Health Care Cost Containment System], or uninsured); and education level (high school diploma or no diploma). Race was categorized as white, black, or other. Missing responses for Hispanic or Latino ethnicity were imputed to be no. Insurance type was used as a proxy measurement for socioeconomic status and was categorized as private insurance or not insured/underinsured. The presence of children in the household was determined by asking "Do you have children under the age of 18 living in your household?" We ascertained the age of the youngest child in the household. The presence of other smokers in the household was evaluated by asking "Do others smoke at home?" and dichotomized as yes or no.

Having a chronic or mental health condition was self-reported at the time of enrollment. Individuals were categorized as having a chronic health condition if they had at least one of the following: asthma, hypertension, cancer, chronic obstructive pulmonary disease, diabetes, or heart disease. Presence of a mental health condition was ascertained by asking if they had ever been treated for "mental health or emotional challenges, such as anxiety disorder, depression, bipolar disorder, alcohol or drug abuse, or schizophrenia." Responses included yes, no, or "I don't know." Callers could also refuse to answer these questions. Refusals were considered missing data, and responses of "I don't know" were inferred to be no.

Variables describing tobacco use were also assessed at enrollment. The variables included age of initiation (years); nicotine dependence as measured by the Fagerström Test for Nicotine Dependence score (ranging from 0–10), with higher scores indicating greater dependence (12); and confidence to quit for 24 hours, dichotomized as "confident" (caller's response of "confident," "very confident" or "extremely confident") and "not confident" (responses of "somewhat confident" or "not confident").

Variables included in the analysis that described cessation strategies were use of medication for tobacco use cessation and the number of coaching sessions completed by the caller. Self-reported use of any medication for tobacco use cessation (eg, nicotine replacement therapy or medications such as Zyban [GlaxoSmithKline] or Chantix [Pfizer]) was categorized as either yes or no. Data on the number of coaching sessions a caller completed between

enrollment and 7-month follow-up were obtained from ASHLine records. Number of coaching sessions was considered both as a continuous variable and a binary variable, zero to 4 coaching sessions and 5 or more coaching sessions, as recommended by the North American Quitline Consortium best practice protocols (13).

Statistical analyses

Logistic regression was used to estimate associations between 30-day quit and demographic characteristics, health conditions, tobacco use, and cessation strategy variables. Covariates included in the model were prespecified and based on theoretical relevance. All reported odds ratios (ORs) and 95% confidence intervals (CIs) were adjusted for all covariates in the model. Sensitivity analysis was performed by using multiple imputation with chained equations to assess the sensitivity of our results to missing covariates (14); only covariates specified in the analytical model and the outcome were used for this step. The imputation models contained all the covariates from the analytical model, the smoking cessation outcome, covariates associated with missingness, and auxiliary covariates found to be associated (Pearson correlation coefficient >0.20) with predictors that were being imputed. Twenty complete data sets were imputed and analyzed with logistic regression, and estimates were combined by using Rubin's Rules (15).

Linearity in the logit for continuous variables was tested by using restricted cubic splines (16). If linearity in the logit was not met for a continuous covariate, the covariate was categorized to meet the assumption for logistic regression. Linearity in the logit was met for age at enrollment, age of tobacco use initiation, and tobacco dependence. Number of coaching sessions did not meet this assumption and was therefore categorized as zero to 4 sessions and 5 or more sessions.

All statistical tests used a significance level of .05 and were performed using SAS 9.4 (SAS Institute, Inc).

Results

Of the original 49,284 callers, 38,948 callers with a complete or partial HSB at enrollment or missing data on HSB status were excluded from analysis (Figure). Of the remaining 10,336 callers, 9,587 were excluded because they were missing data on 30-day quit status (n = 5,865) or they reported not implementing a complete HSB or were missing data on home smoking ban (n = 3,722) at 7-month follow-up. The remaining 749 callers had 7-month quit information; 350 of these callers were excluded because they had missing data on covariates. We found missing values for almost all covariates; the covariates with the highest percentage of missing values were race (11.2%) and use of medication for tobacco use cessation (21.9%). This left 399 callers for the primary analysis; of these, 261 (65.4%) were quitters and 138 (34.6%) were nonquitters.

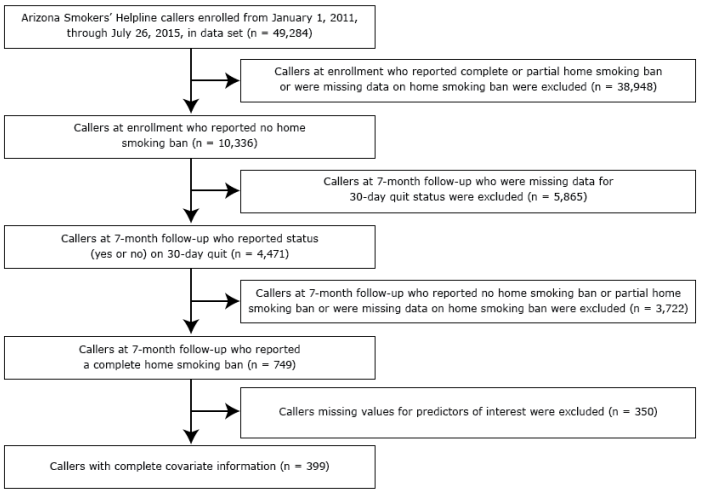

Figure. Selection of callers who enrolled in the Arizona Smokers' Helpline (ASHLine) and were included in analysis of home smoking bans, Arizona, January 1, 2011, through July 26, 2015. Thirty-day quit was defined as callers who said they had not used tobacco products in the last 30 days at 7-month follow-up.

Callers ranged in age from 19 to 89 years, and most callers were white, were non-Hispanic, had at least a high school diploma, and had no children under the age of 18 at home (Table 1). The distribution of covariates was similar between quitters and nonquitters, with a few significant exceptions. Nonquitters were more likely than quitters to live with another smoker in the home (53.1% vs 39.2%) and have at least 1 chronic condition (73.3% vs 64.6%). Quitters were more likely than nonquitters to report using medication for tobacco use cessation (67.0% vs 45.9%) and completing more coaching sessions (median of 7 sessions vs median of 3 sessions). Although the difference was not significant, we observed that nonquitters were more likely than quitters to be white (76.2% vs 68.4%) and to be uninsured (23.1% vs 20.3%).

The adjusted odds of tobacco use cessation at 7-month follow-up were lower for callers who reported living with other smokers in the home (OR, 0.46; 95% CI, 0.29–0.73) or having at least 1 chronic health condition (OR, 0.31; 95% CI, 0.18–0.56). Callers were more likely to quit if they were confident in their ability to quit (OR, 2.05; 95% CI, 1.05–3.99) or if they completed 5 or more coaching sessions (OR, 2.48; 95% CI, 1.54–3.98) (Table 2).

Using the multiply imputed data for missing values, the results of the primary analysis changed for several covariates (Table 3). The effects of living with other smokers and having at least 1 chronic condition were attenuated but still significant. The association for

confidence to quit was no longer significant in the sensitivity analysis. The association between completing 5 or more coaching sessions and quitting smoking increased from an OR of 2.48 (95% CI, 1.54–3.98) to an OR of 3.25 (95% CI, 2.33–4.55).

Discussion

To our knowledge, this is the first study to examine factors that predict tobacco use cessation among a subgroup of callers who implemented a complete HSB after enrolling in quitline services. Only 65.4% of callers who implemented HSBs reported a 30-day quit at 7-month follow-up. Thus, callers did not equally benefit from implementing a complete HSB during the quitting process. Callers who implemented a complete HSB and had increased odds of tobacco use cessation at 7-month follow-up were more likely to not have a chronic health condition, to not live with another smoker in the home, and to have participated in more coaching sessions. The identified predictors among callers who implemented complete HSBs were consistent with predictors of cessation among the general population of smokers (4,17–21). For example, a Cochrane review found evidence of a dose-response relationship between the number of coaching sessions and higher quit rates (17). Other studies indicated that having a chronic health condition is associated with a lower likelihood of tobacco use cessation, although cessation rates among quitline users are higher than cessation rates from primary-care–based smoking interventions (20). Previous studies suggested that the absence of other smokers in the home is an important predictor of changes in smoking behavior (4,21) and aids in the implementation of HSBs since households with fewer smokers potentially have fewer barriers to restricting smoking.

Our findings may be particularly valuable for quitlines that want to continue the trend of increasing their breadth of services (22). Quitlines that help callers implement complete HSBs and promote cessation and smoke-free homes support 2 major goals of the Centers for Disease Control and Prevention. The goals are promoting quitting among adults and youths and eliminating exposure to secondhand smoke through the development of comprehensive state plans to decrease tobacco-use rates (7). Our findings suggest that quitlines interested in implementing HSB interventions should develop specialized protocols for callers with particular characteristics to optimize quitline service delivery and increase quit rates. However, tobacco users who have chronic health conditions and/or live with other smokers may also benefit from HSB interventions if quitlines address the unique challenges faced by these tobacco users in implementing and enforcing smoking bans. For example, these tobacco users may need additional skills, strategies, and support to change multiple health behaviors and involve other smokers in the home in their quitting process.

This study had several limitations. One limitation was the lack of available data on HSBs between enrollment and 7-month follow-up. No information was available on when the HSB was implemented during the quitting process, length of implementation, or enforcement of the HSB, all of which may have influenced cessation. Additionally, the study lacked temporal data and was unable to determine if the complete HSB preceded or followed quitting tobacco. To reduce participation burden, callers were not asked to indicate their level of income during enrollment; instead, we used type of health insurance as a proxy for socioeconomic status (23). Another limitation was the use of self-reported data, which may have resulted in recall and social desirability biases; however, the collection of self-reported data is standard practice among quitlines. We also found a substantial amount of missing data at enrollment and 7-month follow-up. However, the initial data set was large, and multiple imputation in the sensitivity analysis generally supported the results of the primary analysis.

Although implementation of HSBs is associated with smoking behaviors and cessation (2,3,24–26), little research exists on the acceptability, feasibility, and effectiveness of interventions to establish smoke-free households among quitline callers. This study suggested that certain groups of quitline callers may be more likely than other groups of callers to quit tobacco use when they implement complete HSBs as part of their quitting process. Expanding quitline services to include HSB interventions may have other advantages, including improving callers' engagement, motivation, and confidence in quitline services. These advantages could contribute to increased cessation rates among the quitline population.

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Tables

Table 1. Enrollment Characteristics of ASHLine Study Population Enrolled From January 1, 2011, Through July 26, 2015, Who Implemented a Complete Home Smoking Ban (n = 749), Stratified By 7-Month Quit Status[a]

Variable	Nonquitters	Quitters
All, n (%)	277 (37.0)	472 (63.0)
Sex, n (%)		
Male	111 (40.1)	196 (41.5)
Female	164 (59.2)	273 (57.8)
Missing data	2 (0.7)	3 (0.6)
Age, y		
Median (IQR)	54 (47–62)	58 (50–64)
Missing data, n (%)	0	3 (0.6)
Race, n (%)		
White	211 (76.2)	323 (68.4)
Black	28 (10.1)	55 (11.7)
Asian	2 (0.7)	2 (0.4)
American Indian	3 (1.1)	12 (2.5)
Multiracial/Other	8 (2.9)	21 (4.5)
Missing data	25 (9.0)	59 (12.5)
Hispanic or Latino, n (%)	20 (7.2)	65 (13.8)
Insurance type, n (%)		
Private	132 (47.7)	258 (54.7)
AHCCCS	80 (28.9)	114 (24.2)
None	64 (23.1)	96 (20.3)
Missing data	1 (0.4)	4 (0.9)
Has high school diploma, n (%)		
Yes	217 (78.3)	379 (80.3)
No	38 (13.7)	78 (16.5)
Missing data	22 (7.9)	15 (3.2)
Age of youngest child in household, n (%), y		
No children <18	230 (83.0)	406 (86.0)
<1	1 (0.4)	1 (0.2)
1–4	8 (2.9)	15 (3.2)
5–11	15 (5.4)	15 (3.2)

Abbreviations: AHCCCS, Arizona Health Care Cost Containment System; ASHLine, Arizona Smokers' Helpline; IQR, interquartile range.
[a] Percentages may not sum to 100 due to rounding.
[b] Measured by the Fagerström Test for Nicotine Dependence score (ranging from 0–10), with higher scores indicating greater dependence (12).
[c] Dichotomized as "confident" (caller's response of "confident," "very confident," or "extremely confident") and "not confident" (responses of "somewhat confident" or "not confident").
[d] One or more of the following: asthma, hypertension, cancer, chronic obstructive pulmonary disease, diabetes, or heart disease.
[e] Treated for any of the following conditions: mental health or emotional challenges, such as anxiety disorder, depression, bipolar disorder, alcohol or drug abuse, or schizophrenia.

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Table 1. Enrollment Characteristics of ASHLine Study Population Enrolled From January 1, 2011, Through July 26, 2015, Who Implemented a Complete Home Smoking Ban (n = 749), Stratified By 7-Month Quit Status[a]

Variable	Nonquitters	Quitters
12–17	13 (4.7)	21 (4.5)
Missing data	10 (3.6)	14 (3.0)
Other smokers reside in household, n (%)		
Yes	147 (53.1)	185 (39.2)
No	118 (42.6)	265 (56.1)
Missing data	12 (4.3)	22 (4.7)
Nicotine dependence[b]		
Median (IQR) score	6 (4–7)	5 (4–7)
Missing data, n (%)	3 (1.1)	43 (9.1)
Age of tobacco use initiation, y		
Median (IQR)	16 (14–18)	16 (14–19)
Missing data, n (%)	19 (6.8)	37 (7.8)
Has confidence to quit for 24 hours[c], n (%)		
Yes	227 (82.0)	380 (80.5)
No	37 (13.4)	74 (15.7)
Missing data	13 (4.7)	18 (3.8)
Has at least 1 chronic health condition[d], n (%)		
Yes	203 (73.3)	305 (64.6)
No	74 (26.7)	167 (35.4)
Has a mental health condition[e], n (%)		
Yes	111 (40.1)	186 (39.4)
No	163 (58.8)	283 (60.0)
Missing data	3 (1.1)	3 (0.6)
Uses medication for tobacco use cessation, n (%)		
Yes	127 (45.9)	316 (67.0)
No	50 (18.0)	92 (19.5)
Missing data	100 (36.1)	64 (13.6)
Number of telephone coaching sessions before 7-month follow-up, median (IQR)	3 (1–6)	7 (3–10)

Abbreviations: AHCCCS, Arizona Health Care Cost Containment System; ASHLine, Arizona Smokers' Helpline; IQR, interquartile range.
[a] Percentages may not sum to 100 due to rounding.
[b] Measured by the Fagerström Test for Nicotine Dependence score (ranging from 0–10), with higher scores indicating greater dependence (12).
[c] Dichotomized as "confident" (caller's response of "confident," "very confident," or "extremely confident") and "not confident" (responses of "somewhat confident" or "not confident").
[d] One or more of the following: asthma, hypertension, cancer, chronic obstructive pulmonary disease, diabetes, or heart disease.
[e] Treated for any of the following conditions: mental health or emotional challenges, such as anxiety disorder, depression, bipolar disorder, alcohol or drug abuse, or schizophrenia.

Table 2. Odds Ratios of 30-Day Quit[a], by Demographic, Tobacco Use History, Tobacco Dependence, and Cessation Strategy Covariates Among ASHLine Callers Who Implemented Complete Home Smoking Bans (n = 399), Arizona, January 1, 2011, Through July 26, 2015

Variable	Odds Ratio (95% Confidence Interval)[b]
Sex	
Male	1.09 (0.68–1.74)
Female	1 [Reference]
Age (per 5-y increase in age)[c]	1.11 (0.99–1.24)
Race	
White	1 [Reference]
Black	1.35 (0.63–2.95)
Other	1.56 (0.61–3.99)
Hispanic or Latino	
Yes	1.17 (0.29–4.68)
No	1 [Reference]
Insurance type	
Private	1 [Reference]
Not insured or AHCCCS	0.90 (0.56–1.46)
Has high school diploma, n (%)	
No	1 [Reference]
Yes	0.65 (0.31–1.38)
Child (<18 y) resides in household	
Yes	1.08 (0.48–2.46)
No	1 [Reference]
Other smokers reside in household	
Yes	0.46 (0.29–0.73)
No	1 [Reference]
Nicotine dependence (per 1-point increase in score)[d]	0.92 (0.83–1.02)
Age of tobacco use initiation (per 5-y increase in age)[e]	1.03 (0.83–1.27)
Has confidence to quit for 24 hours[f]	
Yes	2.05 (1.05–3.99)
No	1 [Reference]

Abbreviations: AHCCCS, Arizona Health Care Cost Containment System; ASHLine, Arizona Smokers' Helpline.
[a] Defined as no use of tobacco in the previous 30 days, reported at 7-month follow-up.
[b] Odds ratios have been adjusted for all other covariates in the model.
[c] Odds ratios were calculated for an increment of 5 years in age. That is, for every 5-year increase in age, the odds of quitting tobacco for those who implemented a complete home smoking ban was 1.11 times the odds of those who had not implemented a ban.
[d] Measured by the Fagerström Test for Nicotine Dependence score (ranging from 0–10), with higher scores indicating greater dependence (12). Odds ratios were calculated for a 1-point increase in the Fagerström Test score.
[e] Odds ratios were calculated for an increment of 5 years in age.
[f] Dichotomized as "confident" (caller's response of "confident," "very confident," or "extremely confident") and "not confident" (responses of "somewhat confident" or "not confident").
[g] One or more of the following: asthma, hypertension, cancer, chronic obstructive pulmonary disease, diabetes, or heart disease.
[h] Treated for any of the following issues: mental health or emotional challenges, such as anxiety disorder, depression, bipolar disorder, alcohol or drug abuse, or schizophrenia.

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Table 2. Odds Ratios of 30-Day Quit[a], by Demographic, Tobacco Use History, Tobacco Dependence, and Cessation Strategy Covariates Among ASHLine Callers Who Implemented Complete Home Smoking Bans (n = 399), Arizona, January 1, 2011, Through July 26, 2015

Variable	Odds Ratio (95% Confidence Interval)[b]
Has at least 1 chronic health condition[g]	
Yes	0.31 (0.18–0.56)
No	1 [Reference]
Has a mental health condition[h]	
Yes	1.28 (0.78–2.11)
No	1 [Reference]
Uses medication for tobacco use cessation	
Yes	1.20 (0.71–2.03)
No	1 [Reference]
Number of telephone coaching sessions before 7-month follow-up	
0–4	1 [Reference]
≥5	2.48 (1.54–3.98)

Abbreviations: AHCCCS, Arizona Health Care Cost Containment System; ASHLine, Arizona Smokers' Helpline.
[a] Defined as no use of tobacco in the previous 30 days, reported at 7-month follow-up.
[b] Odds ratios have been adjusted for all other covariates in the model.
[c] Odds ratios were calculated for an increment of 5 years in age. That is, for every 5-year increase in age, the odds of quitting tobacco for those who implemented a complete home smoking ban was 1.11 times the odds of those who had not implemented a ban.
[d] Measured by the Fagerström Test for Nicotine Dependence score (ranging from 0–10), with higher scores indicating greater dependence (12). Odds ratios were calculated for a 1-point increase in the Fagerström Test score.
[e] Odds ratios were calculated for an increment of 5 years in age.
[f] Dichotomized as "confident" (caller's response of "confident," "very confident," or "extremely confident") and "not confident" (responses of "somewhat confident" or "not confident").
[g] One or more of the following: asthma, hypertension, cancer, chronic obstructive pulmonary disease, diabetes, or heart disease.
[h] Treated for any of the following issues: mental health or emotional challenges, such as anxiety disorder, depression, bipolar disorder, alcohol or drug abuse, or schizophrenia.

Table 3. Results of Sensitivity Analysis: Odds Ratios (ORs) of 30-Day Quit[a] for Demographics, Tobacco Use History, Tobacco Dependence and Cessation Strategy Covariates Among ASHLine Callers Who Implemented a Home Smoking Ban, Using Multiply Imputed Data (n = 749), Arizona, January 1, 2011, Through July 26, 2015

Variable	Odds Ratio (95% Confidence Interval)
Sex	
Male	1.06 (0.75–1.48)
Female	1 [Reference]
Age (per 5-y increase in age)[b]	1.08 (0.99–1.17)
Race	
White	1 [Reference]
Black	1.06 (0.62–1.22)
Other	1.75 (0.86–3.58)
Hispanic or Latino ethnicity	
Yes	1.55 (0.87–2.76)
No	1 [Reference]
Insurance type	
Private	1 [Reference]
Not insured or AHCCCS	0.87 (0.62–1.22)
Has high school diploma, n (%)	
Yes	1 [Reference]
No	0.82 (0.51–1.31)
Child (<18 y) resides in household	
Yes	0.92 (0.54–1.56)
No	1 [Reference]
Other smokers reside in household	
Yes	0.60 (0.43–0.84)
No	1 [Reference]
Nicotine dependence (per 1-point increase in score)[c]	0.98 (0.91–1.06)
Age of first initiation (per 5-y increase in age)[d]	1.11 (0.95–1.30)
Has confidence to quit for 24 hours[e]	
Yes	0.77 (0.48–1.23)
No	1 [Reference]
Has at least 1 chronic health condition[f]	

Abbreviations: AHCCCS, Arizona Health Care Cost Containment System; ASHLine, Arizona Smokers' Helpline.
[a] Defined as no use of tobacco in the previous 30 days, reported at 7-month follow-up.
[b] Odds ratios were calculated for an increment of 5 years in age. That is, for every 5-year increase in age, the odds of quitting tobacco for those who implemented a complete home smoking ban was 1.08 times the odds of those who had not implemented a ban.
[c] Measured by the Fagerström Test for Nicotine Dependence score (ranging from 0–10), with higher scores indicating greater dependence (12). Odds ratios were calculated for a 1-point increase in the Fagerström Test score.
[d] Odds ratios were calculated for an increment of 5 years in age.
[e] Dichotomized as "confident" (caller's response of "confident," "very confident," or "extremely confident") and "not confident" (responses of "somewhat confident" or "not confident").
[f] One or more of the following: asthma, hypertension, cancer, chronic obstructive pulmonary disease, diabetes, or heart disease.
[g] Treated for any of the following conditions: mental health or emotional challenges, such as anxiety disorder, depression, bipolar disorder, alcohol or drug abuse, or schizophrenia.

(continued on next page)

(continued)

Table 3. Results of Sensitivity Analysis: Odds Ratios (ORs) of 30-Day Quit[a] for Demographics, Tobacco Use History, Tobacco Dependence and Cessation Strategy Covariates Among ASHLine Callers Who Implemented a Home Smoking Ban, Using Multiply Imputed Data (n = 749), Arizona, January 1, 2011, Through July 26, 2015

Variable	Odds Ratio (95% Confidence Interval)
Yes	0.48 (0.32–0.70)
No	1 [Reference]
Has a mental health condition[g]	
Yes	0.94 (0.67–1.34)
No	1 [Reference]
Uses medication for tobacco use cessation	
Yes	1.16 (0.76–1.79)
No	1 [Reference]
Number of telephone coaching sessions before 7-month follow-up	
0–4 calls	1 [Reference]
≥5 calls	3.25 (2.33–4.55)

Abbreviations: AHCCCS, Arizona Health Care Cost Containment System; ASHLine, Arizona Smokers' Helpline.
[a] Defined as no use of tobacco in the previous 30 days, reported at 7-month follow-up.
[b] Odds ratios were calculated for an increment of 5 years in age. That is, for every 5-year increase in age, the odds of quitting tobacco for those who implemented a complete home smoking ban was 1.08 times the odds of those who had not implemented a ban.
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[e] Dichotomized as "confident" (caller's response of "confident," "very confident," or "extremely confident") and "not confident" (responses of "somewhat confident" or "not confident").
[f] One or more of the following: asthma, hypertension, cancer, chronic obstructive pulmonary disease, diabetes, or heart disease.
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ORIGINAL RESEARCH

Predictors of Severe Obesity in Low-Income, Predominantly Hispanic/Latino Children: The Texas Childhood Obesity Research Demonstration Study

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PEER REVIEWED

Abstract

Introduction
The objective of this study was to identify predictors of severe obesity in a low-income, predominantly Hispanic/Latino sample of children in Texas.

Methods
This cross-sectional analysis examined baseline data on 517 children from the secondary prevention component of the Texas Childhood Obesity Research Demonstration (TX CORD) study; data were collected from September 2012 through February 2014. Self-administered surveys were used to collect data from parents of children who were aged 2 to 12 years, had a body mass index (BMI) in the 85th percentile or higher, and resided in Austin, Texas, or Houston, Texas. Multivariable logistic regression models adjusted for sociodemographic covariates were used to examine associations of children's early-life and maternal factors (large-for-gestational-age, exclusive breastfeeding for ≥4 months, maternal severe obesity [BMI ≥35.0 kg/m^2]) and children's behavioral factors (fruit and vegetable consumption, physical activity, screen time) with severe obesity (BMI ≥120% of 95th percentile), by age group (2–5 y, 6–8 y, and 9–12 y).

Results
Across all ages, 184 (35.6%) children had severe obesity. Among children aged 9 to 12 years, large-for-gestational-age at birth (odds ratio [OR] = 2.31; 95% confidence interval [CI], 1.13–4.73) was significantly associated with severe obesity. Maternal severe obesity was significantly associated with severe obesity among children aged 2 to 5 years (OR = 2.67; 95% CI, 1.10–6.47) and 9 to 12 years (OR = 4.12; 95% CI, 1.84–9.23). No significant association was observed between behavioral factors and severe obesity in any age group.

Conclusion
In this low-income, predominantly Hispanic/Latino sample of children, large-for-gestational-age and maternal severe obesity were risk factors for severe obesity among children in certain age groups. Promoting healthy lifestyle practices during preconception and prenatal periods could be an important intervention strategy for addressing childhood obesity.

Introduction

Childhood obesity is a major public health challenge in the United States because of its high prevalence, adverse metabolic effects, racial/ethnic and socioeconomic disparities, and high economic costs. The prevalence of obesity among children leveled off between 2003–2004 and 2009–2010 in the United States (1); however, the prevalence of severe obesity increased (2). The National Health and Nutrition Examination Survey showed that the

prevalence of severe obesity among children aged 2 to 19 years was 3.8% in 1999–2000 and 5.9% in 2011–2012 (3). The health and economic consequences of obesity (2,4,5) make it imperative to understand the associated risk factors. The determinants of severe obesity may be similar to the lifestyle, environmental, familial, and societal risk factors for overweight or obesity (4). Because obesity originates as early as the prenatal period (6), it is important to examine early-life, maternal, and childhood behavioral factors. Few studies have investigated the risk factors and protective factors of severe obesity. One study among a nationally representative sample of children in the United States identified early-life and maternal factors such as crossing the 85th percentile of BMI at an early age, maternal pre-pregnancy severe obesity, gestational diabetes, and Latino ethnicity as risk factors and certain behavioral factors, such as attending a child care facility and eating fruit at least weekly at kindergarten age, as protective factors for severe obesity (7). Thus, opportunities exist to explore and identify potentially modifiable factors for severe obesity among children.

The objective of this study was to assess the associations of early-life, maternal, and behavioral factors with severe obesity among a sample of low-income, predominantly Hispanic/Latino children aged 2 to 12 years with overweight, obesity, and severe obesity who participated in the secondary prevention randomized controlled trial (RCT) of the Texas Childhood Obesity Research Demonstration (TX CORD) study.

Methods

The TX CORD study was an integrated, systems-oriented model that incorporated primary and secondary obesity prevention approaches across multiple sectors (primary health care clinics, early care and education centers, elementary schools, and community organizations) and levels (child, family, community, and environment/policy) in Austin, Texas, and Houston, Texas. The secondary prevention component was an RCT that compared an intensive 12-month childhood obesity management program with a primary care provider–based intervention in the primary catchment area. Baseline data for the secondary prevention study were collected from September 2012 through February 2014 (8,9). The target population resided in low-income medically underserved areas and consisted of children aged 2 to 12 years who were eligible for public health insurance. Catchment areas in Austin and Houston were determined by using an index that comprised data on income and racial/ethnic composition and data from geographical information systems. Details of the study design and methodology of selection and distribution of the catchment areas are provided elsewhere (8,9).

The RCT was originally designed with a sample size of 576 to provide sufficient statistical power to determine the effect of the intervention on the primary outcome, body mass index (BMI) *z* score (8). The study recruited 549 participants. We restricted this analysis to children born from 23.0 to 41.0 weeks of gestation (n = 517). We conducted a secondary analysis of cross-sectional data on baseline measures, before randomization.

For the RCT, children aged 2 to 12 years with overweight and obesity were recruited from the primary health care clinics in TX CORD catchment areas and randomized to either the intervention group or comparison group by age group (2–5 y [n = 149], 6–8 y [n = 173], and 9–12 y [n = 195]). The age groups encompassed the age range in the program's funding guidelines and thus clustered children with similar verbal and physical skills by age. During the RCT, data were collected on anthropometric, physiologic, and fitness measures of children; anthropometric measures of parents; and dietary, physical activity, and psychosocial health measures of parents and children (8). The institutional review board of the University of Texas Health Science Center at Houston Committee for Protection of Human Subjects approved this analysis (Clinical Trial nos. NCT02724943 and HSC-SPH-11–0513).

Measures

Outcome. The outcome of interest was severe obesity status. Anthropometric data, including child's height and weight, were obtained by trained research staff members using standard equipment (8). BMI was calculated as weight in kilograms divided by height in meters squared (kg/m^2). The Centers for Disease Control and Prevention's 2000 growth charts were used to express each child's BMI as sex-specific and age-specific BMI percentile and as a percentage of sex-specific and age-specific BMI above the 95th percentile (10). Children with a BMI that was 120% or more above the 95th percentile of sex-specific and age-specific BMI (2,11) were categorized as having severe obesity. Children with a BMI in the 85th percentile or above to less than 120% of BMI above the 95th percentile were categorized as having overweight or obesity.

Exposures. Two sets of exposures were of interest: early-life and maternal factors (large-for-gestational-age, exclusive breastfeeding ≥4 months, and maternal severe obesity) and child's behavioral factors (fruit and vegetable consumption, physical activity, and the presence of television in the room where the child sleeps).

Two questions were used to ask parents about birth weight and gestational age of their child: 1) "What was your child's weight at birth?" (parents were given open spaces to input numbers in pounds and ounces), and 2) "At how many weeks was your child born?" (parents were given open spaces to input numbers in

weeks). Gestational age ranged from 23.0 to 46.0 weeks. To be consistent with research in which growth curves were used to calculate large-for-gestational-age (12), we restricted the study sample to children born from 23.0 weeks to 41.0 weeks. Using birth weight and gestational age, we computed sex-specific large-for-gestational-age (birth weight >90th percentile), adequate-for-gestational-age (birth weight in the 10th–90th percentile), and small-for-gestational-age (birth weight <10th percentile) variables, which correspond with the new intrauterine growth curves created and validated for US neonatal intensive care units (12). These 3 categories were collapsed into 2 categories: large-for-gestational-age (birth weight > 90th percentile) and not large-for-gestational-age (birth weight ≤90th percentile).

Parents were asked 2 questions about infant breastfeeding practices: "For how long was your child breastfed?" and "How old was your child when infant formula milk was introduced?" The response options were "less than 1 week," "less than 1 month," "2–3 months," "4–6 months," and "more than 6 months" for the breastfeeding question, and "didn't give formula," "less than 1 month," "2–3 months," "4–6 months," and "more than 6 months" for the formula-feeding question. Children who were breastfed for at least 4 months and not introduced to formula until 4 months were classified as exclusively breastfed for the first 4 months of life or more.

Maternal severe obesity at the time of study enrollment was defined as having a BMI of 35.0 kg/m^2 or more; thus it included both class 2 and 3 obesity (13). Procedures for measuring height and weight of mothers were similar to procedures used for their children (8).

Child's fruit and vegetable consumption was determined by parental report of how many times a child ate a fruit, ate a vegetable, or drank fruit juice "yesterday"; response options were "no," "1 time," "2 times," and "3 or more times" for each item. We summed the responses for fruits, vegetables, and fruit juice when the parent selected 1 time or fewer for the fruit juice item. Otherwise, we summed the responses for fruit and vegetables only.

Child's physical activity level was operationalized as whether the child met the current physical activity recommendations of 60 minutes per day of physical activity in the past 7 days. The item was measured by using the following question: "During the past 7 days, on how many days was your child physically active for a total of ≥60 minutes per day? (Add up all the time your child spent in any kind of physical activity that increased their heart rate and made them breathe hard some of the time.)"; response options were "0 days," "1 day," "2 days," "3 days," "4 days," "5 days," "6 days," and "7 days." Children were classified as meeting physical activity recommendations if parents indicated 7 days of activity.

Screen time was determined by parental report (yes or no) of a television in the room where the child sleeps.

Covariates. Covariates were selected on the basis of research and plausible direct or indirect association with the outcome variable (6,7,14–16): sex of child, parent-reported race/ethnicity of child, poverty-income ratio (PIR), parental marital status, and parent's physical activity level. Race/ethnicity was categorized as Hispanic/Latino or non-Hispanic black. Seven (1.4%) children were neither Hispanic/Latino nor non-Hispanic black, and they were included in the non-Hispanic black category. PIR was based on household size and income and was calculated by using poverty guidelines of the US Department of Health and Human Services (17). PIR was classified as less than 125% or 125% or more. Parents' physical activity was operationalized as whether or not they were physically active for 30 minutes per day on 5 or more days per week.

Data analysis

The RCT was powered for the primary outcome by age group: 2 to 5 years, 6 to 8 years, and 9 to 12 years (8); thus, the secondary-data analyses were conducted by age group. We calculated descriptive statistics for the total sample, by age group, for the outcome of interest as medians and interquartile ranges for continuous variables and frequencies and percentages for categorical variables.

We used multiple logistic regression models separately for each age group to assess the associations of early-life and maternal factors with severe obesity, after adjusting for the covariates. We repeated the same modeling strategy to assess the associations of behavioral factors with severe obesity, after adjusting for the covariates. Approximately 10% of the data for the exposures and covariates were missing. Thus, we conducted a complete case analysis for the 2 analytic models (the early-life and maternal model [n = 461] and the behavioral model [n = 505]). We calculated odds ratios (ORs) and 95% confidence intervals (CIs). We performed a sensitivity analysis using an alternative approach of multiple imputation to account for missing data that were assumed to be missing at random (18). The imputation models (2 models for each age group) included the variables used in corresponding analytic models. Ten data sets were imputed, using chained equations, for each of the 6 imputation models. The data sets were then pooled for the final statistical analysis. A P value of $< .05$ was considered significant. Additionally, we compared sociodemographic characteristics of responders and nonresponders. STATA software version 14.0 (StataCorp LLC) was used for data analysis.

Results

Across all ages, 184 (35.6%) children had severe obesity. Among participants aged 2 to 5 years, one-quarter (38 of 149) had severe obesity (Table 1). Among participants aged 6 to 8 years (69 of 173) and 9 to 12 years (77 of 195), about 40% had severe obesity. Overall, about half (263 of 517) of the participants were girls, most (449 of 517) were Hispanic/Latino, and most (434 of 517) had a PIR of less than 125%. Participants who did not complete questionnaires were more likely to be boys and have a PIR of 125% or more.

Large-for-gestational-age children were more likely to have severe obesity, but the relationship was significant only for children aged 9 to 12 years (OR = 2.31; 95% CI, 1.13–4.73) (Table 2). Maternal severe obesity was associated with severe obesity among children aged 2 to 5 years (OR = 2.67; 95% CI, 1.10–6.47) and 9 to 12 years (OR = 4.12; 95% CI, 1.84–9.23). Children aged 6 to 8 years whose mothers had severe obesity had 1.58 higher odds of having severe obesity, but this association was not significant (OR = 1.58; 95% CI, 0.74–3.35). Being breastfed exclusively for the first 4 months of life or more was not significantly associated with severe obesity in any of the age groups.

None of the behavioral factors (children's fruit and vegetable consumption, physical activity, or screen time) was significantly associated with severe obesity in our sample (Table 2), although the associations were in the expected direction for these factors. With every unit increase in fruit and vegetable consumption, children aged 2 to 5 years and 9 to 12 years had lower odds of severe obesity, but not significantly lower. Children aged 2 to 5 years and 9 to 12 years who met physical activity recommendations were at lower risk of severe obesity, but, again, not significantly. Similarly, having a television in the room where the child sleeps was more common among children with severe obesity in all age groups, but the relationship was not significant. The sensitivity analysis that used multiple imputation methods confirmed our findings (Table 3).

Discussion

Our findings indicated that large-for-gestational-age and maternal severe obesity were significantly associated with severe obesity after adjusting for child's sex, child's race/ethnicity, PIR, parental marital status, and parent's physical activity level among low-income, predominantly Hispanic/Latino children with overweight and obesity. However, in the same cohort, neither being breastfed exclusively for the first 4 months of life or more nor behavioral factors (children's fruit and vegetable consumption, physical activity, and screen time) were significantly associated with severe obesity.

Studies have reported an association between large-for-gestational-age and childhood overweight/obesity (19,20), but none has examined severe obesity. A meta-analysis of 66 prospective studies worldwide reported that infants with high birth weight (>4,000 g) had 1.6 times greater odds of childhood overweight/obesity than infants with normal birth weight (2,500–4,000 g) (21). In line with our findings, one large prospective study conducted in The Netherlands (2001–2005) reported that maternal obesity was more likely to be associated with childhood obesity (OR = 5.02, 95% CI, 2.97–8.45) when compared to maternal normal weight (22). In our study, being breastfed exclusively for at least 4 months was a potentially (but not significantly) protective factor for severe obesity among children aged 6 to 8 years and 9 to 12 years. Evidence for the link between breastfeeding and childhood overweight and obesity is inconsistent, but one meta-analysis of 10 prospective studies reported that any breastfeeding, compared with formula feeding, reduced the risk of childhood overweight by 15% (6). Overall, our study adds to evidence that the prenatal environment influences the development of severe obesity and should be a target of intervention.

We observed no relationships between behavioral factors and severe obesity when we compared children with overweight and obesity to children with severe obesity. This finding may have been due to several reasons, including a similarity in lifestyle factors between children with overweight or obesity and children with severe obesity (4) or a similar reporting bias in the 2 groups in our study. Or, perhaps behavioral factors have little influence on the severity of weight gain when comparing children with overweight and obesity to those with severe obesity.

Our study has limitations, many of which are common to secondary analyses of cross-sectional data. The nonresponse rates in the exposures and covariates were around 10%, resulting in a reduced sample size in the complete case analysis. Our outcome measure was binary, which further limited the power of the study. We cannot make temporal inferences because the study was cross-sectional. Some degree of confounding bias, selection bias, reporting bias (including selective reporting of behavioral factors), or measurement error was likely. We could not control for important variables such as maternal cigarette smoking during pregnancy, gestational weight gain, gestational diabetes, adiposity rebound, and early-life dietary practices associated with childhood overweight/obesity (6,23,24). Research participants were children with overweight and obesity; thus, we cannot extrapolate our findings to normal-weight children. Furthermore, all participants consented to

be part of the study, and their characteristics might differ from those of nonparticipants, thus subjecting the study to further selection bias. The outcome measure, severe obesity, measured as the percentage of sex-specific and age-specific BMI above the 95th percentile, does not reflect true body fat mass. Being breastfed exclusively was measured as being breastfed exclusively for 4 months or more, not for 6 months or more, which is recommended by the American Academy of Pediatrics (25); the response option in the TX CORD study indicated 4 months or more. Finally, the self-reported and retrospectively collected data were subject to measurement and recall bias; however, we would expect this bias to affect responses similarly in all categories.

Despite the limitations, our study has several strengths. Our study sample comprised predominantly Hispanic/Latino children from low-income families in Texas, and we used reliable and validated measures (12,26,27). Although a few studies have examined the determinants of severe obesity among children (7,28), none, to the best of our knowledge, has investigated the risk factors of severe obesity in an underrepresented and at-risk population. A recent review reported that the lifestyle, environmental, familial, and societal risk factors were similar for severe obesity and overweight/obesity among children (4). Our findings indicate that severe obesity has some of the same risk factors as obesity in Hispanic/Latino children.

More than one-third of the children in our study had severe obesity, a finding that is consistent with previous findings (29). Policy makers, health practitioners, researchers, and community health workers should work together to design culturally appropriate interventions and obesity-prevention strategies to stem the rising rate of severe obesity in low-income Hispanic/Latino populations, beginning as early as the preconception period. These strategies should target multiple modifiable factors, incorporate family-based lifestyle modifications (30), and be tailored toward population needs. Future studies should explore the associations of multiple early-life risk factors (maternal cigarette smoking during pregnancy, gestational weight gain, gestational diabetes, adiposity rebound, and early-life dietary practices) with childhood severe obesity and the mechanisms linking them.

Our study suggests that large-for-gestational-age and maternal severe obesity contribute to severe obesity in a low-income, predominantly Hispanic/Latino sample of children. Furthermore, our study indicates that several determinants of severe obesity, such as dietary behaviors, physical activity, and screen time are not different from the determinants of overweight and obesity in this population.

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Tables

Table 1. Baseline Characteristics of Participants, by Age Group, in the Secondary Prevention Randomized Controlled Trial of the Texas Childhood Obesity Research Demonstration Study, 2012–2014[a]

Characteristic	All	Overweight or Obesity[b]	Severe Obesity[c]
Age group 2–5 y			
No.	149	111	38
Female, n (%)	73 (49.0)	53 (47.8)	20 (52.6)
Hispanic/Latino, n (%)	133 (89.3)	99 (89.2)	34 (89.5)
Poverty-income ratio[d] <125%, n (%)	128 (85.9)	98 (88.3)	30 (79.0)
Parent married, n (%)	112 (75.2)	82 (73.9)	30 (79.0)
Parent physically active ≥30 minutes for ≥5days/week, n (%)	25 (16.8)	14 (12.6)	11 (29.0)
Large for gestational age, n (%)	25 (16.8)	15 (13.5)	10 (26.3)
Exclusively breastfed for ≥4 months, n (%)	43 (28.9)	32 (28.8)	11 (29.0)
Maternal severe obesity (BMI ≥35 kg/m^2), n (%)	49 (32.9)	31 (27.9)	18 (47.4)
Child's fruit and vegetable consumption[e], median (IQR)	3.0 (2.0-4.0)	3.0 (2.0-4.0)	2.5 (1.0-4.0)
Child physically active ≥60 minutes per day for 7 days/week, n (%)	37 (24.8)	28 (25.2)	9 (23.7)
Presence of television in the room where the child sleeps, n (%)	105 (70.5)	76 (68.5)	29 (76.3)
Age group 6–8 y			
No.	173	104	69
Female, n (%)	93 (53.8)	58 (55.8)	35 (50.7)
Hispanic/Latino, n (%)	145 (83.8)	93 (89.4)	52 (75.4)
Poverty-income ratio[d] <125%, n (%)	142 (82.1)	86 (82.7)	56 (81.2)
Parent married, n (%)	127 (73.4)	80 (76.9)	47 (68.1)
Parent physically active ≥30 minutes for ≥5days/week, n (%)	23 (13.3)	16 (15.4)	7 (10.1)
Large for gestational age, n (%)	36 (20.8)	18 (17.3)	18 (26.1)
Exclusively breastfed for ≥4 months, n (%)	54 (31.2)	39 (37.5)	15 (21.7)
Maternal severe obesity (BMI ≥35 kg/m^2), n (%)	50 (28.9)	24 (23.1)	26 (37.7)
Child's fruit and vegetable consumption[e], median (IQR)	2.0 (1.0-4.0)	2.0 (1.0-4.0)	3.0 (2.0-4.0)
Child physically active ≥60 minutes per day for 7 days/week, n (%)	27 (15.6)	15 (14.4)	12 (17.4)
Presence of television in the room where the child sleeps, n (%)	130 (75.1)	74 (71.2)	56 (81.2)
Age group 9–12 y			
No.	195	118	77
Female, n (%)	97 (49.7)	66 (55.9)	31 (40.3)
Hispanic/Latino, n (%)	171 (87.7)	106 (89.8)	65 (84.4)

Abbreviations: BMI, body mass index; IQR, interquartile range.
[a] Missing data for all variables of interest was approximately 10%; thus, these data were not included in the table.
[b] Overweight or obesity defined as BMI ≥85th percentile to <120% above the 95th percentile of the sex-specific and age-specific BMI.
[c] Severe obesity defined as BMI that was ≥120% above the 95th percentile of sex-specific and age-specific BMI.
[d] Poverty-income ratio was based on household size and income and was calculated by using poverty guidelines of the US Department of Health and Human Services poverty guidelines (17).
[e] Number of times child ate fruits and vegetables "yesterday."

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Table 1. Baseline Characteristics of Participants, by Age Group, in the Secondary Prevention Randomized Controlled Trial of the Texas Childhood Obesity Research Demonstration Study, 2012–2014[a]

Characteristic	All	Overweight or Obesity[b]	Severe Obesity[c]
Poverty-income ratio[d] <125%, n (%)	164 (84.1)	97 (82.2)	67 (87.0)
Parent married, n (%)	147 (75.4)	88 (74.6)	59 (76.6)
Parent physically active ≥30 minutes for ≥5days/week, n (%)	27 (13.9)	18 (15.3)	9 (11.7)
Large for gestational age, n (%)	58 (29.7)	28 (23.7)	30 (39.0)
Exclusively breastfed for ≥4 months, n (%)	55 (28.2)	34 (28.8)	21 (27.3)
Maternal severe obesity (BMI ≥35 kg/m^2), n (%)	55(28.2)	24 (20.3)	31 (40.3)
Child's fruit and vegetable consumption[e], median (IQR)	3.0 (1.0-4.0)	3.0 (1.0-4.0)	2.0 (2.0-4.0)
Child physically active ≥60 minutes per day for 7 days/week, n (%)	25 (12.8)	19 (16.1)	6 (7.8)
Presence of television in the room where the child sleeps, n (%)	130 (66.7)	78 (66.1)	52 (67.5)

Abbreviations: BMI, body mass index; IQR, interquartile range.
[a] Missing data for all variables of interest was approximately 10%; thus, these data were not included in the table.
[b] Overweight or obesity defined as BMI ≥85th percentile to <120% above the 95th percentile of the sex-specific and age-specific BMI.
[c] Severe obesity defined as BMI that was ≥120% above the 95th percentile of sex-specific and age-specific BMI.
[d] Poverty-income ratio was based on household size and income and was calculated by using poverty guidelines of the US Department of Health and Human Services poverty guidelines (17).
[e] Number of times child ate fruits and vegetables "yesterday."

Table 2. Complete Case Analysis: Associations of Early-Life, Maternal, and Behavioral Factors With Severe Obesity, by Age Group, at Baseline, in Sample of Children in the Secondary Prevention Randomized Controlled Trial of the Texas Childhood Obesity Research Demonstration Study, 2012–2014

Factor	Adjusted Odds Ratio[a] (95% Confidence Interval)	*P* Value
Age Group 2–5 y		
Early-life and maternal factors (n = 137)[b]		
Large for gestational age (birth weight >90th percentile)	2.36 (0.85–6.53)	.10
Exclusively breastfed for ≥4 months	1.69 (0.63–4.51)	.30
Maternal severe obesity (BMI ≥35 kg/m^2)	2.67 (1.10–6.47)	.03
Child's behavioral factors (n = 147)[b]		
Fruit and vegetable consumption (no. of times "yesterday")	0.89 (0.70–1.13)	.33
Physically active ≥60 minutes per day for 7 days/week	0.76 (0.29–2.02)	.59
Presence of television in the room where the child sleeps	1.91 (0.72–5.05)	.19
Age Group 6–8 y		
Early-life and maternal factors (n = 152)[b]		
Large for gestational age (birth weight >90th percentile)	1.48 (0.62–3.53)	.38
Exclusively breastfed for ≥4 months	0.55 (0.26–1.20)	.13
Maternal severe obesity (BMI ≥35 kg/m^2)	1.58 (0.74–3.35)	.24
Child's behavioral factors (n = 172)[b]		
Fruit and vegetable consumption (no. of times "yesterday")	1.11 (0.91–1.35)	.29
Physically active ≥60 minutes per day for 7 days/week	1.29 (0.53–3.14)	.57
Presence of television in the room where the child sleeps	1.76 (0.80–3.87)	.16
Age Group 9–12 y		
Early-life and maternal factors (n = 172)[b]		
Large for gestational age (birth weight >90th percentile)	2.31(1.13–4.73)	.02
Exclusively breastfed for ≥4 months	0.94 (0.43–2.03)	.87
Maternal severe obesity (BMI ≥35 kg/m^2)	4.12 (1.84–9.23)	.001
Child's behavioral factors (n = 186)[b]		
Fruit and vegetable consumption (no. of times "yesterday")	0.98 (0.81–1.19)	.85
Physically active ≥60 minutes per day for 7 days/week	0.38 (0.13–1.10)	.08
Presence of television in the room where the child sleeps	1.09 (0.57–2.07)	.80

Abbreviation: BMI, body mass index.
[a] Adjusted for child's sex, child's race/ethnicity, poverty income ratio <125% or not, parental marital status, and parent's physical activity (≥30 minutes per day of physical activity for ≥5 days/week).
[b] Sample sizes in categories differ from the sample sizes in Table 1 because of missing data.

Table 3. Sensitivity Analysis Using Multiple Imputation: Associations of Early-Life, Maternal, and Behavioral Factors With Severe Obesity, by Age Group, at Baseline, in Sample of Children in the Secondary Prevention Randomized Controlled Trial of the Texas Childhood Obesity Research Demonstration Study, 2012–2014

Factor	Adjusted Odds Ratio[a] (95% Confidence Interval)	*P* Value
Age Group 2–5 y (n = 149)		
Early-life and maternal factors		
Large for gestational age (birth weight >90th percentile)	1.95 (0.72–5.28)	.19
Exclusively breastfed for ≥4 months	1.35 (0.53–3.45)	.53
Maternal severe obesity (BMI ≥35 kg/m^2)	2.90 (1.24–6.83)	.02
Child's behavioral factors		
Fruit and vegetable consumption (no. of times "yesterday")	0.87 (0.69–1.11)	.27
Physically active ≥60 minutes per day for 7 days/week	0.78 (0.30–2.03)	.60
Presence of television in the room where the child sleeps	1.92 (0.72–5.12)	.19
Age Group 6–8 y (n = 173)		
Early-life and maternal factors		
Large for gestational age (birth weight >90th percentile)	1.66 (0.74–3.70)	.22
Exclusively breastfed for ≥4 months	0.50 (0.24–1.04)	.06
Maternal severe obesity (BMI ≥35 kg/m^2)	1.65 (0.72–3.78)	.24
Child's behavioral factors		
Fruit and vegetable consumption (no. of times "yesterday")	1.11 (0.92–1.35)	.28
Physically active ≥60 minutes per day for 7 days/week	1.29 (0.53–3.13)	.57
Presence of television in the room where the child sleeps	1.79 (0.82–3.93)	.15
Age Group 9–12 y (n = 195)		
Early-life and maternal factors		
Large for gestational age (birth weight >90th percentile)	2.13 (1.07–4.24)	.03
Exclusively breastfed for ≥4 months	1.06 (0.52–2.17)	.88
Maternal severe obesity (BMI ≥35 kg/m^2)	4.58 (2.08–10.11)	<.001
Child's behavioral factors		
Fruit and vegetable consumption (no. of times "yesterday")	0.97 (0.80–1.17)	.77
Physically active ≥60 minutes per day for 7 days/week	0.39 (0.14–1.15)	.09
Presence of television in the room where the child sleeps	1.03 (0.55–1.94)	.93

Abbreviation: BMI, body mass index.
[a] Adjusted for child's sex, child's race/ethnicity, poverty income ratio <125% or not, parental marital status, and parent's physical activity (≥30 minutes per day of physical activity for ≥5 days/week).

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ORIGINAL RESEARCH

Neighborhood Disadvantage and Allostatic Load in African American Women at Risk for Obesity-Related Diseases

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PEER REVIEWED

Abstract

Introduction
African American women have higher rates of obesity and related chronic disease than other demographic groups. The poorer health of African American women compared with other groups may be explained by allostatic load, or cumulative physiologic stress, due to chronic socioeconomic disadvantage. The objective of this study was to evaluate neighborhood and individual factors contributing to allostatic load in African American women at risk for obesity-related diseases.

Methods
This study evaluated the relationship of allostatic load with neighborhood disadvantage, individual socioeconomic determinants, and synergism between neighborhood and socioeconomic disadvantage, along with health behaviors and other factors as mediators in African American women. Our sample consisted of 220 African American women at risk of obesity-related diseases enrolled in the Better Me Within program (mean [standard deviation] age, 50.1 [11.2] y; mean [standard deviation] body mass index, 36.7 [8.4] kg/m^2). Allostatic load score for each participant was calculated by summing the number of biomarkers (of 9 biomarkers) that were determined to be in the high-risk quartile.

Results
Poisson regression of neighborhood disadvantage and individual socioeconomic determinants found that neighborhood disadvantage, but not education level or household income, was significantly associated with allostatic load ($\beta = 0.22$, SE, 0.10, $P = .04$). Tests for mediators showed that household income and alcohol consumption partially mediated the relationship between allostatic load score and neighborhood disadvantage but were not significant.

Conclusion
More research is necessary to determine the mechanisms by which neighborhoods can exacerbate and attenuate cumulative disadvantage among African American women. Policies and interventions that focus on neighborhood health may improve the outcomes of individual-level health interventions among women who reside in disadvantaged communities.

Introduction

African American women have a higher prevalence of obesity (>50%) and associated chronic conditions than black men and non-Hispanic white men and women (1). The high prevalence of obesity may be associated with harmful coping behaviors used to manage the many roles that African American women are expected to fulfill in their daily lives (2). One clinical model that may explain these persistent health disparities is allostatic load, that is, the physiologic cost of cumulative stress (3). The concept of allostatic load is based in part on the weathering hypothesis, which attributes the poor health of African American women to chronic socioeconomic disadvantage (4). The inverse relationship between socioeconomic status (SES) and allostatic load in African American women may be due to poverty-related adversity and psychological responses to chronic stressors and disadvantage (5,6).

Although recent studies demonstrated the independent effect of neighborhood poverty on the relationship between low SES and the biomarkers of allostatic load in African Americans, limited research has focused exclusively on African American women (7,8). Neighborhood disadvantage in the context of allostatic load may be a proxy for exposure to multiple, chronic, stressful events; perceived safety; and access to health resources (9–11). One study of African American men and women found that health behaviors (diet, exercise, and smoking) partially mediated the relationship between neighborhood poverty and allostatic load (12). Another study of African Americans suggested that educational attainment, a component of individual SES, differentially affects the relationship between allostatic load and neighborhood disadvantage (13).

This study aimed to 1) expand the limited research on neighborhood disadvantage and low-income status, including possible synergism, on allostatic load and 2) investigate how education, income, health behaviors, and perceived stress influence allostatic load. We hypothesized that low-income status and neighborhood disadvantage independently and synergistically influence allostatic load and that education and health behaviors mediate the relationship.

Methods

Trained staff members collected baseline data on 220 participants (from among 333 women who were screened for eligibility) before implementation of the Better Me Within cluster randomized controlled trial. The trial was conducted in 11 churches from February 2014 to May 2016 in Dallas, Texas, to test the efficacy of a church-based diabetes prevention program on weight reduction among overweight African American women. Participants resided in 148 census tracts in greater Dallas; most resided in Dallas County. Eligible participants self-identified as African American, were aged 18 years or older, had a body mass index (BMI, measured as weight in kilograms divided by height in meters squared [kg/m^2]) of 25.0 or more, were not currently enrolled in another weight-loss program, attended an enrolled church, and did not have a health condition that restricted physical activity or altered their diet. Women with self-reported diabetes, a medical diagnosis of diabetes, or who had elevated fasting glucose (>126 mg/dL) and elevated hemoglobin A1c (>6.4%) were excluded.

The institutional review board at The University of North Texas Health Science Center approved this study. All participants provided informed consent.

Measures

Neighborhood disadvantage. Census tracts are small geographic areas that are used to predict small-area estimations of neighborhood deprivation (14). We examined 10 previously developed measures of neighborhood disadvantage: percentage of households living in poverty, percentage of households receiving public assistance, percentage of unoccupied housing units, percentage of renter-occupied housing, percentage of households living in the same house 5 years ago, percentage of occupied housing units with no vehicle, percentage of occupied housing units with more than 1 person per room (crowding), percentage of adults aged 25 or older without a high school diploma or equivalent, percentage of unemployed individuals 16 years or older in the civilian work force, and percentage of female-headed households (13). These data were collected from the 2015 American Community Survey, which determines poverty status by income, household size, and household members' ages (15,16). For example, a 3-person household in 2015 with 1 member under age 18 and an annual household income below $19,043 is considered to be living in poverty (16). We used exploratory principal component analysis, a dimension-reduction technique, to create a composite socioeconomic score (13,17,18). The first principal component served as a composite score of neighborhood disadvantage that explained 49.9% of the variation. The median value of the first principal component was used to dichotomize the neighborhood of each participant as most disadvantaged or least disadvantaged (13). We used varimax orthogonal rotation to estimate the weights of the 10 neighborhood indicators used in the principal component analysis (Appendix A).

Allostatic load score. Of the various methods for measuring allostatic load, we selected the quartile method and 9 biomarkers: BMI, waist circumference, high-density lipoprotein (HDL) cholesterol, total cholesterol/HDL cholesterol ratio, triglycerides, glycosylated hemoglobin A1c (HbA1c), systolic blood pressure, diastolic blood pressure, and salivary cortisol (19). Height, measured with a stadiometer, and weight, measured with a medical-grade digital scale, were collected twice and averaged to calculate BMI. Waist circumference was measured (in duplicate and averaged) directly above the iliac crests with a tape measure by trained researchers. Data on HDL cholesterol, total cholesterol/HDL cholesterol ratio, triglycerides, and HbA1c were collected by using 2 fasting finger-stick samples and analyzed by using point-of-care tests on-site. Systolic and diastolic blood pressure was measured by using a standard automatic blood pressure cuff after the participant sat for 5 minutes; measurement was repeated after 3 minutes. Cortisol was measured by collecting a morning, fasting saliva sample and analyzed in a laboratory; cortisol measurement is a noninvasive way to measure physiologic stress (20). For each participant, we calculated an allostatic load score by summing the number of biomarkers for which the participant was categorized as high risk (19). A participant was categorized as high risk for a given biomarker if the biomarker value was in the highest quartile of

our sample, except for HDL, for which the lowest quartile was considered high risk (Table 1). A participant's biomarker was considered lower risk if the value was below the threshold of the highest quartile of the sample. Participants who reported current use of medications for hypertension, hypercholesterolemia, or prediabetes were categorized as high-risk for the corresponding biomarkers, regardless of their measurements (21).

Individual socioeconomic variables. Data on participants' annual household income (categorized as <$25,000, $25,000–$49,999, $50,000–$74,999, and ≥$75,000) and highest level of educational attainment (categorized as ≤high school diploma or equivalent, some college or a technical degree, and college degree) were collected through self-reported surveys that used questions adapted from the Behavioral Risk Factor Surveillance System (BRFSS).

Health behaviors. Alcohol and tobacco use were measured through self-reported surveys by using questions adapted from the BRFSS and the National Institute on Alcohol Abuse and Alcoholism. Data on alcohol consumption was dichotomized as yes for participants who had at least 1 drink in the past 30 days and no for those who did not. Tobacco use was dichotomized as never for those who smoked fewer than 100 cigarettes in their lifetime and former or current for others. Physical activity data were collected from the Past Week Modifiable Physical Activity Questionnaire (22). Number of minutes of leisure-time physical activity was dichotomized according to meeting, or not meeting, guidelines of at least 150 minutes of weekly physical activity (23).

Perceived stress. Perceived stress was measured by using the 10-item Perceived Stress Scale in a self-report survey in which respondents reported feelings of stress and coping in the past month on a 5-point Likert scale from 0 (lowest) to 4 (highest) (24). The 10 items were summed to create a composite score for stress (score range, 0–40) in which greater values indicate greater levels of perceived stress.

Statistical analysis

The distributions of education and income among individuals were assessed in the most disadvantaged neighborhoods and the least disadvantaged neighborhoods to examine mediating effects (Path B, Figure). We also assessed the distributions of health behaviors (alcohol consumption, smoking, and physical activity) and perceived stress between neighborhood types to examine mediating effects (Path B', Figure). To test whether the relationship between neighborhood disadvantage and allostatic load was mediated by individual SES (education and income, Path C, Figure) and health behaviors (Path C', Figure), we regressed allostatic load score on each factor separately. To determine the mediating effect of income on the relationship between allostatic load and neighborhood disadvantage, we regressed with an interaction term for synergistic effects.

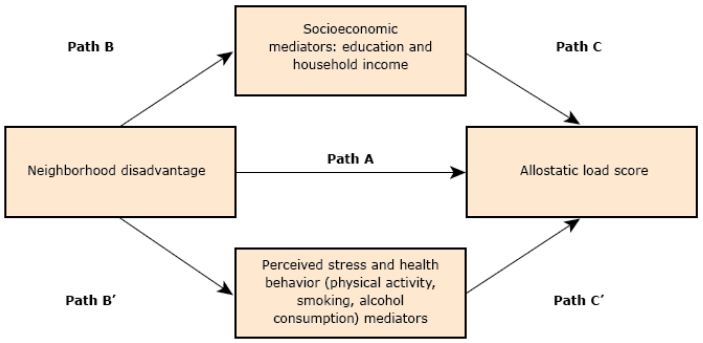

Figure. Hypothesized pathways mediating relationships between neighborhood disadvantage and allostatic load.

Approximately 12% (n = 26) of participants had missing values for some variables. Because a sensitivity analysis confirmed that data were missing at random, we used the Markov chain Monte Carlo method (25) to estimate a set of 20 imputed data for further analysis. We used SAS version 9.3 to analyze the data (SAS Institute Inc) with a 5% level of significance. We used PROC MI to estimate missing data and PROC GLIMMIX to create a 2-level mixed-effect model with a random intercept for each imputed data set. We used PROC MIANALYZE to estimate the effect of each variable on allostatic load score with a valid estimate of standard error (SE). Repeating the analysis with original data validated that imputation did not change the direction of results.

To assess the cluster effects of our data, we estimated the intraclass correlation coefficient as 0.12. The mean and variance of the outcome variable, allostatic load score, were close (2.34 and 2.87 respectively), satisfying the main assumption for Poisson regression for count data, which was confirmed by a goodness-of-fit test. A 2-level (hierarchical) Poisson regression model with a random intercept was used to estimate the effect of neighborhood disadvantage on allostatic load score after adjusting for demographic and health behavior variables. A 2-level negative binomial model to accommodate the model's dispersion parameter did not alter the direction of results and showed similar effect sizes to the Poisson model and Akaike Information Criterion and Bayesian Information Criterion values. Ultimately, the Poisson model was performed for analyses (Appendix B).

Results

The mean (standard deviation [SD]) age of participants was 50.1 (11.2) years, mean (SD) BMI was 36.7 (8.4), and mean (SD) waist circumference was 41.4 (6.1) inches (Table 2). The average age of participants living in each neighborhood type was similar.

About one-fifth (22.1%) of participants had no high-risk biomarkers, and about half (47.5%) had a college degree. Because education was not significantly different between neighborhood types, we could not establish the mediating effects of individual SES (Path B, Figure). However, participants with higher income were clustered in the least disadvantaged neighborhoods ($F_{1, 194} = 5.64$, $P = .02$), which partially established a mediating effect (Path B, Figure).

About one-third (33.8%) of participants reported 150 minutes or more of physical activity per week, which did not differ by neighborhood type (Table 2). Similar proportions in each neighborhood type consumed alcohol in the last 30 days and were current or former smokers. Perceived stress was approximately equal between neighborhood types. Therefore, health behavior and perceived stress variables did not establish a mediating effect (Path B', Figure).

The most disadvantaged neighborhoods had significantly higher percentages of households living in poverty, households receiving public assistance, unoccupied housing units, renter-occupied housing, households without a vehicle, crowding, adults aged 25 or older without a high school diploma or equivalent, and unemployed individuals age 16 or older, compared with the least disadvantaged neighborhoods ($P < .001$ for each) (Table 3). The percentage of households who lived in their homes for 5 or more years and the percentage of female-headed households were similar between the most and least disadvantaged neighborhoods.

After we adjusted for participant age, we found a significant positive association between the most disadvantaged neighborhood and allostatic load score (Model 1: $\beta = 0.24$; SE, 0.10; $P = .02$, Table 4), which established the effect hypothesized as Path A (Figure). In this model, women living in the most disadvantaged neighborhoods had a 1.3-unit higher allostatic load score on average than women living in the least disadvantaged neighborhoods. In Model 2, after adjustment for age, individual socioeconomic factors, and a synergistic effect of neighborhood disadvantage and income, the association between neighborhood disadvantage and allostatic load score was no longer significant (Table 4, Model 2). This result may have occurred because of the multicollinearity introduced by the interaction term. However, income showed a trend for lower allostatic load score with higher levels of income. After adjustment for health behaviors and perceived stress in Model 3, neighborhood disadvantage ($\beta = 0.25$; SE, 0.10; $P = .02$) and alcohol consumption ($\beta = -0.23$; SE, 0.10; $P = .02$) were significant. In the full model (Model 4), which adjusted for socioeconomic characteristics and health behaviors, alcohol consumption ($\beta = -0.20$; SE, 0.10; $P = .07$) was no longer significant, and neighborhood disadvantage remained significant, although slightly weakened ($\beta = 0.22$; SE, 0.10; $P = .04$).

Discussion

In this sample of African American women at risk for obesity-related diseases, after adjustment for socioeconomic and health behavior variables, our results partially support one of our hypotheses: that living in a disadvantaged neighborhood is associated with higher allostatic load. This finding is consistent with previous research showing that neighborhood disadvantage is associated with higher allostatic load in African Americans (13,17). Previous studies of African American women also showed that women residing in areas of greater neighborhood poverty had higher cumulative biological risk than women living in less impoverished neighborhoods (8). Conversely, individuals living in high-income neighborhoods had lower cumulative biological risk than those who live in low-income neighborhoods (12). Our study adds to this research by evaluating health behaviors and individual socioeconomic factors as mediators in the relationship between neighborhood disadvantage and allostatic load exclusively in African American women who are at risk for obesity-related diseases.

Although neither a significant mediator nor synergism between low-income status and neighborhood disadvantage was discovered in the final model, we found nonsignificant trends of lower allostatic load for both alcohol consumption in the past 30 days and higher household income. These trends may indicate that household income and alcohol consumption partially mediate the relationship between neighborhood disadvantage and allostatic load. Harmful health behaviors that are used for coping with high levels of stress (eg, low levels of physical activity, smoking) were not significantly associated with allostatic load in our study.

That household income did not significantly predict allostatic load is consistent with the findings of Barber et al (13). Our findings contrast with those of several studies of neighborhood poverty and cumulative biological risk; these studies found household income to be an independent and significant predictor among women (7,8,12). However, the association of higher household income with lower allostatic load in our study, although not significant, suggests that women may weather both individual and neighborhood socioeconomic disadvantage.

The lack of a significant relationship between educational attainment and allostatic load reflects a complex relationship. Some studies found that low educational attainment and low income were associated with high allostatic load (5,17). In contrast, another study found that the relationship of neighborhood disadvantage and cumulative biological risk had a weaker association among African Americans who did not finish high school than among those who had (13). Other studies found differences in allostatic factor loading (eg, metabolic vs inflammatory) by level of educational attainment (26). Contextual factors, like segregation, may also influence the relationship between education and health; this idea is supported by our finding that neighborhood disadvantage is associated with higher allostatic load (27).

Our study found an inverse relationship between alcohol consumption in the past 30 days and allostatic load. This finding is consistent with research showing that light and moderate levels of drinking are associated with lower levels of heart disease and diabetes (28). Another study found that alcohol consumption was inversely related to allostatic load (7). Future research should investigate how levels of alcohol consumption influence allostatic load; our study provides only general information on alcohol consumption.

Our study has several strengths. To our knowledge, ours is the first study to focus on the neighborhood and individual determinants of allostatic load in a sample of African American women at risk for obesity-related diseases. Our sample population was relatively homogenous demographically, and it excluded the effect of diabetic disease processes on allostatic load biomarkers. Our allostatic load score comprised 9 biomarkers, which reflect anthropomorphic, neuroendocrine, cardiovascular, and metabolic domains of allostatic load. By testing mediators through stepwise models, we minimized the potential for artificial correlations.

Our study has several limitations. We could not establish a causal relationship between neighborhood disadvantage and allostatic load because of the study's cross-sectional design. We did not collect data on the length of participants' residence at their current address or previous residence in a disadvantaged neighborhood; previous residence in a disadvantaged neighborhood is associated with higher rates of cardiometabolic disease than never having left a neighborhood or never having lived in a poor neighborhood (29). The study had a relatively small sample size (N = 220), compared with the sample sizes other studies, which may have limited the power to identify mediating variables such as education. Our measure of physical activity was self-reported and did not distinguish between levels of intensity (30). We were also unable to compare our data with data on other races and ethnicities because we focused exclusively on African American women. However, research focusing on overweight African American women, who are at higher risk for obesity-related chronic diseases compared with other groups, is sparse. Lastly, our measure of alcohol consumption did not evaluate dose, but rather any alcohol intake in the past 30 days, limiting our ability to draw conclusions on this variable.

Despite these limitations, our study has implications for future research on neighborhood disadvantage among African American women. The consistent relationship of neighborhood disadvantage with allostatic load warrants investigation of the social and physical environment of disadvantaged neighborhoods to elucidate the mechanisms by which women accumulate physiologic stress. Several important components of the physical environment for obesity-related health disparities have been identified and may influence allostatic load: accessibility of food stores, exercise facilities, and hospitals; sidewalks; and safety (11,14,). One study in Dallas showed that a change in the previous year's crime rate was associated with higher levels of C-reactive protein, an inflammatory marker, in women (10).

Our cross-sectional findings provide evidence to inform future longitudinal studies on the effects of community-based interventions on allostatic load in African American women. By evaluating these interventions in the context of neighborhood disadvantage, we can determine the individual and neighborhood variables that can mitigate the effects of chronic disadvantage on the health of African American women. Overall, our study adds to the body of knowledge on neighborhood effects on allostatic load in African American women and demonstrates the crucial need for health equity policies that prevent and reduce the health risks associated with living in disadvantaged neighborhoods.

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Tables

Table 1. Mean, Median, Range, and Threshold of High-Risk Quartile for 9 Biomarkers of Allostatic Load at Baseline, Study of African American Women Participating in a Church-Based Diabetes Prevention Program on Weight Reduction (N = 220), Dallas, Texas, 2014–2016[a]

Variable	Mean (SD)	Median (Range)	High-Risk Quartile[b]
Systolic blood pressure, mm Hg	128.4 (19.3)	125.5 (97–216)	>138.5
Diastolic blood pressure, mm Hg	82.3 (10.8)	81.4 (56.6–120)	>88.5
HDL cholesterol, mg/dL	55.6 (13.9)	54 (27–100)	<46
Total cholesterol/HDL cholesterol ratio	3.3 (0.9)	3.52 (1.26–6.42)	>3.77
Hemoglobin A1c, %	6.0 (0.7)	5.9 (1.0–9.4)	>6.4
Body mass index, kg/m^2	36.7 (8.4)	34.5 (25.0–84.6)	>40.6
Cortisol, ng/mL	2.7 (3.3)	2.1 (0.1–38.7)	>2.9
Waist circumference, in	41.3 (6.1)	40.4 (29.0–60.0)	>44.0
Triglycerides, mg/dL	113.4 (58.9)	95 (45–331)	>140

Abbreviation: HDL, high-density lipoprotein; SD, standard deviation.
[a] Missing values varied from 1% to 12% for the 9 biomarkers.
[b] A participant was categorized as high risk for a given biomarker if the biomarker value was in the highest quartile of our sample, except for HDL cholesterol, for which the lowest quartile was considered high risk. Quartiles were determined on the basis of data for each biomarker in our sample of 220 African American women.

Table 2. Descriptive Statistics for Individual and Neighborhood Variables[a] at Baseline, By Neighborhood Type, Study of African American Women Participating in a Church-Based Diabetes Prevention Program on Weight Reduction (N = 220), Dallas, Texas, 2014–2016

Variable	All Neighborhoods (N = 220)	Most Disadvantaged Neighborhoods (n = 110)	Least Disadvantaged Neighborhoods (n = 110)	*P* Value
Age, mean (SD), y	50.1 (11.2)	50.1 (11.7)	50.1 (10.9)	.99[b]
Body mass index, mean (SD), kg/m^2	36.7 (8.4)	37.6 (9.7)	35.7 (7.0)	.13[b]
Waist circumference, mean (SD), in	41.4 (6.1)	42.4 (6.2)	40.4 (5.9)	.06[b]
Allostatic load score,[c] mean (SD)	2.3 (1.7)	2.7 (1.7)	2.0 (1.6)	.01[d]
No. of high-risk biomarkers, no. (%) of participants				
0	47 (22.1)	17 (16.0)	30 (28.0)	.02[d]
1–3	108 (50.7)	53 (50.0)	55 (51.4)	
>3	58 (27.2)	36 (34.0)	22 (20.6)	
Composite neighborhood disadvantage score[e], mean (SD)	0 (1.0)	0.8 (0.7)	−0.8 (0.4)	<.001[b]
Education, no. (%) of participants				
≤High school diploma or equivalent	31 (15.5)	19 (19.4)	12 (11.8)	.39[f]
Some college/technical degree	74 (37.0)	40 (40.8)	34 (33.3)	
College degree	95 (47.5)	39 (39.8)	56 (54.9)	
Annual household income, no. (%) of participants				
<$25,000	40 (20.0)	27 (27.5)	13 (12.8)	.02[f]
$25,000–$49,999	64 (32.0)	34 (34.7)	30 (29.4)	
$50,000–$74,999	47 (23.5)	23 (23.5)	24 (23.5)	
≥$75,000	49 (24.5)	14 (14.3)	35 (34.3)	
Physical activity, no. (%)				
<150 min per week	141 (66.2)	70 (66.0)	71 (66.4)	.96[g]
≥150 min per week	72 (33.8)	36 (34.0)	36 (33.6)	
Alcohol consumption in past 30 days, no. (%)				
Yes	123 (57.7)	61 (57.6)	62 (58.0)	.95[g]
No	90 (42.3)	45 (42.4)	45 (42.0)	
Smoking status, no. (%)				

Abbreviation: SD, standard deviation.

[a] All data were measured at the individual level, except for composite neighborhood disadvantage score.

[b] *P* value obtained from hierarchical mixed-effect model for normal model with a random intercept.

[c] Calculated by summing the number of biomarkers for which the participant was categorized as high risk; score ranged from 0 to 9. Data were collected on 9 biomarkers: body mass index, waist circumference, high-density lipoprotein (HDL) cholesterol, total cholesterol/HDL cholesterol ratio, triglycerides, glycosylated hemoglobin A1c, systolic blood pressure, diastolic blood pressure, and salivary cortisol.

[d] *P* value obtained from hierarchical mixed-effect model for Poisson regression with a random intercept.

[e] Determined by examining 10 previously developed measures of disadvantage at the neighborhood level: percentage of households living in poverty, percentage of households receiving public assistance, percentage of unoccupied housing units, percentage of renter-occupied housing, percentage of households living in the same house 5 years ago, percentage of occupied housing units with no vehicle, percentage of occupied housing units with more than 1 person per room (crowding), percentage of adults aged 25 or older without a high school diploma or equivalent, percentage of unemployed individuals 16 years or older in the civilian work force, and percentage of female-headed households.

[f] *P* value obtained from hierarchical mixed effect model for multicategory logit model with a random intercept.

[g] *P* value obtained from hierarchical mixed effect model for logistic regression with a random intercept.

[h] Measured by using the 10-item Perceived Stress Scale in which respondents reported feelings of stress and coping in the past month on a 5-point Likert scale from 0 (lowest) to 4 (highest) (24). The 10 items were summed to create a composite score (score range, 0–40) for stress in which greater values indicate greater levels of perceived stress.

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Table 2. Descriptive Statistics for Individual and Neighborhood Variables[a] at Baseline, By Neighborhood Type, Study of African American Women Participating in a Church-Based Diabetes Prevention Program on Weight Reduction (N = 220), Dallas, Texas, 2014–2016

Variable	All Neighborhoods (N = 220)	Most Disadvantaged Neighborhoods (n = 110)	Least Disadvantaged Neighborhoods (n = 110)	*P* Value
Never	163 (81.5)	78 (79.6)	85 (83.3)	.50[g]
Former/current	37 (18.5)	20 (20.4)	17 (16.7)	
Perceived stress[h], mean (SD)	15.5 (6.8)	14.9 (6.7)	15.9 (7.2)	.30[b]

Abbreviation: SD, standard deviation.

[a] All data were measured at the individual level, except for composite neighborhood disadvantage score.

[b] *P* value obtained from hierarchical mixed-effect model for normal model with a random intercept.

[c] Calculated by summing the number of biomarkers for which the participant was categorized as high risk; score ranged from 0 to 9. Data were collected on 9 biomarkers: body mass index, waist circumference, high-density lipoprotein (HDL) cholesterol, total cholesterol/HDL cholesterol ratio, triglycerides, glycosylated hemoglobin A1c, systolic blood pressure, diastolic blood pressure, and salivary cortisol.

[d] *P* value obtained from hierarchical mixed-effect model for Poisson regression with a random intercept.

[e] Determined by examining 10 previously developed measures of disadvantage at the neighborhood level: percentage of households living in poverty, percentage of households receiving public assistance, percentage of unoccupied housing units, percentage of renter-occupied housing, percentage of households living in the same house 5 years ago, percentage of occupied housing units with no vehicle, percentage of occupied housing units with more than 1 person per room (crowding), percentage of adults aged 25 or older without a high school diploma or equivalent, percentage of unemployed individuals 16 years or older in the civilian work force, and percentage of female-headed households.

[f] *P* value obtained from hierarchical mixed effect model for multicategory logit model with a random intercept.

[g] *P* value obtained from hierarchical mixed effect model for logistic regression with a random intercept.

[h] Measured by using the 10-item Perceived Stress Scale in which respondents reported feelings of stress and coping in the past month on a 5-point Likert scale from 0 (lowest) to 4 (highest) (24). The 10 items were summed to create a composite score (score range, 0–40) for stress in which greater values indicate greater levels of perceived stress.

Table 3. Descriptive Statistics for Components of Neighborhood Disadvantage, by Neighborhood Type, at Baseline, Study of African American Women Participating in a Church-Based Diabetes Prevention Program on Weight Reduction (N = 220), Dallas, Texas, 2014–2016

Component	Total Sample Mean (SD)	Most Disadvantaged Neighborhoods Mean (SD)	Least Disadvantaged Neighborhoods Mean (SD)	*P* Value[a]
Percentage of households living in poverty	19.7 (12.9)	28.5 (11.7)	10.9 (6.2)	<.001
Percentage of household receiving public assistance	32.8 (18.6)	44.65 (15.5)	21.0 (13.0)	<.001
Percentage of unoccupied housing units	8.8 (6.2)	11.6 (6.5)	5.9 (4.5)	<.001
Percentage of renter-occupied housing	43.9 (24.4)	51.3 (21.9)	36.5 (24.6)	<.001
Percentage of households living in the same house in past 5 years	60.6 (16.1)	60.3 (13.4)	60.9 (18.5)	.76
Percentage of occupied housing units with no vehicle	8.8 (9.0)	13.6 (10.0)	3.9 (3.8)	<.001
Percentage of occupied housing units with >1 person per room (crowding)	4.9 (4.2)	7.4 (4.2)	2.4 (2.2)	<.001
Percentage of adults 25 years or older without a high school diploma or equivalent	20.1 (12.9)	30.1 (10.4)	10.0 (5.0)	<.001
Percentage of unemployed individuals aged 16 years or older in the civilian labor force	8.9 (5.2)	11.8 (5.8)	6.1 (2.3)	<.001
Percentage of female-headed households	18.3 (4.8)	18.5 (4.5)	18.2 (5.0)	.56

Abbreviation: SD, standard deviation.
[a] *P* value obtained from hierarchical mixed-effect model for normal model with a random intercept.

Table 4. Adjusted Association of Allostatic Load Score with Neighborhood and Individual Variables at Baseline, Poisson Regression, Study of African American Women Participating in a Church-Based Diabetes Prevention Program on Weight Reduction (N = 220), Dallas, Texas, 2014–2016

Variable	β (SE) [*P* Value]			
	Model 1	Model 2	Model 3	Model 4
Intercept	−0.10 (0.23) [.67]	−0.04 (0.33) [.89]	−0.15 (0.31) [.62]	−0.13 (0.34) [.70]
Neighborhood disadvantage				
Most disadvantaged	0.24 (0.10) [.02]	0.21 (0.22) [.33]	0.25 (0.10) [.02]	0.22 (0.10) [.04]
Least disadvantaged	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
Age, y	0.02 (0.004) [.001]	0.02 (0.004) [<.001]	0.01 (0.004) [.004]	0.01 (0.004) [.003]
Socioeconomic Mediators				
Annual household income, $				
<25,000	—	1 [Reference]	—	1 [Reference]
25,000–49,999	—	−0.15 (0.23) [.52]	—	−0.13 (0.13) [.31]
50,000–74,999	—	−0.26 (0.24) [.29]	—	−0.20 (0.15) [.18]
≥75,000	—	−0.29 (0.23) [.22]	—	−0.22 (0.16) [.19]
Effect of interaction between neighborhood disadvantage and income				
Least disadvantaged and <$25,000	—	1 [Reference]	—	—
Least disadvantaged and $25,000–$49,999	—	−0.03 (0.27) [.90]	—	—
Least disadvantaged and $50,000–$74,999	—	−0.02 (0.30) [.83]	—	—
Least disadvantaged and ≥ $75,000	—	−0.03 (0.30) [.92]	—	—
Education				
≤High school	—	1 [Reference]	—	1 [Reference]
Some college/technical degree	—	0.26 (0.14) [.08]	—	0.26 (0.15) [.08]
College degree	—	0.07 (0.15) [.66]	—	0.06 (0.15) [.70]
Health Behaviors and Perceived Stress Mediators				
Alcohol consumption in past 30 days				
Yes	—	—	−0.23 (0.10) [.02]	−0.20 (0.10) [.07]
No	—	—	1 [Reference]	1 [Reference]
Physical activity				
<150 min per week	—	—	0.12 (0.10) [.23]	0.11 (0.10) [.30]
≥150 min per week	—	—	1 [Reference]	1 [Reference]
Smoking				
Current/former	—	—	−0.03 (0.12) [.83]	−0.10 (0.13) [.46]
Never	—	—	1 [Reference]	1 [Reference]
Perceived stress	—	—	0.01 (0.01) [.15]	0.01 (0.01) [.22]
σ^2	0.04 (0.03)	0.04 (0.03)	0.04 (0.03)	0.04 (0.03)

Abbreviation: SE, standard error.

Appendix A. Varimax Orthogonal Rotated Weight (Standardized) for the First Principal Component of the Neighborhood Indicators at Baseline, Study of African American Women Participating in a Church-Based Diabetes Prevention Program on Weight Reduction (N = 220), Dallas, Texas[a]

Neighborhood Indicator	Weight
Percentage of households living in poverty	0.22
Percentage of household receiving public assistance	0.17
Percentage of housing units unoccupied	0.07
Percentage of renter-occupied housing	−0.03
Percentage of households living in the same house in past 5 years	0.14
Percentage of occupied housing units with no vehicle	0.12
Percentage of occupied housing units with >1 person per room (crowding)	0.23
Percentage of adults 25 years or older with <high school diploma or equivalent	0.31
Percentage of unemployed individuals 16 years or older in the civilian labor force	0.19
Percentage of female-headed households	−0.13

[a] Six participants were missing census tract data, so for this analysis, n = 214.

Appendix B. Two-Level Poisson Regression Model Used to Perform Regression Analyses

Level 1 (between-subjects effect):

$$\ln(\theta_{ij}) = \beta_{0j} + \beta_{1j} D_{ij} + \sum \beta_{cj} X_{cij} \quad (1)$$

$$Y_{ij} \sim \text{Poisson}(\theta_{ij}) \quad (2)$$

In equation 2, Y_{ij} represents allostatic load score that follows Poisson distribution with mean θ_{ij} for subject i in church j (j = 1, 2, …, 11). In equation 1, β_{0j} is the adjusted mean allostatic load score in natural logarithm base for church j after controlling for all variables. The adjusted effect of neighborhood (D_{ij}) and other variables (X_{cij}) on allostatic load score are estimated using β_{1j} and β_{cj} in natural logarithm base as fixed effect at level-1 for church j.

Level 2 (cluster effect):

$$\beta_{0j} = \gamma_{00} + u_{0j},$$

$$\beta_{1j} = \gamma_{10} + u_{0j} \quad (3)$$

$$\beta_{cj} = \gamma_{c0}, c = 1, 2, \ldots, c$$

In equation 3, γ_{00} is the overall adjusted mean allostatic load score at natural logarithm base after controlling for all variables. γ_{10} and γ_{c0} are the pooled within-church regression coefficients at natural logarithm base for the level-1 covariates, and u_{0j} is an error term representing effects associated with church j, which is assumed to be normally distributed with mean 0 and variance 1. Here, c represents the number of covariates in the model.

GRADUATE CATEGORY

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ORIGINAL RESEARCH

Does Sodium Knowledge Affect Dietary Choices and Health Behaviors? Results From a Survey of Los Angeles County Residents

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PEER REVIEWED

Abstract

Introduction
In 2010, the Los Angeles County Department of Public Health launched a local sodium-reduction initiative to address the rising prevalence of high blood pressure (hypertension) and related cardiovascular conditions in the population. To inform this effort, we evaluated self-reported knowledge and health behaviors related to sodium intake among Los Angeles County residents.

Methods
We administered 3 cross-sectional Internet panel surveys on knowledge about dietary sodium to a sample of Los Angeles County adults, at intervals from December 2014 through August 2016. Multinomial and logistic regression models were constructed to describe associations between sodium knowledge and self-reported health behaviors.

Results
A total of 7,067 panel subjects clicked into the online survey, and 2,862 completed the survey (adjusted response rate = 40.5%). Only 102 respondents (3.6%) were able to accurately report the recommended milligrams of sodium that an average adult should consume daily (1,500 mg to 2300 mg). Knowing about daily sodium intake recommendations was associated with increased odds of using Nutrition Facts labels to make food purchase decisions (adjusted odds ratio [AOR], 3.48; 95% confidence interval [CI], 1.59–7.60) and with decreased odds of taking measures to prevent hypertension (AOR, 0.38; 95% CI, 0.19–0.74).

Conclusions
Los Angeles County residents had a limited knowledge of recommended daily sodium intake. Efforts to increase understanding of these recommendations may encourage wider engagement in healthy behaviors. Health agencies should integrate sodium reduction messages in their diet and nutrition educational efforts.

Introduction

High blood pressure (hypertension) is the main risk factor for heart disease and stroke, 2 of the leading causes of death among US adults (1). Obesity and diets high in sodium contribute to blood pressure elevation (2). The *Dietary Guidelines for Americans 2015–2020* recommends that healthy adults consume no more than 2,300 mg of sodium per day and that at-risk adults (eg, people with hypertension, people aged 51 years or older, black people) consume less than 1,500 mg of sodium per day (3). The high levels of sodium contained in processed foods, which constitute most food purchases in the United States, can make it difficult for adults to meet these recommendations (4).

Los Angeles County (LAC), the most populous county in the United States, has a high prevalence of chronic diseases associated with excess sodium consumption (eg, 29.3% of LAC adult residents have hypertension (5). Sodium knowledge in the population is also problematic. A previous assessment showed that less than 10% of LAC adults knew recommendations for daily sodium consumption (6). To date, few studies have examined the relationships between sodium knowledge and health behaviors, and even

less is known about these relationships in a large urban population. We evaluated self-reported knowledge and health behavior related to sodium intake among LAC residents to inform an initiative to address the rising prevalence of high blood pressure and related cardiovascular conditions in this population.

Methods

Study design

Our study built on a previous assessment of sodium knowledge, attitudes, and behaviors among LAC residents (6) that consisted of a series of 3 cross-sectional Internet panel surveys administered by Global Strategies Group, from December 2014 through August 2016, for the LAC Department of Public Health (DPH). Each survey comprised from 55 to 62 questions distributed across 5 categories: food selection and consumption, support for policy changes related to food environments, nutrition knowledge and awareness, health status, and demographics. Wherever possible, the surveys' questions were derived from validated questionnaires such as the Behavioral Risk Factor Surveillance System (BRFSS) (7) and the National Health and Nutrition Examination Survey (NHANES) (8). Other questions not addressed by NHANES or BRFSS, such as those pertaining to attitudes toward sodium in foods served in the workplace or at restaurants, were developed internally by DPH.

Because data collection from Internet panels is a continuous process, data from the 3 surveys were combined into one data set. Each survey's questions were pretested with a pilot group of either 50 or 100 participants to determine accuracy and quality of the survey's programming. No changes were made after piloting each survey before distribution. Surveys of pilot group participants were included in the final tally of completed surveys. To ensure comparability across surveys, only questions that remained consistent over time were used in the analysis.

Participants

Participants were LAC residents aged 18 years or older who were able to complete the surveys in either English or Spanish. To ensure a representative sample of county residents, quotas and weights generated by using demographic and geographic data from the 2013 American Community Survey (9) and the 2011 Los Angeles County Health Survey were applied (10). These quotas took into account age, race, sex, income, and LAC Service Planning Area (11). After quota criteria were established, the 3 surveys were distributed to participants by Global Strategy Group. The resulting data were weighted to account for potential undercoverage from the survey's web-based format and for differential nonresponse resulting from low response rates for certain hard-to-reach demographic groups, such as young residents (particularly those aged 18 to 24 years) and people without computer access. Incentives provided to participants who completed the survey included various gift cards, points programs, or partner products and services at the discretion of the panel provider working with Global Strategies.

Sociodemographic information was collected for all survey participants. Age was converted from a numeric response into a categorical variable in 6 age categories (18–24 y, 25–34 y, 35–44 y, 45–54 y, 55–64 y, and ≥65 y). Race/ethnicity responses were collapsed into 5 categories: African American/black, white, Asian, Hispanic/Latino, and other. Participants were asked to provide their education and annual income level. Body mass index (BMI, measured as weight in kg/height in m^2) was self-reported. BMI values that were implausible by guidelines of the Centers for Disease Control and Prevention (CDC) (ie, weight >600 lbs or height >8 ft) were excluded from the study (12).

Measures

Frequencies and weighted percentages were generated for all categorical variables encompassing the demographic characteristics of the survey population, knowledge of nutritional concepts, and health behaviors. To assess participants' knowledge of daily sodium intake recommendations, participants were asked "How many milligrams of sodium should an average adult consume on a daily basis?" Participants were also asked to identify the number of calories an average adult should consume daily, to compare their knowledge of recommendations for calorie and sodium consumption. To examine their understanding of the consequences of excess sodium consumption, participants were asked, "How harmful do you think consuming salt is for your health?" These questions were used in a previous survey analysis to assess sodium knowledge among LAC residents (6).

General health status was assessed by asking participants how they felt about their general health and whether a doctor or other health care provider had told them to watch their salt intake or told them they had hypertension. Sodium consumption was assessed by asking whether participants added salt to their food and whether they were watching their salt intake. Food purchasing behavior and decision making were assessed by asking how often participants changed their mind about a food purchase on the basis of its sodium content and how often they used Nutrition Facts labels or other food labels during a food purchase. Use of these questions has been described elsewhere (6).

Analyses

Frequencies and weighted percentages were generated for all categorical variables, which encompassed the population's demo-

graphic characteristics, weight status, knowledge about nutrition, and health behaviors. Logistic and multinomial multiple regressions were constructed to assess associations between knowledge about sodium and health behavior variables. Each regression model controlled for demographic characteristics and included one main predictor per outcome. We used logistic regression to analyze relationships between outcome variables with 2 response levels and used multinomial regressions for outcomes with more than 2 response levels. All analyses were performed using SAS version 9.4 (SAS Institute, Inc). All study protocols and instruments were approved by the LAC DPH institutional review board.

The second and third surveys used 2 sets of questions to assess participants' ability to correctly read Nutrition Facts labels and to identify high-sodium food items. These questions were not asked in the first survey. Two variables were created by using these sets of questions. The first variable was based on a set of questions that assessed participants' ability to compare the sodium content of foods from Nutrition Facts labels. The second variable was based on a set of questions that asked participants to identify high-salt foods from a list. For the first variable, 2 groups of Nutrition Facts labels were shown to participants: 1) 2 labels where participants were asked to identify the healthier of 2 food items and 2) 3 labels where participants were asked to identify the item with the least sodium per cup (Figure). Responses to these 2 questions were collapsed into a single variable with 3 values: 1) answering neither question correctly 2) answering one question but not the other correctly, or 3) answering both questions correctly. For the second variable, 10 to 15 foods were shown to participants who were then asked whether the foods contained high, medium, or low amounts of sodium. Only the foods previously promoted as high sodium to LAC residents during the Salt Shocker health marketing campaign (https://www.choosehealthla.com/eat/salt/) were analyzed (13). These included bread, ketchup, cottage cheese, and canned vegetables. For each of these foods, the response "high sodium" was classified as answered correctly, and the responses "medium sodium" or "low sodium" were classified as answered incorrectly. Variables for the 4 items were then collapsed into a dichotomous variable where participants who correctly identified at least 2 of the 4 items were sorted into one category, "gave the correct response," and participants who correctly identified either one or none of the items were sorted into another, "gave the incorrect response."

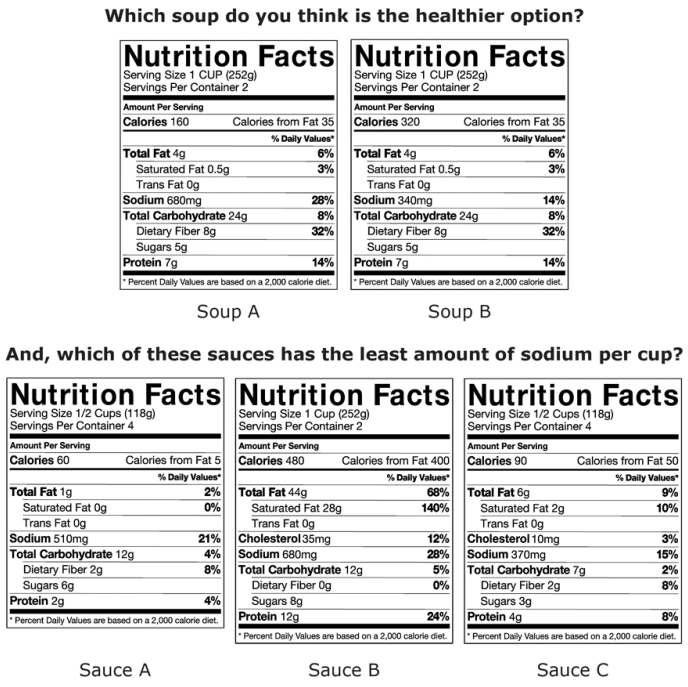

Figure. Nutrition Facts labels presented to participants for evaluation, Los Angeles County, Internet panel survey, 2014–2016. Participants were asked to use the 2 labels at the top to select the healthier of the 2 soups, A or B. They were also asked to identify which of the 3 Nutrition Facts labels on the bottom, A, B, or C, had the least sodium per cup.

Results

Throughout the sampling period, 7,067 panel subjects clicked into the online survey. Of these, 2,862 completed the survey, resulting in an adjusted response rate for all 3 surveys of approximately 40.5%. This adjusted response rate was calculated by dividing the number of completed surveys by the number of eligible participants. Participants were excluded from the final sample if they were younger than 18 years, did not live in LAC, or because of quota criteria.

Participants were evenly distributed across age groups with the largest group aged 25 to 34 years (20.9%). Most were white (40.2%), female (51.3%), had some college or an associate's degree or bachelor's degree (54.6%), and had an annual income of $25,000 to $49,999 (22.6%). More than half reported perceiving themselves as overweight (53.5%); similarly, BMI calculations (based on participants' self-reported heights and weights) showed that 58.7% of participants were overweight or obese (Table 1).

Only 3.6% of participants were able to accurately report the daily recommended sodium intake for an adult (1,500 mg to 2,300 mg). Conversely, 31.7% of participants knew the correct daily calorie intake recommendation. About half (50.7%) believed that consuming salt was somewhat harmful to their health. More than half (54.8%) reported currently watching or reducing their salt intake. Less than a third (31.4%) indicated they had ever been told by a doctor or other health professional to watch their salt intake (Table 2). Although most participants were able to correctly answer 1 of 2 questions regarding Nutrition Facts labels (57.8%), only 21.4% were able to correctly identify at least half of the high-sodium foods presented in the survey.

Participants who believed that consuming salt was very harmful to their health compared with those who believed sodium consumption was only somewhat harmful had increased odds of not adding salt to their food (adjusted odds ratio [AOR], 2.91; 95% confidence interval [CI], 2.16–3.92) and changing one's mind about a food purchase based on its salt content (AOR, 2.30; 95% CI, 1.70–3.10) (Table 3). Participants who believed consuming salt was very harmful to their health compared with those who believed it was only somewhat harmful had increased odds of watching or reducing their salt intake (AOR, 2.71; 95% CI, 2.09–3.49) and decreased odds of doing anything to control or prevent high blood pressure (AOR, 0.84; 95% CI, 0.64–1.07). Conversely, participants who did not believe consuming salt was harmful to their health compared with those who believed it is somewhat harmful were found to have lower odds of changing their mind about purchasing a food item because of its sodium content (AOR, 0.47; 95% CI, 0.33–0.67). The odds of taking measures to prevent high blood pressure (ie, exercising regularly, controlling or trying to lose weight, reducing sodium intake, taking medicine prescribed by a doctor, or avoiding alcohol or cigarettes) among participants who accurately reported the daily recommended sodium intake for adults was lower than for those who could not accurately report the recommendation (AOR, 0.38; 95% CI, 0.19–0.74). Participants who accurately reported the recommended daily sodium intake had higher odds of reporting watching or reducing salt intake (AOR, 1.59; 95% CI, 0.87–2.89). These participants also had higher odds of having had a doctor or health professional recommend watching salt intake (AOR, 1.24; 95% CI, 0.68–2.24). In addition, knowing about daily sodium intake recommendations was associated with increased odds of using Nutrition Facts labels to make food purchase decisions (AOR, 3.48; 95% CI, 1.59–7.60). In subanalyses, participants who were able to accurately identify high-sodium foods when shown Nutrition Facts labels or a panel of 4 high-sodium foods showed increased odds of changing their mind about buying foods because of their sodium content (Nutrition Facts questions, AOR, 2.35; 95% CI, 1.60–3.45, 4-food panel, AOR, 1.47; 95% CI, 1.01–2.12) (Table 3). Similarly, these same participants had increased odds of currently watching or reducing their salt intake (Nutrition Facts label questions AOR, 1.49; 95% CI, 1.04–2.13; 4-food panel, AOR, 2.14; 95% CI, 1.42–3.48).

Discussion

Our study yielded 2 main findings. First, although participants appeared to understand the consequences of excess sodium intake, they did not know recommendations for daily sodium consumption or the sodium content of foods that are high contributors to salt in the American diet, as demonstrated by participants' limited understanding of how sodium content is displayed on food labels. This finding supports previous work that suggests that the level of knowledge pertaining to daily sodium recommendations is low among LAC residents (6). Second, increased knowledge about the harmful effects of sodium was associated with increased engagement in some healthy behaviors, such as watching salt intake or declining a food purchase because of its salt content. This finding aligns with previous studies that found positive associations between increased knowledge of nutritional concepts and improved food choices (14,15). Although increased knowledge about specific sodium consumption recommendations was associated with increased use of Nutrition Facts labels to guide food purchasing decisions, this finding was conversely associated with lower odds of doing anything to control or prevent hypertension.

The LAC DPH continues to encourage residents to reduce salt consumption through an array of strategies, including applying nutrition standards to food venues such as hospitals and universities and modifying their menus. Results from our study suggest that LAC residents require further nutrition education to take advantage of increased availability of low sodium foods as a result of these implemented sodium reduction strategies. LAC DPH conducted the Salt Shocker campaign, including educational videos, to make residents aware of recommendations for sodium consumption and the amount of sodium in common foods that add significantly to the volume of salt in the American diet. For example, the campaign highlighted that 3 fast-food packets of ketchup (over 500 mg) and 1 cup of cottage cheese (900 mg) each contain over 20% of the *Dietary Guidelines for Americans*' recommendation for daily sodium intake (13). While sliced bread and canned vegetables do not contain the highest amounts of sodium per serving of popular prepared foods, they contribute heavily to the amount of sodium Americans consume through their frequent use as ingredients in commonly prepared dishes. Consequently, CDC recommends that Americans choose low sodium or no-added-salt varieties of bread and canned vegetables (16).

Findings from our study suggest that health education messaging, especially in regard to reducing sodium intake, should be integrated with policy and system-level change interventions such as those from recent chronic disease–related efforts (17). Previous studies found that residents of developed countries such as the United States and Canada are receptive to some, but not all, dietary sodium recommendations or warnings with differences in knowledge and receptiveness tied to socioeconomic status and race/ethnicity (14). Future campaigns should take into account that although recommendations and warnings about sodium intake are generally accepted (15), specific warnings against consumption of processed foods containing large amounts of sodium, such as breads or cereal, are rarely followed because most people are unable to correctly identify high-sodium foods (18,19). Furthermore, coupling these recommendations or this messaging to multifaceted nutritional interventions may be an effective way to raise public awareness about the dangers of excess salt consumption while simultaneously supporting the implementation of industry-focused efforts, including adherence to voluntary sodium limits for processed foods established by the US Food and Drug Administration (20–22).

Industry acceptance of incremental reductions in the sodium content of processed foods, which are possible without affecting the taste or marketability of such foods, would allow for maximum effectiveness of nutrition education efforts by making low sodium foods more common (23,24). Increasing the market share of low-sodium foods, in addition to increasing knowledge about sodium and its potential health consequences, may improve health outcomes.

Our study has several limitations. First, time may have affected the responses of participants because the series of internet panel surveys was administered over a 2- to 3-year period. However, the sampling method used by Global Strategies Group attempted to make individual participants interchangeable across survey waves and to allow for an analysis of the data independent of time. Second, as with all cross-sectional designs, no causal relationships can be determined between predictors and outcomes; results from the logistic and multinomial regression models can only be interpreted as associations. Third, the nature of the Internet panel survey methodology is linked to potential selection bias, because participants may have self-selected because of the incentives given and because of their desire to contribute to this type of study. The final study population may also be skewed toward people with continuous Internet or computer access. Fourth, questions regarding the perceived sodium content of commonly consumed foods may have been interpreted with mixed accuracy. Although all the foods were promoted by prior health marketing campaigns as high contributors to dietary sodium, not all foods that were highlighted contained high amounts of sodium per single serving. Lastly, although many questions used in the Internet panel surveys were validated on the basis of their use in national-level surveys, questions about the Nutrition Facts label or the question about the food panel were designed by the DPH staff. These more tailored questions may or may not be valid when compared with similar questions used in similar studies.

Our study highlights the needs for local jurisdictions such as LAC to educate its residents about daily sodium recommendations. These results may inform the development and dissemination of future sodium reduction efforts and consumer messaging in LAC and elsewhere in the United States.

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Tables

Table 1. Demographic Characteristics of Participants (N = 2,862), Internet Panel Survey, Los Angeles County, 2014–2016

Characteristic	No. (%)[a]
Sex	
Male	1,395 (48.7)
Female	1,467 (51.3)
Age, y	
15–24	405 (14.2)
25–34	597 (20.9)
35–44	525 (18.3)
45–54	526 (18.4)
55–64	390 (13.6)
≥65	418 (14.6)
Race/ethnicity	
African American/black	263 (9.2)
White	1,151 (40.2)
Asian	407 (14.2)
Hispanic/Latino	958 (33.5)
Other	83 (2.9)
Annual income, $	
<15,000	294 (10.3)
15,000–24,999	360 (12.6)
25,000–49,999	647 (22.6)
50,000–74,999	488 (17.1)
75,000–99,999	322 (11.3)
100,000–149,999	396 (13.8)
>150,000	300 (10.5)
Education	
Less than high school diploma	110 (3.9)
High school diploma or general equivalency diploma	839 (29.5)
Some college	734 (25.8)
Associate's degree or bachelor's degree	819 (28.8)
Master's, doctorate, or other professional degree	344 (12.1)
Weight, self-reported	
Underweight	92 (3.2)
Overweight	1,531 (53.5)

[a] Number of participants is unweighted. Percentages are weighted to account for variability in sampling and differential nonresponse. Percentages may not total 100% because of rounding.

[b] Body mass index was calculated by using the Centers for Disease Control and Prevention's formula for adults: weight (kg)/height (m^2) and classified as follows: underweight, <18.5; normal, 18.5–24.9; overweight, 25.0–29.9; obese, >30.0. Implausible weights and heights (ie, weight >600 lbs or height >8 ft) were excluded from analysis (12).

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Table 1. Demographic Characteristics of Participants (N = 2,862), Internet Panel Survey, Los Angeles County, 2014–2016

Characteristic	No. (%)[a]
The right weight	1,122 (39.2)
Don't know	117 (4.1)
Weight, measured, body mass index (kg/m^2)[b]	
Underweight	65 (2.4)
Normal	1,062 (38.9)
Overweight or obese	1,603 (58.7)

[a] Number of participants is unweighted. Percentages are weighted to account for variability in sampling and differential nonresponse. Percentages may not total 100% because of rounding.

[b] Body mass index was calculated by using the Centers for Disease Control and Prevention's formula for adults: weight (kg)/height (m^2) and classified as follows: underweight, <18.5; normal, 18.5–24.9; overweight, 25.0–29.9; obese, >30.0. Implausible weights and heights (ie, weight >600 lbs or height >8 ft) were excluded from analysis (12).

Table 2. Nutritional Knowledge and Associated Health Behaviors of Participants (N = 2,862), Internet Panel Survey, Los Angeles County, 2014–2016 (N = 2,862)

Question and Answer	No. (%)[a]
Health Behaviors	
In general, how would you rate your health?	
Excellent/very good	421 (14.7)
Good	1,215 (42.5)
Fair/poor	1,226 (42.8)
Has a doctor or other health professional ever told you to watch your salt intake?	
Yes	900 (31.4)
No	1,962 (68.6)
Are you doing anything to control or prevent high blood pressure?	
Yes	746 (26.1)
No	2,116 (73.9)
Are you currently watching or reducing your salt intake?	
Yes	1,567 (54.8)
No	1,293 (45.2)
How often do you add salt to your food?	
Never/rarely	1,465 (51.2)
Sometimes	874 (30.5)
Always/most of the time	523 (18.3)
How often do you change your mind about buying a food product because of its salt content?	
Never/rarely	881 (32.6)
Sometimes	715 (26.5)
Always/most of the time	1,107 (41.0)
How often do you use a food label or Nutrition Facts label to help you decide what food to purchase?	
Never/rarely	892 (31.2)
Sometimes	805 (28.1)
Always/most of the time	1,165 (40.7)
Nutritional Knowledge	
What impact, if any, do you think consuming salt has on your health?	
Not harmful	555 (19.4)
Somewhat harmful	1,449 (50.7)
Harmful	858 (30.0)
How many calories should an average adult consume on a daily basis?	
Between 1,800 and 2,400 (acceptable range)	914 (31.7)
Answers outside acceptable range	1,948 (68.1)
How many milligrams of sodium should an average adult consume on a daily basis?	
Between 1500 mg and 2300 mg (acceptable range)	102 (3.6)
Answers outside acceptable range	2,760 (96.5)

[a] Number of participants is unweighted. Percentages are weighted to account for variability in sampling and differential nonresponse. Percentages may not total 100% because of rounding.

Table 3. Multinomial Regression Analysis[a] of Participant (N = 2,862) Responses, Internet Panel Survey, Los Angeles County, 2014–2016

Independent Variable (Answer)	Dependent Variables (Responses)							
	Self-Reported Health Status[b]		How often do you add salt to your food?[c]		How often do you change your mind about buying a food product because of its salt content?[d]		How often do you use a food label or Nutrition Facts label to help you decide what food to purchase?[d]	
	Excellent/Very Good	Fair/Poor	Never/Rarely	Always/Most of the Time	Sometimes	Always/Most of the Time	Sometimes	Always/Most of the Time
Main Analysis — All 3 Surveys								
What impact, if any, do you think consuming salt has on your health?[e]								
Very harmful	1.13 (0.78–1.64)	1.10 (0.84–1.43)	2.91 (2.16–3.92)	1.27 (0.85–1.91)	1.36 (0.96–1.91)	2.30 (1.70–3.10)	0.83 (0.58–1.17)	1.63 (1.20–2.23)
Not harmful	1.03 (0.66–1.60)	1.25 (0.92–1.68)	0.99 (0.72–1.38)	1.22 (0.82–1.79)	0.47 (0.33–0.67)	0.49 (0.35–0.69)	0.61 (0.43–0.87)	0.82 (0.58–1.16)
How many calories should an average adult consume on a daily basis?								
Answered within acceptable range (1,800–2,400)	0.85 (0.60–1.20)	1.15 (0.90–1.47)	1.03 (0.80–1.33)	0.80 (0.58–1.11)	1.11 (0.83–1.47)	1.03 (0.80–1.33)	0.98 (0.72–1.32)	1.41 (1.06–1.86)
How many milligrams of sodium should an average adult consume on a daily basis?								
Answered within acceptable range (1,500–2,300)	0.89 (0.28–2.85)	1.12 (0.61–2.05)	0.68 (0.36–1.27)	0.40 (0.17–0.96)	1.87 (0.86–4.06)	1.72 (0.89–3.32)	1.61 (0.67–3.87)	3.48 (1.59–7.60)
Subanalysis — Surveys 2 and 3 (N = 2,014)								
High sodium food panel								
Correctly identified at least 50% of items (ie, panel of 4 high-sodium foods) as high sodium	1.62 (1.00–2.61)	1.10 (0.78–1.55)	0.90 (0.63–1.28)	1.07 (0.67–1.71)	1.20 (0.78–1.85)	1.47 (1.01–2.12)	1.50 (0.96–2.34)	1.87 (1.26–2.78)
Nutrition Facts label questions								
Answered 1 question correctly	1.12 (0.66–1.88)	1.42 (0.99–2.03)	1.37 (0.93–2.02)	1.18 (0.72 −1.95)	1.73 (1.11–2.70)	2.35 (1.60–3.45)	0.90 (0.58–1.41)	1.16 (0.78–1.77)
Answered both questions correctly	0.81 (0.44–1.49)	1.36 (0.90–2.06)	1.23 (0.78–1.93)	0.76 (0.41–1.43)	1.67 (1.02–2.74)	2.25 (1.44–3.53)	1.23 (0.73–2.07)	1.98 (1.23–3.20)

[a] Values are adjusted odds ratios (95% confidence intervals). Although a narrow CI suggests a more precise estimate, a wider CI should be interpreted with caution.
[b] Reference is "good."
[c] Reference is "sometimes."
[d] Reference is "never."
[e] Reference is "somewhat harmful."

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ORIGINAL RESEARCH

When Should "Pre" Carry as Much Weight in the Diabetes Comorbidity Debate? Insights From a Population-Based Survey

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PEER REVIEWED

Abstract

Introduction
Estimates indicate that 86 million people in the United States fit the clinical definition of prediabetes, which contributes to the epidemic of nearly 2 million new diagnoses of type 2 diabetes mellitus each year. Effort has focused on preventing prediabetes from progressing to clinical diabetes. We investigated the sociodemographic, behavioral, and health factors in people diagnosed with diabetes or prediabetes and associated leading indicators and comorbidities.

Methods
We used Behavioral Risk Factor Surveillance System data from 2011 through 2015 (N = 1,699,754). All respondents aged 18 years or older with complete covariate data were included, differentiating between self-reported diagnosis of diabetes or prediabetes. Weighted univariate and multivariable logistic regression analyses of 28 variables were developed, with adjusted odds of diagnosis, and standardized coefficients were calculated to rank predictors for diabetes and prediabetes.

Results
Prevalence of prediabetes increased each year between 2011 and 2014. After adjusting for demographic, lifestyle, and health variables, the most significant predictors in magnitude of importance for prediabetes and diabetes were age and body mass index. Although adjusted odds for cardiovascular disease and kidney disease were higher in respondents with diabetes than in those with prediabetes, respondents with prediabetes had higher adjusted odds of arthritis, depressive disorder, cancer, and chronic obstructive pulmonary disease.

Conclusions
Concurrent chronic diseases occur in people with prediabetes even at normal and overweight classifications. By identifying the conditions that are concomitant with diabetes, people with prediabetes can be provided with more rigorous and individualized treatments that can lead to better population health.

Introduction

Type 2 diabetes mellitus is a multifactorial chronic condition caused by defects in the metabolic system relating to insulin secretion and insulin resistance (1). According to the Centers for Disease Control and Prevention (CDC), an estimated 1.7 million incident cases of diabetes among Americans aged 20 years or older were reported in 2012, an equivalent of 4,657 daily cases (2). In 2014, the World Health Organization estimated that 387 million people worldwide have type 2 diabetes, with half as many cases still undiagnosed, projecting prevalence of type 2 diabetes at 592 million by 2035 (3).

The global epidemic of type 2 diabetes was predicted as early as 1971, as the result of a rapid increase in the prevalence of this disease among indigenous populations who adopted Western lifestyles (4,5). Over the past 4 decades, many epidemiological studies demonstrated that the Western way of life has contributed to the increased prevalence of type 2 diabetes and its complications (6–8). Prediabetes is an early stage of dysglycemia that occurs before diagnosis of overt diabetes (9). According to CDC, as of 2014, one in 3 adults older than 20 years (86 million people) had clinical prediabetes, with an estimated 8% to 12% diagnosed (2,10); without any intervention to treat prediabetes through lifestyle modification, medication, or both, 5% to 10% of them will progress to type 2 diabetes each year, compared with 2% of nor-

moglycemic people (2,9,11). We used data from a large, representative, cross-sectional national survey to investigate the trend in type 2 diabetes and prediabetes from 2011 through 2015 in the United States.

Methods

Population and data source

Our study used a serial cross-sectional design using Behavioral Risk Factor Surveillance System (BRFSS) survey data from 2011 through 2015, for adults aged 18 or older with complete covariate data. BRFSS is an annual survey of randomly selected US residents contacted via telephone landline and cellular telephone in all 50 states, the District of Columbia, and 3 US territories, collected in either English or Spanish (12). Only 1 member of each household is surveyed, and the data are valid, reliable, and generalizable to the US population (13). The average response rate for the 2011 through 2015 BRFSS was 48%. BRFSS data are publicly available and contain no personal identifiers; for this reason, this study was determined to be exempt from review by the National University Institutional Review Board.

Variables

Measures

We used data for respondents who self-reported a diagnosis of diabetes or prediabetes for whom there were full covariant data, based on their answers to 2 questions: 1) "Have you ever been told by a doctor or a health provider you have diabetes?"; and 2) "Ever been told by a doctor or a health provider you have prediabetes or borderline diabetes?" The aggregate 5-year affirmative responses for the questions were 1) n = 215,441 (12.7%; weighted frequency 10.5%) and 2) n = 63,567 (3.7%; weighted frequency 3%). Women who self-reported having diabetes or prediabetes during pregnancy (gestational diabetes) were excluded from this study. Clinically, prediabetes is defined as the condition where glycemic parameters are above normal but below diabetes thresholds (14). The American Diabetes Association describes prediabetes as fasting plasma glucose (FPG) of 5.6 to 6.9 mmol/L, referred to as an impaired fasting glucose level, and/or postload plasma glucose level of 7.8 to 11.1 mmol/L, referred to as impaired glucose tolerance (14), or hemoglobin A_{1c} levels of 5.7% to 6.4% (15). We used data on respondents who self-reported a diagnosis of type 2 diabetes or prediabetes.

Demographic and socioeconomic factors

Self-reported age in years (18–34, 35–49, 50–64, or ≥65), marital status (married, never married, or other), military veteran status (yes or no), education level (≤high school graduate, or some college and above), annual household income (<$15,000, $15,000 to <$25,000, $25,000 to <$35,000, $35,000 to <$50,000, or ≥$50,000), consistent access to health provider (yes or no), routine annual checkup in the past 12 months (yes or no), race/ethnicity (white non-Hispanic, black non-Hispanic, Hispanic, or other), and sex. Data were also analyzed by geographic regions according to the 9 US Census Bureau designations (16): Northeast (New England division and Middle Atlantic division); Midwest (East North Central division and West North Central division); South (South Atlantic division, East South Central division, and West South Central division); and West (Mountain division and Pacific division) (for detailed list of states included in each division see https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf).

Health variables

Self-reported body mass index (BMI) was stratified into 4 categories: underweight (BMI <18.5 kg/m^2 [weight in kg divided by height in m^2]), normal weight (BMI, 18.5–24.9), overweight (BMI 25.0–30.0), or obese (BMI >30.0). Other variables were general health condition (excellent/very good, good/fair, or poor); limited activity because of physical, mental, or emotional health (yes or no); and ever diagnosed with any of the following health conditions (yes or no): arthritis (eg, rheumatoid arthritis, gout, lupus, fibromyalgia), depressive disorder, asthma, chronic obstructive pulmonary disease (COPD) or pulmonary disease, kidney disease, cancer, or cardiovascular disease (CVD) (including chronic heart disease, heart attack, and stroke).

Lifestyle variables

Binary questions (yes or no) included smoking (100 or more cigarettes in lifetime), habitual drinking (men >14 drinks/week, women >7 drinks/week), and habitual exercise (any physical activity or exercise other than daily work-related routine in the past 30 days).

Statistical analysis

Descriptive and univariate analyses of the study population, prediabetes, and diabetes were conducted for all variables ($P < .05$ to assess significance). BRFSS weighting was used to adjust for differences in noncoverage and nonresponse in the sample to produce more generalizable estimates (17). Weighted multivariable logistic regression controlling for demographic, health, and lifestyle variables was used to obtain weighted and adjusted odds ratios (AORs) and 95% confidence intervals (CIs) for each variable with respect to prediabetes and diabetes. A multicollinearity assessment, using a variance inflation factor, was performed, with values 4 and above indicating collinearity. Fisher scoring algorithm was used to calculate maximum likelihood and identify

the most influential factors in diabetes and prediabetes. Statistical analysis and data management were performed by using SAS software, version 9.4 (SAS Institute, Inc.).

Results

All year-to-year differences in frequency distribution for each variable for the study population (N = 1,699,754) were significant, except for sex (P = .19) (Table 1). Most health conditions included in this study did not show a substantial increase in prevalence in the 5-year period, with 2 exceptions: depressive disorder increased from 16.9% to 18.1%, and obesity increased from 28.4% to 29.8%. A reduction in smoking occurred, from 45.4% in 2011 to 42.5% in 2015. The prevalence of education beyond high school increased from 58.7% to 61.3%; households with annual incomes from $15,000 to less than $25,000 decreased slightly from 17.6% to 15.8%; households with annual incomes greater than $50,000 increased from 44.9% to 49.9% (all values 2011, 2015, respectively). During 2011 through 2015, regular annual physical checkups increased from 67.0% to 70.0%; more than half of the population steadily reported a self-perceived health condition as excellent or very good (5-year average 52.6%); 42.7% reported good to fair, and 4.6% reported poor general health (P = .03) (Table 1).

Bivariate analysis of the respondents indicated that health condition, lifestyle, and demographic variables were significantly different for people reporting diabetes or prediabetes and the general population (Table 2). People diagnosed with diabetes and prediabetes were more likely to have obesity than the general public (54.0% and 47.6%, respectively, vs 29.1%), be current or past smokers (52.7% and 52.6%, respectively, vs 43.7%), have regular access to a physician (92.8% and 88.3%, respectively, vs 79.4%), and receive a regular annual checkup (86.0% and 79.2%, respectively, vs 68.7%). People with both diabetes and prediabetes reported less regular exercise (62.8% and 70.4%, respectively) compared with the general population (76.1%) (Table 2). Geographically, the distribution of diabetes and prediabetes varied. Although reporting differences existed, prevalence of prediabetes was proportionately lower in Western areas and proportionately higher in the South (Table 2).

The 5-year aggregate study population was 50.5% male and 49.5% female (Table 2). People diagnosed with prediabetes or diabetes were more likely to be white non-Hispanic than the survey population (70.5% and 62.6%, respectively, vs 68.1%). Similarly, people diagnosed with prediabetes or diabetes were more likely to be black non-Hispanic than the survey population (15.2% and 16.2%, respectively, vs 11.6%) (Table 2). The risk of diabetes and prediabetes increased with age; respondents aged 18 to 34 years and 35 to 49 years had a higher proportion of prediabetes compared with diabetes (Table 2).

After adjusting for all health, lifestyle, and demographic variables, BMI and age remained most predictive in determining odds of prediabetes and diabetes. Adjusted odds of overweight among respondents with prediabetes (AOR, 1.61; 95% CI, 1.54–1.68) and diabetes (AOR, 1.77; 95% CI, 1.71–1.83) were similar. However, participants with obesity had higher adjusted odds of diabetes (AOR, 3.66; 95% CI, 3.55–3.78) than prediabetes (AOR, 2.47; 95% CI, 2.36–2.58). The most significant predictors of prediabetes, in magnitude of importance, were obesity and age, which were also predictors for diabetes, although the order of magnitude was reversed, with age followed by obesity. Multicollinearity assessment using a variance inflation factor indicated no collinearity among the variables (collinearity <4).

Adjusted odds for prediabetes showed a steady year-to-year increase from 2.4 in 2012 to 3.5 in 2014 (2015 data missing), yet diabetes prevalence remained steady for years 2011 through 2015 (Table 3). Among the 8 health conditions in this study, the unadjusted prevalence of CVD and kidney disease was higher among those with diabetes than among those with prediabetes (Table 2). After adjusting for all other variables, the adjusted odds for CVD and kidney disease remained significantly higher among those with diabetes than those with prediabetes: with CVD and diabetes, AOR of 1.56 (95% CI, 1.52–1.60), and with prediabetes, AOR of 1.06 (95% CI, 1.01–1.10); kidney disease with diabetes, AOR of 1.97 (95% CI, 1.88–2.06), and with prediabetes, AOR of 0.84 (95% CI, 0.78–0.91) (Table 3). For the other 5 chronic health conditions, the percentage prevalences and AORs for those with prediabetes and those with diabetes were comparable or slightly higher (Tables 2 and 3).

The aggregate prevalence of chronic diseases for the 5-year period 2011 through 2015 was calculated in the general population and for prediabetes and diabetes (Figure). All values were significant (data not shown). The unadjusted bivariate analysis indicated that the prevalence of chronic diseases was higher among respondents with obesity who had diabetes. A higher percentage of people with prediabetes was found in the underweight (not shown), normal, and overweight categories (Figure).

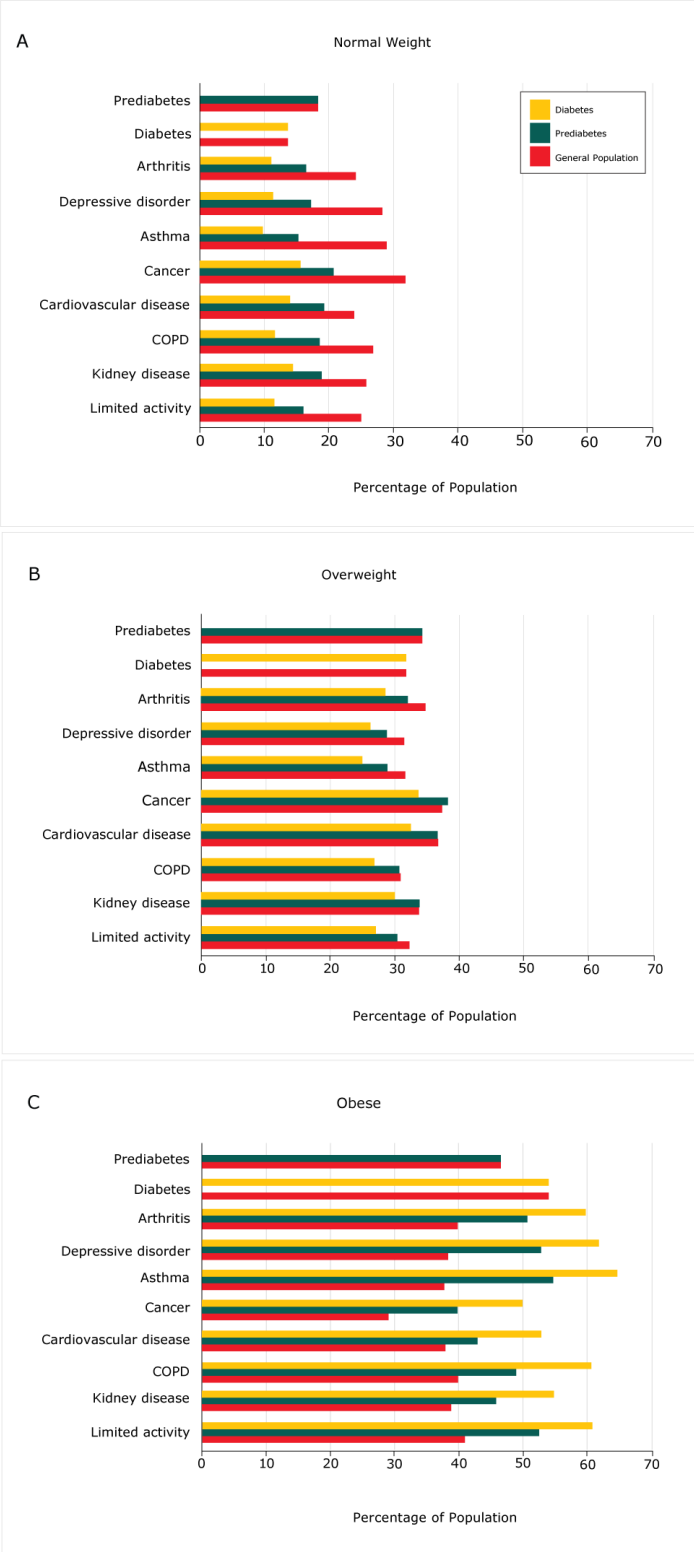

Figure. Unadjusted bivariate analysis of prevalence of chronic diseases among persons with prediabetes and diabetes by body mass index category, Behavioral Risk Factor Surveillance System, 2011–2015. Abbreviation: COPD, chronic obstructive pulmonary disease.

Discussion

Prediabetes is an early indicator of diabetes and contributes to the worldwide pandemic (3,7). Between 5% and 10% of people with prediabetes are estimated to progress annually to diabetes, depending on race/ethnicity and the detailed pathogenesis of their prediabetes (2,9,11). Of the estimated 86 million individuals with prediabetes in the United States, only 8% to 11.6%, or between 7 and 10 million individuals, have received a diagnosis and are aware of their prediabetes condition. Furthermore, a consistent set of chronic diseases associated with diabetes is seen in people with diagnosed prediabetes, even at lower BMI. This is alarming and may indicate a greater need for more rigorous diagnosis of prediabetes. It also raises the question of whether current treatments and interventions for prediabetes, although successful in delaying progression to diabetes, sufficiently address other chronic diseases concomitant with prediabetes. Many of the chronic health conditions included in this study are closely related to obesity, and are most prevalent among populations with obesity who have diabetes (Figure). However, the increasing frequency of these conditions among people with diagnosed prediabetes at lower BMI (normal and overweight) may signify an unwelcome trend of increased risk of comorbidities at lower BMI in prediabetes.

In an extensive meta-analysis of 16 prospective cohort studies that included more than 890,000 participants, Huang et al found that people with prediabetes at baseline had a significantly increased risk of cancer (18). Additional literature has associated increased risk for kidney disease (19), CVD (20), and arthritis (21) with prediabetes. Risk factors for diabetes and prediabetes (age, obesity, and physical inactivity) have been documented (22,23) and are confirmed in our study, with age and BMI being most highly predictive for both conditions. Conversely, regular annual checkups and access to physicians had a protective effect on diabetes. Accordingly, the focus has been on changing lifestyle habits among people with prediabetes and diabetes and using medication (24,25).

Several international trials have demonstrated the reversion from prediabetes to normoglycemia, based on lifestyle and drug-based interventions. The Finnish Diabetes Prevention Study reported average weight loss of 4.2 kg during a 3-year period using lifestyle intervention and medication (26). However, there are concerns that treating prediabetes with medication is an overtreatment of a nondisease condition and should be approached only in cases with

other comorbidities, such as heart disease (27). One of the many debates about treatments of prediabetes is the question of whether the focus should be on reversing the condition or simply delaying development of diabetes. Studies suggest that prolonged duration of prediabetes can result in both microvascular and macrovascular complications of diabetes, even in the absence of overt development of diabetes (11). Our results concur with such concerns and add to the body of knowledge addressing the possible public health implications of an extended long-term prediabetes condition.

Our study has limitations. First, we used self-reported data, which were not confirmed by medical records or other health history information. Self-reported data may not reflect the continuum of disease and may better be assessed with a simple functional health assessment, which was outside the limits of this study. Furthermore, the survey questions were designed as "Have you ever…," eliminating any distinction between prevalence and those who may have reverted to normoglycemia, resulting in possible overestimation of current prevalence. Second, self-reported diabetes does not distinguish between type 1 and type 2 diabetes; however, it is generally accepted that more than 90% of diabetes in the United States is type 2 (15). Although limitations are inherent in the depth and accuracy of any self-reported survey data, it nonetheless allows us to identify consistencies in variables common in both diabetes and prediabetes. Third, although BRFSS data encompass a large cross-section of the population, including both cellular telephone and landline telephone surveys since 2011, they still exclude or could underrepresent certain groups and races/ethnicities with language limitations, telephone access limitations, or those who are institutionalized. Fourth, reporting frequencies on prediabetes-specific questions has been inconsistent among the 50 states and the District of Columbia; some states did not report on that survey question during 1 or more of the 5 periods of this study, and in particular 39 states did not collect data on prediabetes for the 2015 survey year. As such we expect the prevalence of diagnosed prediabetes to be an underestimation and not valid for geographic region comparisons. This has also precluded us from estimating prediabetes prevalence for 2015. Another possible bias is that prediabetes overall is more prevalent than diagnosed prediabetes. As such, there may be a differential misclassification for diagnosed prediabetes with concurrent comorbidities. More prospective data may provide an excellent source to isolate the effect size of any such bias. Fifth, the nature of the cross-sectional survey prevents any extrapolation of causal relationships between the various health conditions used in this study and diabetes or prediabetes. Therefore, it cannot be determined if impaired glucose metabolism is responsible for other health conditions or perhaps caused by some combination of comorbidities included in this study. However, it is generally accepted that obesity is a common cause for most chronic health conditions. Furthermore, the self-reported diagnosis of prediabetes is likely an underestimation of actual prediabetes in the United States, because the American Diabetes Association only recommends screening for this condition starting at age 45, and then only if there are other health factors (15); similarly, adults younger than 50 may not be aware that they have diabetes. Lastly, BRFSS does not include any questions about frequency of testing the blood glucose level, glycated hemoglobin A_{1c}, or any other screening or treatments of those diagnosed with prediabetes. As such, it is unknown if people with diagnosed prediabetes are getting the same or similar care as people diagnosed with diabetes.

Although much attention has been given to diagnosis of at-risk populations at the stage of prediabetes to reduce incidence of diabetes, efforts are focused on preventing prediabetes from progressing to diabetes. Implied in this attitude is the view that prediabetes has lower rates of morbidity compared with diabetes. However, the validity of this assumption is not clear. This study highlights that many chronic disease conditions are present at high rates in prediabetes and that a prolonged period of prediabetes does not necessarily reduce the risk of certain comorbidities compared with diabetes. Our results suggest that there may even be an increased risk at lower BMI among people with prediabetes to present with other chronic comorbid health conditions. In light of potential comorbidities that may occur in this at-risk population, substantial effort should be considered to identify prediabetes at a lower BMI and younger age, where rigorous attempts to reverse prediabetes to normoglycemia could prove far more beneficial in promoting public health.

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Tables

Table 1. Characteristics of Respondents (N = 1,699,754) Who Responded Yes for Condition or Behavior, Behavioral Risk Factor Surveillance System, 2011–2015[a]

Characteristic	2011, %	2012, %	2013, %	2014, %	2015, %	*P* Value[b]
Health Condition						
Chronic condition						
Arthritis[c]	25.4	26.2	26.1	26.6	25.7	<.001
Depressive disorder	16.9	17.1	18.0	18.3	18.1	<.001
Asthma	13.3	13.0	13.8	13.5	13.6	<.001
Cancer[d]	11.6	11.3	11.8	11.6	12.1	<.001
Cardiovascular disease[e]	8.4	8.7	8.8	8.9	8.6	<.001
Chronic obstructive pulmonary disease (COPD)[f]	6.4	6.5	6.6	6.8	6.6	.001
Kidney disease	2.5	2.7	2.7	2.8	2.7	.01
Limited activity[g]	23.8	20.5	20.0	21.0	20.7	<.001
General health						
Excellent, very good	52.6	52.6	52.5	52.8	52.8	.03
Good, fair	42.8	42.6	42.9	42.5	42.8	
Poor	4.6	4.8	4.6	4.7	4.4	
BMI[h]						
Underweight	1.6	1.7	1.7	1.8	1.5	<.001
Normal	33.9	33.7	33.2	32.8	32.5	
Overweight	36.1	36.1	35.9	35.6	36.2	
Obese	28.4	28.6	29.2	29.8	29.8	
Lifestyle						
Smoking[i]	45.4	44.2	43.5	42.8	42.5	<.001
Consume alcohol regularly[j]	6.8	6.2	6.3	6.2	6.2	<.001
Exercise regularly[k]	75.4	77.8	74.7	77.5	75.2	<.001

[a] Percentages are weighted.
[b] *P* values based on Pearson χ^2 test of association; significant at $P < .05$.
[c] Ever been diagnosed with arthritis (eg, rheumatoid arthritis, gout, lupus, fibromyalgia).
[d] Ever been diagnosed with any type of cancer.
[e] Ever been diagnosed with chronic heart disease, heart attack, or stroke.
[f] Ever been diagnosed with COPD or pulmonary disease.
[g] Limited in any way in any activity because of physical, mental, or emotional problems.
[h] Body mass index (BMI, kg/m^2) is categorized as underweight (BMI <18.5), normal weight (BMI, 18.5–24.9), overweight (BMI, 25.0–30.0), or obese (BMI >30.0).
[i] Smoked more than 100 cigarettes during lifetime.
[j] Men having more than 14 drinks per week and women having more than 7 drinks per week.
[k] During the past month, other than for your regular job, did you participate in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise.
[l] Separated, widowed, never married, a member of an unmarried couple.
[m] Geographic regions based on US Census (a detailed list of states included in each division is available at https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf).

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Table 1. Characteristics of Respondents (N = 1,699,754) Who Responded Yes for Condition or Behavior, Behavioral Risk Factor Surveillance System, 2011–2015[a]

Characteristic	2011, %	2012, %	2013, %	2014, %	2015, %	*P* Value[b]
Demographics/socioeconomics						
Military status						
Veteran	12.2	12.0	11.8	12.5	12.2	<.001
Nonveteran	87.8	88.0	88.2	87.5	87.8	
Education level						
High school graduate or less	41.3	40.8	40.2	40.1	38.7	<.001
Some college and above	58.7	59.2	59.8	59.9	61.3	
Marital status						
Married	55.3	54.1	56.1	55.3	55.4	<.001
Never married	24.0	25.2	22.7	23.6	23.2	
Other[l]	20.7	20.7	21.2	21.2	21.3	
Sex						
Male	50.6	50.5	50.3	50.4	50.9	.19
Female	49.4	49.5	49.7	49.6	49.1	
Race/ethnicity						
White non-Hispanic	69.7	67.5	67.6	68.1	67.5	<.001
Black non-Hispanic	11.2	11.8	11.5	11.8	11.4	
Hispanic	12.1	13.2	13.5	12.7	13.5	
Other	7.0	7.5	7.3	7.3	7.6	
Income, $						
<15,000	11.9	12.2	11.9	11.4	10.2	<.001
15,000 to <25,000	17.6	17.3	17.0	16.9	15.8	
25,000 to <35,000	11.4	11.0	10.8	10.7	10.3	
35,000 to <50,000	14.3	14.4	14.3	13.9	13.8	
≥50,000	44.9	45.1	46.0	47.1	49.9	
Health care access						

[a] Percentages are weighted.
[b] *P* values based on Pearson χ^2 test of association; significant at $P < .05$.
[c] Ever been diagnosed with arthritis (eg, rheumatoid arthritis, gout, lupus, fibromyalgia).
[d] Ever been diagnosed with any type of cancer.
[e] Ever been diagnosed with chronic heart disease, heart attack, or stroke.
[f] Ever been diagnosed with COPD or pulmonary disease.
[g] Limited in any way in any activity because of physical, mental, or emotional problems.
[h] Body mass index (BMI, kg/m^2) is categorized as underweight (BMI <18.5), normal weight (BMI, 18.5–24.9), overweight (BMI, 25.0–30.0), or obese (BMI >30.0).
[i] Smoked more than 100 cigarettes during lifetime.
[j] Men having more than 14 drinks per week and women having more than 7 drinks per week.
[k] During the past month, other than for your regular job, did you participate in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise.
[l] Separated, widowed, never married, a member of an unmarried couple.
[m] Geographic regions based on US Census (a detailed list of states included in each division is available at https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf).

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Table 1. Characteristics of Respondents (N = 1,699,754) Who Responded Yes for Condition or Behavior, Behavioral Risk Factor Surveillance System, 2011–2015[a]

Characteristic	2011, %	2012, %	2013, %	2014, %	2015, %	*P* Value[b]
Consistent access to health provider	80.1	79.4	78.1	79.0	80.4	<.001
Annual health checkup	67.0	67.6	68.5	70.1	70.0	<.001
Age, y						
18–34	27.0	27.4	26.9	27.3	26.8	<.001
35–49	27.9	26.6	25.7	25.2	25.1	
50–64	27.5	27.9	28.6	28.3	28.2	
≥65	17.5	18.1	18.8	19.2	19.8	
Geographic region[m]						
Midwest: East North Central division	16.2	15.9	16.0	16.2	16.0	<.001
Midwest: West North Central division	6.9	6.8	6.4	6.9	6.8	
South: South Atlantic division	19.6	19.7	19.7	20.0	19.9	
South: East South Central division	5.7	5.9	5.5	6.0	5.8	
South: West South Central division	11.3	11.5	11.1	11.2	11.3	
Northeast: New England division	4.8	4.7	4.7	4.7	4.4	
Northeast: Middle Atlantic division	12.9	12.7	12.9	13.2	12.8	
West: Mountain division	7.1	7.0	7.2	7.2	7.1	
West: Pacific division	15.5	15.8	16.4	14.6	15.9	

[a] Percentages are weighted.
[b] *P* values based on Pearson χ^2 test of association; significant at $P < .05$.
[c] Ever been diagnosed with arthritis (eg, rheumatoid arthritis, gout, lupus, fibromyalgia).
[d] Ever been diagnosed with any type of cancer.
[e] Ever been diagnosed with chronic heart disease, heart attack, or stroke.
[f] Ever been diagnosed with COPD or pulmonary disease.
[g] Limited in any way in any activity because of physical, mental, or emotional problems.
[h] Body mass index (BMI, kg/m^2) is categorized as underweight (BMI <18.5), normal weight (BMI, 18.5–24.9), overweight (BMI, 25.0–30.0), or obese (BMI >30.0).
[i] Smoked more than 100 cigarettes during lifetime.
[j] Men having more than 14 drinks per week and women having more than 7 drinks per week.
[k] During the past month, other than for your regular job, did you participate in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise.
[l] Separated, widowed, never married, a member of an unmarried couple.
[m] Geographic regions based on US Census (a detailed list of states included in each division is available at https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf).

Table 2. Characteristics of Respondents That Have Ever Been Diagnosed with Prediabetes (N = 63,567) or Diabetes (N = 215,441), Behavioral Risk Factor Surveillance System, 2011–2015[a]

Characteristic	General Population, %	*P* Value[b]	Prediabetes, %	*P* Value[b]	Diabetes, %	*P* Value[b]
Survey year						
2011	19.4		1.4		10.0	
2012	20.9		3.3		10.4	
2013	19.9	<.001	3.7	<.001	10.6	<.001
2014	20.5		4.8		10.8	
2015	19.2		—[c]		10.9	
Health Condition						
Chronic condition						
Arthritis[d]	26.0	<.001	43.6	<.001	49.3	<.001
Depressive disorder	17.7	<.001	27.5	<.001	26.1	<.001
Asthma	13.4	<.001	17.7	<.001	17.6	<.001
Cancer[e]	11.7	<.001	17.3	<.001	19.3	<.001
Cardiovascular disease[f]	8.7	.002	15.4	<.001	25.3	<.001
Chronic obstructive pulmonary disease (COPD)[g]	6.6	<.001	12.7	<.001	14.1	<.001
Kidney disease	2.7	<.01	3.7	<.001	8.9	<.001
Limited activity[h]	21.2	<.001	33.5	<.001	41.4	<.001
General health						
Excellent, Very good	52.6		35.8		19.0	
Good, Fair	42.7	.03	56.4	<.001	65.5	<.001
Poor	4.6		7.8		15.5	
BMI[i]						
Underweight	1.7		0.9		0.6	
Normal	33.2	<.001	17.3	<.001	13.7	<.001

[a] Values reflect weighted percentages affirmative for condition or behavior.
[b] *P* values based on Pearson χ^2 test of association; significant at $P < .05$.
[c] Prediabetes prevalence for 2015 is not included because a large number of states did not report on prediabetes.
[d] Ever been diagnosed with arthritis (eg, rheumatoid arthritis, gout, lupus, fibromyalgia).
[e] Ever been diagnosed with any type of cancer.
[f] Ever been diagnosed with chronic heart disease, heart attack, or stroke.
[g] Ever been diagnosed with COPD or pulmonary disease.
[h] Limited in any way in any activity because of physical, mental, or emotional problems.
[i] Body mass index (BMI, kg/m^2) is categorized as underweight (BMI <18.5), normal weight (BMI 18.5–24.9), overweight (BMI 25.0–30.0), or obese (BMI >30.0).
[j] Smoked more than 100 cigarettes during lifetime.
[k] Men having more than 14 drinks per week and women having more than 7 drinks per week.
[l] During the past month, other than for your regular job, did you participate in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise.
[m] Separated, widowed, never married, a member of an unmarried couple.
[n] Geographic regions based on United States Census (a detailed list of states included in each division is available at https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf).

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Table 2. Characteristics of Respondents That Have Ever Been Diagnosed with Prediabetes (N = 63,567) or Diabetes (N = 215,441), Behavioral Risk Factor Surveillance System, 2011–2015[a]

Characteristic	General Population, %	*P* Value[b]	Prediabetes, %	*P* Value[b]	Diabetes, %	*P* Value[b]
Overweight	36.0		34.2		31.7	
Obese	29.1		47.6		54.0	
Lifestyle						
Smoking[j]	43.7	<.001	52.6	<.001	52.7	<.001
Consume alcohol regularly[k]	6.3	<.001	5.4	<.001	2.6	<.001
Exercise regularly[l]	76.1	<.001	70.4	<.001	62.8	<.001
Demographics/socioeconomics						
Military status						
Veteran	12.2	<.001	16.1	<.001	18.7	<.001
Nonveteran	87.8		83.9		81.3	
Education level						
High school graduate or less	40.2	<.001	44.4	<.001	51.5	<.001
Some college and above	59.8		55.6		48.5	
Marital status						
Married	55.3	<.001	57.6	<.001	56.1	<.001
Never married	23.7		15.0		11.9	
Other[m]	21.0		27.3		32.1	
Sex						
Male	50.5	.19	49.0	<.001	52.8	<.001
Female	49.5		51.0		47.2	
Race/ethnicity						
White non-Hispanic	68.1	<.001	70.5	<.001	62.6	<.001
Black non-Hispanic	11.6		15.2		16.2	
Hispanic	13.0		7.6		14.2	

[a] Values reflect weighted percentages affirmative for condition or behavior.
[b] *P* values based on Pearson χ^2 test of association; significant at $P < .05$.
[c] Prediabetes prevalence for 2015 is not included because a large number of states did not report on prediabetes.
[d] Ever been diagnosed with arthritis (eg, rheumatoid arthritis, gout, lupus, fibromyalgia).
[e] Ever been diagnosed with any type of cancer.
[f] Ever been diagnosed with chronic heart disease, heart attack, or stroke.
[g] Ever been diagnosed with COPD or pulmonary disease.
[h] Limited in any way in any activity because of physical, mental, or emotional problems.
[i] Body mass index (BMI, kg/m^2) is categorized as underweight (BMI <18.5), normal weight (BMI 18.5–24.9), overweight (BMI 25.0–30.0), or obese (BMI >30.0).
[j] Smoked more than 100 cigarettes during lifetime.
[k] Men having more than 14 drinks per week and women having more than 7 drinks per week.
[l] During the past month, other than for your regular job, did you participate in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise.
[m] Separated, widowed, never married, a member of an unmarried couple.
[n] Geographic regions based on United States Census (a detailed list of states included in each division is available at https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf).

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Table 2. Characteristics of Respondents That Have Ever Been Diagnosed with Prediabetes (N = 63,567) or Diabetes (N = 215,441), Behavioral Risk Factor Surveillance System, 2011–2015[a]

Characteristic	General Population, %	*P* Value[b]	Prediabetes, %	*P* Value[b]	Diabetes, %	*P* Value[b]
Other	7.3		6.6		7.0	
Income, $						
<15,000	11.5		12.7		18.2	
15,000 to <25,000	16.9		19.3		23.2	
25,000 to <35,000	10.8	<.001	12.1	<.001	12.8	<.001
35,000 to <50,000	14.1		15.2		14.1	
≥50,000	46.6		40.6		31.7	
Health care access						
Consistent access to health provider	79.4	<.001	88.3	<.001	92.8	<.001
Annual health checkup	68.7	<.001	79.2	<.001	86.0	<.001
Age, y						
18–34	27.1		11.5		4.3	
35–49	26.1	<.001	22.3	<.001	16.0	<.001
50–64	28.1		38.6		40.1	
≥65	18.7		27.6		39.6	
Geographic region[n]						
Midwest: East North Central division	16.1		16.5		15.9	
Midwest: West North Central division	6.8		5.7		6.1	
South: South Atlantic division	19.8		28.0		21.1	
South: East South Central division	5.8		12.8		7.0	
South: West South Central division	11.3	<.001	5.2	<.001	12.6	<.001
Northeast: New England division	4.7		4.7		3.9	
Northeast: Middle Atlantic division	12.9		13.6		12.5	
West: Mountain division	7.1		6.2		6.1	
West: Pacific division	15.6		7.4		14.8	

[a] Values reflect weighted percentages affirmative for condition or behavior.
[b] *P* values based on Pearson χ^2 test of association; significant at $P < .05$.
[c] Prediabetes prevalence for 2015 is not included because a large number of states did not report on prediabetes.
[d] Ever been diagnosed with arthritis (eg, rheumatoid arthritis, gout, lupus, fibromyalgia).
[e] Ever been diagnosed with any type of cancer.
[f] Ever been diagnosed with chronic heart disease, heart attack, or stroke.
[g] Ever been diagnosed with COPD or pulmonary disease.
[h] Limited in any way in any activity because of physical, mental, or emotional problems.
[i] Body mass index (BMI, kg/m^2) is categorized as underweight (BMI <18.5), normal weight (BMI 18.5–24.9), overweight (BMI 25.0–30.0), or obese (BMI >30.0).
[j] Smoked more than 100 cigarettes during lifetime.
[k] Men having more than 14 drinks per week and women having more than 7 drinks per week.
[l] During the past month, other than for your regular job, did you participate in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise.
[m] Separated, widowed, never married, a member of an unmarried couple.
[n] Geographic regions based on United States Census (a detailed list of states included in each division is available at https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf).

Table 3. Logistic Regression Model and Estimate of Maximum Likelihood for Prediabetes and Diabetes, Adjusting for Health Conditions, Lifestyle, and Demographics, Behavioral Risk Factor Surveillance System, 2011–2015

Characteristic	Prediabetes AOR (95% CI)	Diabetes AOR (95% CI)	Prediabetes Max Likelihood	Diabetes Max Likelihood
Survey year				
2011				1 [Reference]
2012	2.43 (2.29–2.58)	1.03 (1.00–1.07)	4.44	0.15
2013	2.71 (2.56–2.87)	1.03 (1.00–1.07)	4.89	0.15
2014	3.48 (3.30–3.67)	1.05 (1.02–1.09)	6.18	0.25
2015	—[a]	1.05 (1.02–1.09)	—[a]	0.25
Health Condition				
Chronic condition				
Arthritis[b]	1.20 (1.16–1.24)	1.04 (1.02–1.07)	0.97	0.22
Depressive disorder	1.36 (1.31–1.41)	1.11 (1.08–1.14)	1.44	0.50
Asthma	1.14 (1.09–1.20)	1.10 (1.06–1.13)	0.56	0.38
Cancer[c]	1.10 (1.05–1.14)	0.94 (0.91–0.96)	0.36	−0.25
Cardiovascular disease[d]	1.06 (1.01–1.10)	1.56 (1.52–1.60)	0.19	1.53
Chronic obstructive pulmonary disease (COPD)[e]	1.13 (1.07–1.20)	0.92 (0.88–0.95)	0.38	−0.27
Kidney disease	0.84 (0.78–0.91)	1.97 (1.88–2.06)	−0.34	1.35
Limited activity[f]	1.08 (1.04–1.13)	1.07 (1.05–1.10)	0.40	0.35
General health				
Excellent, Very Good				1 [Reference]
Good, Fair	1.38 (1.33–1.43)	2.89 (2.81–2.97)	1.94	6.44
Poor	1.18 (1.09–1.27)	4.78 (4.56–5.01)	0.42	4.04
BMI[g]				
Underweight	0.96 (0.82–1.13)	0.69 (0.60–0.80)	−0.06	−0.59
Normal				1 [Reference]

Abbreviations: AOR, adjusted odds ratio; CI, confidence interval.
[a] Prediabetes prevalence for 2015 is not included because of large number of states not reporting on prediabetes.
[b] Ever been diagnosed with arthritis (eg, rheumatoid arthritis, gout, lupus, fibromyalgia).
[c] Ever been diagnosed with any type of cancer.
[d] Ever been diagnosed with chronic heart disease, heart attack, or stroke.
[e] Ever been diagnosed with COPD or pulmonary disease.
[f] Limited in any way in any activity because of physical, mental, or emotional problems.
[g] Body mass index (BMI, kg/m^2) is categorized as underweight (BMI <18.5), normal weight (BMI 18.5–24.9), overweight (BMI 25.0–30.0), or obese (BMI >30.0).
[h] Smoked more than 100 cigarettes during lifetime.
[i] Men having more than 14 drinks per week and women having more than 7 drinks per week.
[j] During the past month, other than for your regular job, did you participate in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise.
[k] Separated, widowed, never married, a member of an unmarried couple.
[l] Geographic regions based on United States Census (a detailed list of states included in each division is available at https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf).

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Table 3. Logistic Regression Model and Estimate of Maximum Likelihood for Prediabetes and Diabetes, Adjusting for Health Conditions, Lifestyle, and Demographics, Behavioral Risk Factor Surveillance System, 2011–2015

Characteristic	Prediabetes AOR (95% CI)	Diabetes AOR (95% CI)	Prediabetes Max Likelihood	Diabetes Max Likelihood
Overweight	1.61 (1.54–1.68)	1.77 (1.71–1.83)	2.79	3.36
Obese	2.47 (2.36–2.58)	3.66 (3.55–3.78)	5.04	7.24
Lifestyle				
Smoking[h]	1.13 (1.10–1.17)	1.02 (1.00–1.05)	0.75	0.14
Consume alcohol regularly[i]	1.02 (0.96–1.10)	0.55 (0.51–0.58)	0.07	−1.82
Exercise regularly[j]	1.04 (1.00–1.08)	0.91 (0.88–0.93)	0.19	−0.52
Demographics/socioeconomics				
Military status				
Veteran	1.08 (1.04–1.13)	1.07 (1.04–1.11)	0.32	0.29
Nonveteran				1 [Reference]
Education level				
High school graduate or less				1 [Reference]
Some college and above	1.02 (0.99–1.06)	0.99 (0.96–1.01)	0.13	−0.09
Marital status				
Married				1 [Reference]
Never married	0.96 (0.91–1.02)	1.00 (0.96–1.04)	−0.22	−0.01
Other[k]	0.98 (0.95–1.02)	0.95 (0.92–0.97)	−0.08	−0.26
Sex				
Male				1 [Reference]
Female	1.01 (0.98–1.05)	0.79 (0.77–0.81)	0.08	−1.48
Race/ethnicity				
White non-Hispanic				1 [Reference]
Black non-Hispanic	1.14 (1.08–1.20)	1.47 (1.42–1.52)	0.52	1.51
Hispanic	0.84 (0.78–0.92)	1.51 (1.45–1.58)	−0.70	1.71

Abbreviations: AOR, adjusted odds ratio; CI, confidence interval.
[a] Prediabetes prevalence for 2015 is not included because of large number of states not reporting on prediabetes.
[b] Ever been diagnosed with arthritis (eg, rheumatoid arthritis, gout, lupus, fibromyalgia).
[c] Ever been diagnosed with any type of cancer.
[d] Ever been diagnosed with chronic heart disease, heart attack, or stroke.
[e] Ever been diagnosed with COPD or pulmonary disease.
[f] Limited in any way in any activity because of physical, mental, or emotional problems.
[g] Body mass index (BMI, kg/m^2) is categorized as underweight (BMI <18.5), normal weight (BMI 18.5–24.9), overweight (BMI 25.0–30.0), or obese (BMI >30.0).
[h] Smoked more than 100 cigarettes during lifetime.
[i] Men having more than 14 drinks per week and women having more than 7 drinks per week.
[j] During the past month, other than for your regular job, did you participate in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise.
[k] Separated, widowed, never married, a member of an unmarried couple.
[l] Geographic regions based on United States Census (a detailed list of states included in each division is available at https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf).

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Table 3. Logistic Regression Model and Estimate of Maximum Likelihood for Prediabetes and Diabetes, Adjusting for Health Conditions, Lifestyle, and Demographics, Behavioral Risk Factor Surveillance System, 2011–2015

Characteristic	Prediabetes AOR (95% CI)	Diabetes AOR (95% CI)	Prediabetes Max Likelihood	Diabetes Max Likelihood
Other	1.38 (1.29–1.48)	1.61 (1.52–1.71)	1.03	1.53
Income, $				
<15,000				1 [Reference]
15,000 to <25,000	1.09 (1.02–1.16)	0.91 (0.88–0.95)	0.38	−0.44
25,000 to <35,000	1.11 (1.04–1.19)	0.83 (0.79–0.86)	0.40	−0.73
35,000 to <50,000	1.10 (1.03–1.18)	0.75 (0.71–0.78)	0.42	−1.26
≥50,000	1.01 (0.95–1.08)	0.66 (0.63–0.69)	0.09	−2.57
Health care access				
Consistent access to health provider	0.81 (0.76–0.86)	0.53 (0.51–0.56)	−1.06	−3.13
Annual health checkup	0.82 (0.79–0.86)	0.54 (0.53–0.56)	−1.13	−3.47
Age, y				
18–34				1 [Reference]
35–49	1.61 (1.50–1.73)	2.91 (2.73–3.11)	2.56	5.77
50–64	2.23 (2.08–2.39)	6.21 (5.82–6.62)	4.42	10.08
≥65	2.28 (2.12–2.46)	9.46 (8.85–10.1)	3.95	10.75
Geographic region[l]				
Midwest: East North Central division				1 [Reference]
Midwest: West North Central division	0.85 (0.79–0.90)	0.99 (0.96–1.03)	−0.51	−0.03
South: South Atlantic division	1.43 (1.36–1.51)	1.05 (1.02–1.09)	1.76	0.26
South: East South Central division	2.13 (2.01–2.26)	1.10 (1.05–1.14)	2.17	0.26
South: West South Central division	0.46 (0.42–0.50)	1.12 (1.07–1.17)	−3.02	0.44
Northeast: New England division	1.03 (0.97–1.07)	0.94 (0.91–0.98)	0.07	−0.16
Northeast: Middle Atlantic division	1.07 (1.00–1.14)	0.97 (0.93–1.01)	0.27	−0.14
West: Mountain division	0.96 (0.90–1.03)	1.01 (0.97–1.05)	−0.12	0.03
West: Pacific division	0.51 (0.48–0.54)	1.08 (1.03–1.13)	−3.01	0.33

Abbreviations: AOR, adjusted odds ratio; CI, confidence interval.
[a] Prediabetes prevalence for 2015 is not included because of large number of states not reporting on prediabetes.
[b] Ever been diagnosed with arthritis (eg, rheumatoid arthritis, gout, lupus, fibromyalgia).
[c] Ever been diagnosed with any type of cancer.
[d] Ever been diagnosed with chronic heart disease, heart attack, or stroke.
[e] Ever been diagnosed with COPD or pulmonary disease.
[f] Limited in any way in any activity because of physical, mental, or emotional problems.
[g] Body mass index (BMI, kg/m^2) is categorized as underweight (BMI <18.5), normal weight (BMI 18.5–24.9), overweight (BMI 25.0–30.0), or obese (BMI >30.0).
[h] Smoked more than 100 cigarettes during lifetime.
[i] Men having more than 14 drinks per week and women having more than 7 drinks per week.
[j] During the past month, other than for your regular job, did you participate in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise.
[k] Separated, widowed, never married, a member of an unmarried couple.
[l] Geographic regions based on United States Census (a detailed list of states included in each division is available at https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf).

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ORIGINAL RESEARCH

Association Between Online Information-Seeking and Adherence to Guidelines for Breast and Prostate Cancer Screening

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PEER REVIEWED

Abstract

Introduction
From 2012 through 2014, the US Preventive Services Task Force (USPSTF) recommended biennial mammography for women aged 50 to 75 and recommended against the prostate specific antigen (PSA) test for men of any age, emphasizing informed decision making for patients. Because of time constraints and other patient health priorities, health care providers often do not discuss benefits and risks associated with cancer screening. We analyzed the association between seeking information online about breast and prostate cancer and undergoing mammography and PSA screening.

Methods
We assessed guideline concordance in mammogram and PSA screening, according to USPSTF guidelines for those at average risk for disease. We used data on 4,537 survey respondents from the National Cancer Institute's Health Information National Trends Survey (HINTS) for 2012 through 2014 to assess online information-seeking, defined as whether people searched for cancer-related information online in the past 12 months. We used HINTS data to construct multivariable logistic regression models to isolate the effect of exposure to online information on the incidence of cancer screening.

Results
After controlling for available covariates, we found no significant association between online information-seeking and guideline-concordant screening for breast or prostate cancer. Significant covariate values suggest that factors related to access to care were significantly associated with conformance to mammography guidelines for women recommended for screening and that physician discussion was significantly associated with nonconformance to guidelines for prostate-specific antigen screening (ie, having a PSA test in spite of the recommendation not to have it). Decomposition of differences between those who sought online information and those who did not indicated that uncontrolled confounders probably had little effect on findings.

Conclusion
We found little evidence that online information-seeking significantly affected screening for breast or prostate cancer in accordance with USPSTF guidelines among people at average risk.

Introduction

Most cancer screening guidelines incorporate informed decision making as a required element (1–3). To qualify as informed decision making, people must be aware of their cancer risk and discuss the benefits and possible harms of screening with their health care provider (4). Despite the emphasis on the value of informed decision making in guidelines issued by the US Preventive Services Task Force (USPSTF) and other organizations, studies show that few people with average risk for cancer are aware of the ongoing debate about the potential harms associated with some types of cancer screening and may overestimate benefits and underestimate potential risks (5–7). Some studies show that interventions at clinics, with decision aids such as questionnaires and counseling, can increase patient understanding of potential harms of screening and may facilitate discussion between patients and their health care providers (7–11). However, little is known about how people

at average risk acquire screening-related information and if and how they use this information in discussions with their providers to arrive at a screening decision.

To characterize the patient-centered issues surrounding informed decision making, we examined the relationship between online information-seeking and adherence to USPSTF recommendations for breast cancer and prostate cancer screening. USPSTF recommends that women aged 50 to 75 and at average risk for breast cancer undergo mammography screening every 2 years (3) and recommends against screening average-risk men with the prostate-specific antigen (PSA) test (during the 2012–2014 timeframe relevant to this study) (1). We hypothesized that people who engaged in online information-seeking would be more likely to adhere to USPSTF screening recommendations and that such information could be used to improve online information-seeking and informed decision making about cancer screening.

Methods

Data source

We conducted a secondary analysis of 3 years of cross-sectional data from the Health Information National Trends Survey (HINTS) for 2012 through 2014. HINTS is a nationally representative survey, administered annually by the National Cancer Institute since 2003, that collects information on the American public's use of cancer- and health-related information. Paper questionnaire surveys were mailed to 38,065 households. The HINTS sampling frame is a stratified random sample grouped by US region and by concentration of racial/ethnic minority populations. A detailed description of sampling strategies and methodology can be found on the HINTS website (https://hints.cancer.gov/dataset.aspx). We collected data on 4,537 respondents, 2,067 men and 2,470 women. We included all non-Hispanic whites and non-Hispanic blacks (specifying a 2-level indicator variable accordingly), but excluded other racial/ethnic groups (eg, Hispanics) because of small sample sizes. Black men have a higher risk of prostate cancer than white men, and black women have a lower risk of being diagnosed with breast cancer than white women but a higher risk of dying from the disease (12,13). We included people aged 40 to 75, because our study focused on people at average risk for breast and prostate cancer; people under age 40 are at lower risk for breast and prostate cancer (12,13). People with a previous history of cancer were excluded because cancer survivors are subject to different screening protocols than those at average risk.

Measures

Breast and prostate cancer screening. Women who responded to HINTS were asked whether they had had a mammogram and when they had their most recent one. Because USPSTF recommends mammography every 2 years, women aged 50 to 75 who said they received their last mammogram within the past 2 years were classified as compliers. Women younger than 50 who received a mammogram were classified as non-compliers. (1,14). Men were asked if they ever had a PSA test. Respondents who said yes were classified as noncompliers to the screening guideline. A dichotomous variable was created for each analytic sample to categorize respondents as compliers and noncompliers.

Online information-seeking. Online information-seeking was assessed by using measures of how people search for cancer-related information. HINTS asks respondents whether they search for cancer-related information. They are also asked to identify the source they went to first in searching for cancer-related information. We categorized respondents as online information seekers (seekers) if they reported using the Internet as their primary source of information the last time they looked for cancer-related information, or as non-online seekers (nonseekers) if they answered no to using the Internet or reported using any source other than the Internet when they most recently searched for cancer-related information.

Covariates in the model. Covariates included in the analyses were age, general health, physician discussion, race, marital status, education, income, occupation, family cancer history, usual source of care, health insurance, number of physician visits in the past year, and health locus of control. Physician discussion refers to whether respondents' physicians discussed whether respondents should or should not have a PSA test or whether respondents should or should not have a mammogram. Health locus of control refers to respondents' perception of their ability to control their likelihood of having cancer (15). Respondents were asked to rate their control over their chance of having cancer on a Likert scale from 1 to 4 with 1 being least likely and 4 being most likely. All covariates were self-reported.

Statistical analysis

We calculated descriptive statistics for variables of interest for the total sample stratified by sex (male and female), which effectively grouped respondents into those at risk for breast cancer or for prostate cancer. Each sample was split again into groups by recommended age criteria. Women respondents were divided into 2 groups: one recommended for cancer screening (50 y to ≤75 y) and one not recommended for screening on the basis of the age criteria of the USPSTF guideline, which does not recommend screening for women younger than 50. Men were in one group be-

cause the guideline in effect during our study recommended against routine PSA screening regardless of age. Both samples were constructed by using HINTS data from 2012 through 2014, in light of the USPSTF guideline for prostate cancer screening released in 2012 and the guideline for breast cancer screening released in 2009.

Our statistical analyses had 2 main components. First, we used multivariable logistic regression analysis to examine the relationship between guideline-adherent screening behavior and online information-seeking, controlling for available covariates that might moderate this relationship. Second, we used the Peters–Belson decomposition analysis approach to explore the robustness of our initial findings in relation to the possible omission of unobserved factors that could account for differences in screening behavior between online seekers and nonseekers.

The Peters–Belson method, also known as the Blinder–Oaxaca decomposition, has been used in economics to look at unexplained variation in outcome variables among different groups, such as wage differences between whites and blacks (16). The Peters–Belson method, as applied here, seeks to investigate and quantify the extent to which the difference in screening rates between seekers and nonseekers can be attributed to online information-seeking. The key difference from the logistic regression model (and a contribution to the analysis) is that this method quantifies the effect of unmeasured variables on the differences in screening rates between online information seekers and non-online seekers (17). The difference in screening rates between seekers and nonseekers can be decomposed into the part explained by the covariates (explained variation) and the part not explained by the covariates (unexplained variation), by estimating a model for only the seekers and then measuring how well the model fits for the nonseekers (17). If we let $\text{Observed}_{\text{seek}}$ and $\text{Observed}_{\text{non-seek}}$ be proportions of screening rates (observed in the data) for seekers and nonseekers, we can define the difference in screening rates between seekers and nonseekers, expressed as Δ (17)

$$\Delta = \text{Observed}_{\text{seek}} - \text{Observed}_{\text{non-seek}}$$

The analysis first fitted a logistic regression model for seekers for breast and prostate cancer screening. Covariate values for nonseekers were then inserted into the model to estimate the level of difference in screening behavior between seekers and nonseekers (16). Thus, $\text{Expected}_{\text{non-seek}}$ is defined as the proportion of nonseekers predicted to have engaged in screening had they been online (that is, if their screening behavior had been in accordance with the model estimated for seekers). The difference in observed screening rates between seekers and nonseekers can be rewritten as:

$$\Delta = \text{Observed}_{\text{seek}} - \text{Observed}_{\text{non-seek}} = (\text{Observed}_{\text{seek}} - \text{Expected}_{\text{non-seek}}) + (\text{Expected}_{\text{non-seek}} - \text{Observed}_{\text{non-seek}})$$

The difference between the observed and the expected proportion for nonseekers is a measure of the extent to which the model estimated for seekers does not account for the behavior of nonseekers. In the same way, the percentage of variation in the screening behavior of nonseekers that can be explained by the model estimated for seekers can be defined as (17):

$$\text{Explained \%} = [(\text{Observed}_{\text{seek}} - \text{Expected}_{\text{non-seek}}) / \Delta\ ] * 100$$

This unexplained portion represents the net influence of factors not available for inclusion in our analyses that could serve to explain differences in screening behavior between seekers and nonseekers. All analyses were performed in Stata Version 14 (StataCorp LLC) and SAS Version 9.4 (SAS Institute Inc) and incorporated sampling weights to account for the complex survey design elements of the data, nonresponse bias, and sampling bias. The study was approved by the Emory University Institutional Review Board.

Results

In our sample of 4,537 HINTS respondents, 1,297 (29.0%) were seekers, and 3,240 (71.0%) were nonseekers. Among men, 911 (44%) reported being guideline adherent (ie, did not get a PSA test). Among women younger than 50 (ie, those for whom USPSTF does not recommend mammography screening), 216 (33%) reported having mammograms; for women for whom USPSTF recommends mammography (ie, those aged 50 y to ≤75 y), 1,426 (79%) reported guideline adherence. For all 3 groups, seekers had higher screening rates than nonseekers.

Not adjusting for the influence of covariates, we found a strong association between online information-seeking and cancer screening. Male seekers were more likely to be nonadherent (ie, to get a PSA test) than nonseekers. Their likelihood of reporting having a PSA test was strongly related to online information-seeking (P = .001). For women aged 50 to 75, the likelihood of having a mammogram, and thus being guideline adherent, was also related to online information-seeking (P = .047), as well as for women younger than 50 for whom USPSTF does not recommend mammography (P = .03). Female seekers were more likely to get mammograms than nonseekers, regardless of recommendation (Table 1).

After adjusting for covariates, we found no significant relationship between online information-seeking and guideline adherence

in breast and prostate cancer screening (Table 2). Guideline nonadherence in PSA screening (ie, having a PSA test) was significantly associated with education and physician discussion. Men with higher education or who had discussion about PSA screening with their physicians were less likely to be guideline adherent.

For women overall, having a physician office visit in the past year was positively associated with having a mammogram regardless of whether they were in the age group recommended for screening. Among women recommended for breast cancer screening, age, income, race, and general health were significantly associated with higher odds of guideline adherence. For black women, having an income at or above $100,000 and health reported as excellent, very good, good, or fair were positively associated with receiving a mammogram. For women not recommended for breast cancer screening (40 y to ≤49 y), age was positively associated with receiving a mammogram.

In decomposition analysis for the logistic regression model (Table 3), the total observed difference in screening rates between seekers and nonseekers was significantly different for each of the 3 groups. The largest difference in screening rates between seekers and nonseekers was among men (9.9%) followed by women younger than 50 (8.8%) and women aged 50 to 75 (6.0%). Overall, most of the differences in screening rates between seekers and nonseekers were explained by the estimated coefficients (from the model estimated for seekers only). For men, two-thirds of the difference was explained by the estimated coefficients. For women, a higher percentage of differences, 82.95% for those not recommended for screening and 85% for those recommended, was explained by the model estimated for seekers only. Peters–Belson analyses indicated that most of the differences in screening rates between seekers and nonseekers are accounted for by the estimated models.

Discussion

Online information-seeking is not significantly associated with adherence to USPSTF guidelines after adjusting for multiple factors. This finding is in contrast with a past study that found a significant positive association between online information-seeking and screening rates for the recommended groups, and is of interest because an increasing number of people in the general population access the Internet for health-related information (19,20). The logistic regression analyses results we report provide insight into how other individual or environmental factors appear to be associated with screening decisions.

For women recommended for breast cancer screening, the key factor influencing receipt of a mammogram appears to be individual-level factors and barriers. Women recommended for mammography who had better health status, had a higher annual income, and visited their physician in the past year were significantly more likely to be guideline adherent. For non-recommended women, those who visited their physician in the past year were significantly less likely to be guideline adherent. These results are in line with an earlier study that that identified factors and barriers for adherence in breast cancer screening (18).

For men, physician discussion and education level were significantly and positively associated with having PSA screening. Our analyses identified 2 types of men most likely to be screened: those with high education levels who actively seek preventive services and those whose source of information is solely their physicians.

Additional analyses with the Peters–Belson method provide estimates of how well our logistic regression models performed by quantifying the level of unexplained differences in screening rates between seekers and nonseekers. The decomposition results showed that 33.3% of the difference in PSA screening between seekers and nonseekers was not explained by the covariates in the model estimated for seekers only. For women not recommended for mammography and those recommended, 17.05% and 15.00% of the differences in mammogram rates, respectively, were not explained by their corresponding logistic regression models. The smaller unexplained percentages in differences for mammography than for PSA testing indicate that covariates in the model accounted for higher portions of differences in mammography rates between seekers and nonseekers than those in PSA screening rates.

The χ^2 tests for the unadjusted association, the logistic regression analyses, and the Peters–Belson analyses for the association between online information-seeking and screening and the decomposition results indicate that a large portion of differences in screening rates derive from individual or physician-related factors rather than online information-seeking. The results indicate that online information-seeking itself does not have a clear effect on screening decisions; rather, factors such as physician visits are significantly associated with screening. Past studies have shown that decision aids and physician-initiated screening discussion significantly influence patient decision making, but to a varying degree for different individuals (8–11,14). In our analyses, physician discussion seemed to be a significant factor for PSA screening, but not for receipt of a mammogram. The number of physician visits was a significant factor for having a mammogram, but not for PSA testing.

It is therefore important to have tailored interventions for people at average risk to maximize the benefits of screening. For prostate cancer, physician discussion seems to be the key driver in the PSA

decision making process, as indicated in our study and previous studies (21,22). Physicians should also discuss risks of screening to adequately inform their patients. For breast cancer, a physician visit seems to be the key factor in receiving a mammogram, whether guidelines recommend screening or not. For those recommended for screening, it may be important to ensure that these women regularly visit their physicians for preventive services. For women not recommended for screening in USPSTF guidelines, physicians should inform their patients about both the benefits and risks of mammography. Although resources, including physician time, are limited and other treatment priorities for patients compete, our study and past findings indicate physician encounters are key to delivering guideline-adherent care (8,11,14).

Our study has several limitations. Receipt of mammograms and PSA tests are self-reported in HINTS and therefore subject to error. In addition, we could not identify the intensity of online information-seeking or the source of information. There may be differences in the effects of online information-seeking as a function of both the quantity and quality of information identified. Variations in frequency of online searching and in the information's scientific quality could influence screening decisions in ways that HINTS cannot capture. We also could not capture and control for variations in cancer risk levels for the individuals included in the study, because of the absence of information in HINTS on clinical factors and family history regarding cancer. The respondent's underlying risk status is therefore an uncontrolled factor in the analyses; however, the decomposition analyses indicate that unmeasured factors play a limited role in explaining the differences in screening rates between seekers and nonseekers.

Finally, it is important to note that a new draft of the USPSTF recommendation for PSA screening was published in early 2017; for men aged 55 to 69, the previous recommendation against PSA screening was changed to a new recommendation that physicians inform patients of potential benefits and harms of screening (22). Because our study analyzed data from 2012 to 2014, the new recommendation does not influence the findings reported here. However, it will be of considerable interest to see whether this change spurs greater online information-seeking among men about prostate cancer and a stronger connection between such information-seeking and having a PSA test, given the emphasis on informed decision making.

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Tables

Table 1. Demographic Characteristics, Respondents (N = 4,537) to Health Information National Trends Survey Regarding Prostate Specific Antigen (PSA) Test and Mammography Screening, 2012–2014

Characteristic	Men, PSA Test[a]			Women, Mammography Not Recommended[a]			Women, Mammography Recommended[a]		
	Not Screened, N = 911	Screened, N = 1,156	*P* Value	Not Screened, N = 216	Screened, N = 440	*P* Value	Not Screened, N = 388	Screened, N = 1,426	*P* Value
Seeks cancer-related information online									
Yes	37	63	.001	17	83	.05	27	73	.03
No	46	54		23	77		37	63	
Age, y (mean, SD)	49.94 (0.28)	57.86 (0.39)	NA	44.05 (0.30)	44.97 (0.18)	NA	59.36 (0.55)	60.20 (0.22)	NA
General health									
Excellent	45	55	.06	30	70	.36	16	84	<.001
Very good	46	54		41	59		17	83	
Good	54	46		31	69		26	74	
Fair	58	42		28	72		31	69	
Poor	63	37		39	61		45	55	
Physician discussion[b]									
Yes	12	88	<.001	31	69	.20	24	76	.44
No	85	15		37	63		22	78	
Race[c]									
White	51	49	.79	33	67	.20	24	76	.01
Black	50	50		42	58		15	85	
Marital status									
Single	59	41	.005	36	64	.72	29	71	.003
Living with a spouse or partner	48	52		34	66		19	81	
Education									
<High school graduate	69	31	.001	44	56	.002	29	71	.004
High school graduate	63	37		56	44		21	79	
Some college	47	53		31	69		29	71	
Undergraduate degree or more	41	59		25	75		14	86	
Annual income, $									
<14,999	71	29	.001	41	59	.26	31	69	.001
15,000–34,999	52	48		33	67		36	64	
35,000–49,999	54	46		38	62		27	73	

[a] According to US Preventive Services Task Force Recommendations, 2012–2014. Values are percentages unless otherwise indicated.
[b] Physician discussed benefits and risks of screening with the patient.
[c] Only non-Hispanic whites and blacks were included to capture race as a risk factor.
[d] Health locus of control refers to one's perception of ability to control the likelihood of cancer (18).

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Characteristic	Men, PSA Test[a]			Women, Mammography Not Recommended[a]			Women, Mammography Recommended[a]		
	Not Screened, N = 911	Screened, N = 1,156	*P* Value	Not Screened, N = 216	Screened, N = 440	*P* Value	Not Screened, N = 388	Screened, N = 1,426	*P* Value
50,000–99,999	48	52		33	67		14	86	
≥100,000	43	57		23	77		6	94	
Employment									
Employed	55	45	.002	35	65	.93	21	79	.59
Unemployed	43	57		34	66		23	77	
Family history of cancer									
Yes	49	51	.02	30	70	.09	21	79	.17
No	51	49		43	57		28	72	
Usual source of health care									
Yes	45	55	.001	30	70	.04	18	82	.001
No	64	36		44	56		37	63	
Health insurance									
Yes	48	52	.004	31	69	.10	19	81	.001
No	62	38		44	56		35	65	
No. physician visits in past year									
None	67	33	.001	66	34	<.001	60	40	<.001
1	53	47		34	66		22	78	
2	45	55		38	62		13	87	
3	39	61		24	76		16	84	
4	51	49		41	59		18	82	
≥5	44	56		18	82		17	83	
Health locus of control[d]									
Strongly agree	64	36	.002	33	67	.91	34	66	.08
Somewhat agree	59	41		39	61		26	74	
Somewhat disagree	51	49		34	66		23	77	
Strongly disagree	44	56		33	67		18	82	

[a] According to US Preventive Services Task Force Recommendations, 2012–2014. Values are percentages unless otherwise indicated.
[b] Physician discussed benefits and risks of screening with the patient.
[c] Only non-Hispanic whites and blacks were included to capture race as a risk factor.
[d] Health locus of control refers to one's perception of ability to control the likelihood of cancer (18).

Table 2. Analyses of the Likelihood of Guideline Adherence, Respondents (N = 4,537) to Health Information National Trends Survey Regarding Prostate Specific Antigen (PSA) Test and Mammography Screening, 2012–2014

Characteristic	PSA Test, OR (95% CI)	Mammography, OR (95% CI)	
	Men, 40–75 Years	Women, 40–49 Years	Women, 50–75 Years
Seeks cancer-related information online			
Yes	0.61 (0.31–1.21)	0.80 (0.33–1.90)	1.16 (0.63–2.11)
No	1 [Reference]	1 [Reference]	1 [Reference]
Physician discussion[a]			
Yes	0.027[b] (0.016–0.046)	0.74 (0.46–2.23)	0.73 (0.46–1.17)
No	1 [Reference]	1 [Reference]	1 [Reference]
Age	0.91[b] (0.88–0.94)	0.84[b] (0.71–0.98)	1.06[b] (1.02–1.10)
General health			
Excellent	1.54 (0.31–7.70)	0.87 (0.076–9.86)	6.39[b] (1.73–23.66)
Very good	1.59 (0.36–7.04)	0.76 (0.066–8.76)	4.54[b] (1.47–13.96)
Good	1.79 (0.42–7.67)	0.46 (0.043–4.90)	3.01 (0.90–10.08)
Fair	1.41 (0.24–8.27)	0.40 (0.037–4.32)	2.28 (0.76–6.87)
Poor	1 [Reference]	1 [Reference]	1 [Reference]
Race[c]			
White	1 [Reference]	1 [Reference]	1 [Reference]
Black	0.70 (0.33–1.46)	1.46 (0.66–3.26)	2.44[b] (1.32–4.51)
Marital status			
Single	0.78 (0.37–1.62)	1.02 (0.38–2.76)	0.80 (0.49–1.32)
Living with a partner	1 [Reference]	1 [Reference]	1 [Reference]
Education			
<High school	1 [Reference]	1 [Reference]	1 [Reference]
High school graduate	0.59 (0.24–1.47)	4.38 (0.38–50.97)	0.81 (0.33–2.04)
Some college	0.24[b] (0.12–0.48)	1.84 (0.24–13.87)	0.53 (0.22–1.29)
≥College	0.27[b] (0.11–0.66)	1.10 (0.12–9.91)	0.62 (0.19–2.00)
Annual income, $			
<14,999	1 [Reference]	1 [Reference]	1 [Reference]
15,000–34,999	0.76 (0.30–1.96)	0.31 (0.086–1.15)	0.77 (0.42–1.42)
35,000– 49,999	0.61 (0.20–1.89)	0.60 (0.14–2.59)	1.05 (0.51–2.16)
50,000– 99,999	0.56 (0.16–1.98)	0.48 (0.07–3.36)	2.69 (0.97–7.46)
≥100,000	0.58 (0.18–1.91)	0.33 (0.033–3.22)	5.48[b] (1.53–19.67)
Employment			
Employed	1.24 (0.70–2.19)	1.10 (0.28–4.37)	1.33 (0.77–2.29)
Unemployed	1 [Reference]	1 [Reference]	1 [Reference]

Abbreviations: CI, confidence interval; OR, odds ratio.
[a] Physician discussed benefits and risks of screening with the patient.
[b] Denotes significance at $P = .05$.
[c] Only non-Hispanic white and blacks were included to capture race as a risk factor.
[d] Health locus of control refers to one's perception of ability to control the likelihood of cancer (18).

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Table 2. Analyses of the Likelihood of Guideline Adherence, Respondents (N = 4,537) to Health Information National Trends Survey Regarding Prostate Specific Antigen (PSA) Test and Mammography Screening, 2012–2014

Characteristic	PSA Test, OR (95% CI)	Mammography, OR (95% CI)	
	Men, 40–75 Years	Women, 40–49 Years	Women, 50–75 Years
Family cancer history			
Yes	1 [Reference]	1 [Reference]	1 [Reference]
No	1.15 (0.76–1.73)	1.77 (0.72–4.36)	0.66 (0.40–1.07)
Usual source of care			
Yes	1.14 (0.60–2.17)	0.72 (0.35–1.47)	1.58 (0.99–2.53)
No	1 [Reference]	1 [Reference]	1 [Reference]
Health insurance			
Yes	0.97 (0.26–3.67)	0.55 (0.18–1.74)	1.40 (0.88–2.23)
No	1 [Reference]	1 [Reference]	1 [Reference]
No. physician visits in past year			
None	1 [Reference]	1 [Reference]	1 [Reference]
1	0.97 (0.26–3.67)	0.16[b] (0.045–0.59)	7.35[b] (3.40–15.89)
2	0.74 (0.30–1.86)	0.27[b] (0.09–0.79)	10.67[b] (4.51–25.24)
3	0.54 (0.20–1.47)	0.19[b] (0.035–0.99)	9.37[b] (4.31–20.36)
4	1.06 (0.334–3.29)	0.29[b] (0.083–1.03)	7.78[b] (2.97–20.40)
≥5	0.67 (0.23–1.98)	0.11[b] (0.029–0.38)	12.62[b] (5.09–31.28)
Health locus of control[d]			
Strongly agree	1.94 (0.60–6.31)	0.52 (0.10–2.71)	0.89 (0.36–2.21)
Somewhat agree	1.14 (0.65–2.02)	1.06 (0.40–2.79)	0.82 (0.47–1.42)
Somewhat disagree	0.88 (0.50–1.56)	1.00 (0.49–2.03)	0.82 (0.52–1.29)
Strongly disagree	1 [Reference]	1 [Reference]	1 [Reference]

Abbreviations: CI, confidence interval; OR, odds ratio.
[a] Physician discussed benefits and risks of screening with the patient.
[b] Denotes significance at $P = .05$.
[c] Only non-Hispanic white and blacks were included to capture race as a risk factor.
[d] Health locus of control refers to one's perception of ability to control the likelihood of cancer (18).

Table 3. Peters–Belson Decomposition Results, Respondents (N = 4,537) to Health Information National Trends Survey Regarding Prostate Specific Antigen (PSA) Test and Mammography Screening, 2012–2014

	PSA		Mammogram			
	Men, 40–75 Years		Women, 40–49 Years		Women, 50–75 Years	
Variable	Coefficient (95% CI)	% of Δ	Coefficient (95% CI)	% of Δ	Coefficient (95% CI)	% of Δ
Total Δ between seekers and nonseekers[a]	9.92 (4.68 to 15.16)	NA	8.82 (1.99 to 15.64)	NA	6.00 (1.56 to 10.45)	NA
Explained part[b]	6.94 (2.24 to 11.63)	66.67	7.30 (3.33 to 11.26)	82.95	5.15 (2.93 to 7.36)	85.71
Unexplained part[c]	2.98 (−0.66 to 6.62)	33.33	1.52 (−4.93 to 7.97)	17.05	0.86 (−3.5 to 5.17)	14.29

Abbreviations: Δ, difference in screening rates; CI, confidence interval; NA, not applicable.
[a] Seeker is a person who searches the Internet for cancer-related information; nonseeker is a person who does not.
[b] Proportion of differences in screening rates attributable to online information-seeking.
[c] Unexplained variation in differences in screening rates.

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ORIGINAL RESEARCH

Health Care Disparities Between Men and Women With Type 2 Diabetes

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PEER REVIEWED

Abstract

Introduction
Regular medical checkups indicate a patient's level of adherence to health care treatment, and the frequency of cancelled appointments or no-shows can indicate adherence. This study investigated the use of health care services by men and women and its impact on the control of their type 2 diabetes.

Methods
This study observed 100 patients with type 2 diabetes aged 45 years or older who lived in Ventura County, California, during January 1, 2015, to January 31, 2016. The data were collected by Magnolia Family Medical Center. A Pearson χ^2 test compared differences between men and women in whether they received a glycated hemoglobin A_{1c} (HbA_{1c}) test in previous 6 months, a low-density lipoprotein cholesterol test in previous year, and a retinal examination in previous year. A Wilcoxon signed-rank test compared attendance to medical appointments and HbA_{1c} values for men and women.

Results
Women had a higher rate of scheduling, cancelling or rescheduling, and showing up to their medical appointments than did men, and men had a higher median HbA_{1c} value than did women; all the Wilcoxon signed-rank tests showed a significant difference ($P <$ .001). None of the χ^2 tests were significant.

Conclusion
Although men and women had similar health care services for diabetes, men had less control of their disease and took less advantage of medical appointments than did women.

Introduction

The prevalence of type 2 diabetes increased from 1980 through 2014 (1). Dieting, exercising, attending regular medical check-ups, and screenings may prevent or control such disease (2). Regular medical checkups indicate a patient's level of adherence to health care treatment, and the frequency of cancelled appointments or no-shows can indicate adherence. Several screenings, such as retinal examinations and laboratory work for glycated hemoglobin A_{1c} (HbA_{1c}) and low-density lipoprotein (LDL) cholesterol, are recommended for proper diabetes care and disease prevention (3).

HbA_{1c} measurements are used to observe the patient's blood glucose level. The higher the HbA_{1c}, the more sugar is found attached to the red blood cells; HbA_{1c} should be less than 5.7% (3). People with diabetes have an HbA_{1c} of 6.5% or higher (3). LDL cholesterol is a measurement of low-density lipid to determine the risk of developing heart disease. Patients are at a higher risk of heart diseases if they have diabetes and have high levels of LDL cholesterol (3). A retinal examination, or a funduscopy, checks for eye diseases. Uncontrolled diabetes can lead to diabetic retinopathy (3). According to American Diabetes Association's *Standards of Medical Care in Diabetes*, HbA_{1c} measurements should be done at least once every 6 months, LDL cholesterol measurements should be done at least once every 5 years, and retinal examinations should be done at least once every 2 years (3). If patients are taking statins to lower blood pressure, the frequency of LDL cholesterol measurements depends on the physician and patient (3). Patients with any levels of diabetic retinopathy should have retinal examinations at least once every year (3).

Proper treatments are done after an individual has had diabetes diagnosed. Preventing or slowing the progression of such disease

depends ultimately on the patient. This is a health issue because a disease can progress without early detection, proper diagnosis, treatment, and full commitment of the patient.

Several factors in a person's life can create difficulties in diabetes prevention and control, including the level of adherence to recommended schedules of medical care services. Shalev et al and Krämer et al have found significant difference between men and women and their use of medical care (4,5). However, both studies were generalizable to individuals outside of the United States. Vaidya et al found that women used preventive care more frequently (6); however, they did not observe patients already diagnosed with diabetes. Bertakis et al found that women used health care services more often than did men (7). However, that study examined data on all health care services, including those that may not pertain to men.

The objective of my study was to determine whether differences exist between men and women in the control of diabetes and the use of medical appointments.

Methods

The study cohort was patients with type 2 diabetes aged 45 years or older who lived in Ventura County, California, and were regularly checked for diabetes care at Magnolia Family Medical Center. I obtained the data from Magnolia Family Medical Center with the approval of the medical director. The Quality Improvement and Research: Spreading Effective and Efficient Diabetes Care (QIR/SEED) department of Magnolia Family Medical Center collected data from the clinic's electronic health records system, Cerner (Cerner Corporation), through Cerner's Explorer Menu application. The Explorer Menu application produced a report of patients with a Systematized Nomenclature of Medicine–Clinical Terms (SNOMED–CT) problem code of 197763012, which was a diagnostic code for diabetes mellitus 2 in Cerner. The application was then used to identify all patients with that SNOMED-CT code who were aged 45 years or older and who came into the clinic with an appointment during January 1, 2015, to January 31, 2016. The report included data on patient demographics, diagnoses, history, primary care provider name, and appointments.

With the report generated by the Explorer Menu, QIR/SEED collected data on patients who had diagnoses of hypertension or hyperlipidemia and who did not have anemia. QIR/SEED screened out patients who were not regular patients of Magnolia Family Medical Center and who were seen only for a nonprovider appointment. Because of the time involved in gathering information for each patient, the first 50 men and 50 women who fit the criteria from a stratified random sample were included in the study. The study focused on the 100 patients' medical activities from January 1, 2015, to January 31, 2016.

Demographic variables analyzed were age (45–54, 55–64, and ≥65 years), race/ethnicity (Asian, black/African American, other or more than 1 race, white Hispanic, and white non-Hispanic), and sex. The racial/ethnic distribution of this sample was compared with that of Ventura County, which is 84.5% white Hispanic and non-Hispanic (8). Patient appointment data analyzed were the number of no-shows, number of cancelled or rescheduled appointments, and total number of appointments. Show-up rates were calculated by subtracting the number of no-shows from the number of total appointments. Laboratory data for HbA_{1c} and LDL cholesterol were reviewed and noted as to whether they were outdated, up to date, or not done. Retinal examination status was noted as to whether the examinations were outdated, up to date, could not be performed, or the patient had never had one. If the patient did not get their HbA_{1c} test done within 6 months of their last HbA_{1c} test during the study period, their HbA_{1c} status was recorded as outdated. Similarly, retinal examinations and LDL cholesterol tests that were not done within 1 year from the last examination during the study period were recorded as outdated. The number of canceled and rescheduled appointments were recorded to observe the patients' commitment to medical appointments concerning diabetes. The number of no-shows is the number of times a patient had an appointment and failed to show up. The total number of appointments scheduled included no-shows and kept appointments during the study's timeframe.

Patients' names, addresses, medical record numbers, date of birth, and any identifying factors were excluded from the data analyzed. Medical record numbers were changed to a random value from 1 to 100 to protect the patients' identities. Factors such as insurance coverage, transportation, jobs, and family commitments were not considered in the study because they are extrinsic factors. Also not recorded was time since a patient received a diagnosis of diabetes. Medication adherence was measured through the patients' verbal responses to their physician's questions about whether or not they were taking their medications; to avoid the limitations associated with self-reported data, data on medication adherence were excluded from the study. A letter of exemption from National University's institutional review board was obtained to investigate these data.

RStudio (RStudio) was used to analyze and interpret the data. In RStudio, box plots were produced to check for outliers and visualization of any possible differences. The box plots were also used for analyzing the distribution of the data set. A Pearson χ^2 test compared differences between men and women in whether they received an HbA_{1c} test in previous 6 months, an LDL cholesterol

test in previous year, and a retinal examination in previous year. The χ^2 test was also used to examine whether these variables were dependent on each other. A Wilcoxon signed-rank test was performed on sex versus total appointments scheduled, appointments cancelled or rescheduled, rate of showing up, and HbA_{1c} values. The Wilcoxon signed-rank test was also used to observe any differences between the medians for men and women. The level of significance used for both the χ^2 test and Wilcoxon signed-rank test was $\alpha = .05$.

Results

Of 100 patients in this study, 7 were Asian, 2 were black/African American, 45 were white non-Hispanic, 32 were white Hispanic, and 3 were other or more than 1 race. Only data on the white non-Hispanic and white Hispanic groups were analyzed because the other 3 groups had small numbers. This racial/ethnic distribution is similar to that of the Ventura County population. Eighty-eight percent of the white non-Hispanic group had an outdated HbA_{1c} test, 45.1% had an outdated LDL cholesterol test, and 66% had an outdated retinal examination. In the white Hispanic group, 86.5% had an outdated HbA_{1c} test, 56.8% had an outdated LDL cholesterol test, and 68.6% had an outdated retinal examination.

Of the 100 patients, 36% were aged 45 to 54 years (21 men and 15 women), 44% were aged 55 to 64 years (23 men and 21 women), and 20% were aged 65 years or older (6 men and 14 women). The range for HbA_{1c} values for women was 5.2 to 12, with an outlier of 12. The range for HbA_{1c} values for men was 5.8 to 12, with no outliers. The range of total appointments for women was 15 to 118 and for men was 6 to 58; for women, 118 was an outlier, and for men 58 was an outlier. The range of values for showing up to an appointment for women was 16 to 116 and for men was 6 to 58; for women, 116 was an outlier, and for men 58 was an outlier. The range of values for cancelled or rescheduled appointments for women was 5 to 57 and for men was 3 to 19; 57 was an outlier for women, and there was no outlier for men.

During January 1, 2015, to January 31, 2016, most men (76%) and most women (70%) had had at least 1 HbA_{1c} test done within 6 months (Table). HbA_{1c} tests were outdated for 18% of men and 30% of women. Most men (90%) and most women (84%) had had an LDL cholesterol test within the previous 6 months; 8% of women and 10% of men had an outdated LDL cholesterol test. At least 1 retinal examination had been recorded in the past year for 62% of men and 56% of women; 18% of the men and 16% of the women had not had a retinal examination in the past year. Sixteen percent of men and 26% of women had an outdated retinal examination. No significant associations were found between sex and whether or not patients received any of these services within the designated time frame.

Men had a higher HbA_{1c} median than did women (Table). The median of appointments that men showed up for was 14.0, while for women the median was 23.5 ($P < .001$). Women had a higher median of cancelled or rescheduled appointments than men did ($P < .001$) and a higher median number of total appointment than men did ($P < .001$). Therefore, differences between use of appointments by men and women and their median HbA_{1c} values were significant (Table).

Discussion

This study found a difference in the control of diabetes as well as the use of medical appointments between men and women. Similar results were observed in studies by Bertakis et al, Legato et al, Grant et al, and Singh-Manoux et al (7,9–11). Each study suggested a difference between the prevalence of diseases, including diabetes, between men and women. Comparable to the findings of Shalev et al, the results of this study also found that women had more scheduled appointments than did men (4).

Men and women at Magnolia Family Medical Center were provided similar health care services and recommendations; such services included getting retinal examinations, complying with schedules for receiving laboratory tests, and showing up to their medical appointments. However, women had better control of their blood glucose levels. Thus, making sure both sex groups had up-to-date blood work and retinal examinations did not guarantee that both sex groups had similar diabetes control.

My study has a few strengths. For instance, the study solely focused on a population with a medical condition; thus, the study was specific. I did not collect the data; hence, no researcher-generated data-collection biases could affect the outcome. The study also had a long time frame of 1 year. Data were not collected from surveys, but rather through physician documents, laboratory reports, retinal examination reports, and scheduling reports. Thus, no biases could result from patient self-report or me.

This study also has limitations. The data collected were from a clinic; therefore, some outliers were found. Clinic providers had different data entry techniques; thus, some data may not have been collected. Because the data were collected through a computerized system that generated reports entered by people, data entry errors and other human errors limit the accuracy of the data. The study did not include data on the length of time that patients had had a diabetes diagnosis, and the findings are pertinent only to the population of patients with diabetes at Magnolia Family Medical

Center. Another limitation was the population size. The study examined data only for patients with type 2 diabetes who had hypertension or hyperlipidemia and who were taking similar medications. The study focused only on patients regularly seen by their primary care provider in Magnolia Family Medical Center. A bigger population size should be considered for future studies. The study was also biased toward recording appointments made with Magnolia Family Medical Center only. Other clinic appointments should be recorded for future studies.

Conclusions drawn from this observation are generalizable only to the population in the study. This study solely observed individuals with type 2 diabetes and focused on the population with diabetes at 1 clinic in Ventura County, California. The observations did not show an association between regular checkups and a decreased gap between proper diabetes care in both sex groups. Although the medical treatments of the men did not differ from those of the women, men had less control of their disease; thus, sex-specific medical treatments and health education should be investigated. Moreover, when treating men with type 2 diabetes, a care provider and health professional must stress the importance of controlling blood glucose levels and health care utilization. Further studies should also investigate what causes men to have less control of their blood glucose levels. For a generalizable study, factors such as medication adherence, types of insurance and coverage, the length of time since type 2 diabetes was diagnosed, age at which type 2 diabetes was diagnosed, and race/ethnicity should be included. Other extrinsic factors should be included because they may influence behaviors related to keeping appointments and compliance with medical treatments.

Overall, men were found to have lower rates of cancelling or rescheduling a medical appointment; however, they also had a lower rate of showing up to their appointments. Regardless of men and women having similar rates of getting their blood work and screening for retinal examinations, men were still found to have a significantly higher HbA_{1c} median compared with women. Therefore, even when both sex groups were provided similar health care services for diabetes, men still had less control of their diabetes. This study will contribute to improving care for diabetes patients and will encourage care managers to work closely with their patients.

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Table

Table. Use of Health Care Services Among 100 Patients With Diabetes Aged 45 Years or Older Regularly Seen at Magnolia Family Medical Center, Ventura County, California, January 1, 2015, to January 31, 2016

Variable	Population	Sex		*P* Value[a]
		Male	Female	
HbA_{1c} value, median	7.2	7.4	6.8	<.001[a]
Total no. of appointments, median	21.5	16.0	25.5	<.001[a]
No. of appointments showed up for, median	18.5	14.0	23.5	<.001[a]
No. of cancelled or rescheduled appointments, median	7.0	6.0	11.5	<.001[a]
Had HbA_{1c} test within previous 6 months, n (%)				
Yes	73 (73)	38 (76)	35 (70)	.99[b]
Not done	3 (3)	3 (6)	0	
No	24 (24)	9 (18)	15 (30)	
Had low-density lipoprotein cholesterol test within previous year, n (%)				
Yes	87 (87)	42 (84)	45 (90)	.54[b]
Not done	4 (4)	3 (6)	1 (2)	
No	9 (9)	5 (10)	4 (8)	
Had retinal examination within previous year, n (%)				
Yes	59 (56)	31 (62)	28 (56)	.63[b]
Not done	17 (17)	9 (18)	8 (16)	
Not applicable[c]	3 (3)	2 (4)	1 (2)	
No	21 (21)	8 (16)	13 (26)	

Abbreviation: HbA_{1c}, glycated hemoglobin A_{1c}.
[a] Based on Wilcoxon signed-rank test where $\alpha = .05$.
[b] Based on Pearson χ^2 test of association where $\alpha = .05$.
[c] Patients not able to obtain a retinal examination because of blindness or surgery (which would mean the patient's care was being handled by an ophthalmologist and the patient would most likely have received a retinal examination).

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ORIGINAL RESEARCH

Do Cancer-Related Fatigue and Physical Activity Vary by Age for Black Women With a History of Breast Cancer?

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PEER REVIEWED

Abstract

Introduction

Cancer-related fatigue (CRF) is the most uncomfortable symptom among women with a history of breast cancer. Black women are more likely than women of other racial/ethnic groups to have CRF risk factors, such as physical inactivity and obesity, yet CRF studies have not focused on black women. We conducted a cross-sectional analysis to assess CRF and physical activity among black women survivors of breast cancer.

Method

In May and July of 2012, 267 members (mean age, 54 y) of the Sisters Network, Inc, completed an online survey of sociodemographic characteristics, medical characteristics, and physical activity, and a fatigue instrument (the Functional Assessment of Chronic Illness Therapy [FACIT]). Multiple linear regression assessed fatigue and physical activity compliance (ie, 150 minutes of moderate to vigorous physical activity per week).

Results

Participants had an average FACIT score of 32.3, Fatigue was greater ($P < .001$) among the 56% of women not meeting physical activity guidelines. In multivariable analysis, correlates of fatigue showed that physical activity compliance ($\beta = 3.20$, $P < .001$) and older age group (50–59 y: $\beta = 3.98$, $P = .001$; ≥60 y,: $\beta = 3.76$, $P = .003$) were associated with less fatigue. The interaction between age and fatigue was also significant: mean differences in fatigue by physical activity level were obvious only among women younger than 50 years. ($P < .001$).

Conclusion

Physical activity compliance was associated with a lower level of fatigue. However, the effect of physical activity on fatigue may differ by age. Interventions aimed at curbing CRF in black women should consider age-appropriate strategies that can be integrated into existing lifestyles.

Introduction

Cancer-related fatigue (CRF) is considered the most uncomfortable symptom experienced by women with a history of breast cancer, a population that in 2015 exceeded 3.1 million in the United States (1,2). Compared with fatigue experienced by women without a cancer history, CRF is chronic and is not relieved by rest. Approximately 25% of breast cancer survivors experience CRF that persists for 10 years or more after an initial breast cancer diagnosis (3–5). CRF disrupts work, sleep, and social relationships, contributing to deficits in quality of life (1,3).

Correlates of CRF are a high body mass index (BMI), adjuvant radiation therapy, time elapsed since treatment completion, breast cancer recurrence, and comorbid conditions such as diabetes and cardiovascular disease (3,6–8). CRF prevalence may be higher in younger women than older women with a history of cancer (9–14). Physical activity is a mitigating factor for CRF (7,15–17).

Disparities in CRF may exist. Black women in particular may experience greater levels of CRF than women of other racial/ethnic groups because of several factors. Black women may undergo aggressive treatment regimens needed to treat late-onset cancers (black women are more likely than women of other races to be diagnosed with late-stage breast cancer) and difficult-to-treat can-

cers (eg, estrogen-receptor-negative or triple negative tumors) (18). In addition, black women are more likely than women of other racial/ethnic groups to be inactive (ie, to engage in <150 min/wk of moderate-intensity physical activity), to be overweight before starting treatment, and to gain more weight during treatment (19–22). These factors may place black women at increased risk for aggressive treatments, which can exacerbate CRF (22). Few studies have examined factors that may protect black women against CRF.

The objective of this study was to examine the relationship between physical activity and CRF in black women with a history of breast cancer. We hypothesized that women engaging in recommended physical activity levels would report lower levels of fatigue than women who were less active. We also hoped to determine factors that put black women at risk for CRF.

Methods

Sample

The study sample was drawn from the Sisters Network Inc, the largest black/African-American breast cancer survivorship organization in the United States. Participants were recruited in May, June, and July 2012 via multiple emails and by posting of anonymous links to our survey on social media blog sites affiliated with the Sisters Network. The potential reach of the email messages was 16,000 members in the Sisters Network database, which includes approximately 3,800 breast cancer survivors and about 12,100 black women without a history of breast cancer. Links posted on Facebook, the Sisters Network social network site, and Twitter were sent to approximately 6,800 women. A total of 525 of a possible 3,800 breast cancer survivors responded to our web-based study. All surveys for this cross-sectional study were completed by using Survey Monkey, a web-based platform that allows investigators to create surveys, perform routine updates, and manage survey responses. Inclusion criteria were 1) receiving a diagnosis of invasive operable breast cancer, 2) being aged 18 to 80 years at the time of the survey, 3) receiving a diagnosis of stage I to stage III C breast cancer, and 4) consenting to the web-based survey administration. Details on identification and recruitment of these women were published previously (20,21). Institutional review board approval was obtained from the University of Texas MD Anderson Cancer Center before data collection. We also obtained approval to analyze these data from the University of Alabama and the University of North Texas Health Science Center institutional review boards. All participants were treated in compliance with ethical standards. Informed consent was obtained from all participants.

Measures

Cancer-related fatigue (CRF). The fatigue outcome variable was reported as a score on the Functional Assessment of Chronic Illness Therapy (FACIT) fatigue scale (Version 4). The FACIT fatigue scale is a validated 13-item self-report measure of the level of fatigue experienced during usual daily activities over the past 7 days. The scale consists of statements on level of fatigue, such as "I feel fatigue," "I feel weak all over," and "I feel tired," rated on a Likert-type response scale (0 = very much fatigued to 4 = not at all fatigued). Positively worded items were reverse scored. The score was calculated by summing the individual item scores for each participant, multiplying by 13, and dividing by the number of questions answered. Higher scores indicated less fatigue, with a score range of 4 to 52. The mean score for a similar age-matched population of women in the United States is 40 (23). We used the fatigue scale to accurately capture fatigue characteristics of black women in the United States with a history of breast cancer.

Physical activity compliance. Physical activity compliance was assessed via a self-administered survey instrument designed for the Women's Health Initiative (20,23). The instrument consists of 9 items that assesses recreational walking and light, moderate, and vigorous physical activity by measuring frequency and duration of physical activity. Estimates of metabolic equivalents (METs) for physical activity were calculated separately for light (METs <3.0), moderate (METs = 3.0–5.9), and vigorous (METs ≥6.0) activities. A variable was also created for moderate to vigorous physical activity (METs ≥3.0), which was then used to create a dichotomous variable (meeting or not meeting physical activity guidelines) based on a cutoff of 10.0 MET hours per week, which equaled approximately 150 minutes per week of moderate-paced walking or the equivalent of other physical activity durations and intensities. The cutoff used in this study was consistent with the current guidelines of the Centers for Disease Control and Prevention for physical activity (24). We opted to use evidence-based guidelines rather than continuous physical activity because the guidelines offer a standard that could be used to compare those meeting a clinically meaningful threshold of physical activity, thus, allowing our results to be compared with other studies of physical activity and CRF.

Demographic and treatment factors. Participants self-reported their age in years, height in inches, and weight in pounds. Employment status was reclassified as "working for pay" if the participant reported working outside the home even if they were retired or "not working for pay" if the participant was unemployed or was retired. Age was reclassified into 3 roughly proportional groups (<50 y, 50–59 y, and ≥60 y). Additionally, study participants self-reported the following treatment-related factors: age at diagnosis (in years), number of years since treatment completion, cancer stage

(I–IIIC), cancer recurrence, and type of primary and adjuvant cancer treatments received (surgery, chemotherapy, radiation therapy, or hormone therapy). Age at the time of study and years since treatment were only moderately correlated ($r = 0.44$), so both were retained. Participants reported other chronic conditions (comorbidities), including diabetes, high cholesterol, osteoporosis, high blood pressure, and arthritis. Number of comorbidities were tabulated on the basis of the count of comorbid conditions that participants indicated. Participants who self-reported never smoking or having quit smoking were classified as "current non-smoker." Income was separated into 7 categories: less than $20,000, $20,000 to $34,999, $35000 to $49,999, $50,000 to $64,999, $65,000 to $79,999, $80,000 to $99,999, and $100,000 or more. Age at cancer diagnosis was coded as number of years since breast cancer diagnosis, and education was coded as high school diploma or any college degree (bachelor's degree or higher).

Statistical analysis

Data were cleaned and analyzed using Stata version 13 (StataCorp LLC). We examined sociodemographic, lifestyle, and cancer diagnosis and treatment characteristics by physical activity compliance level by using *t* tests, χ^2 tests, and analysis of variance tests. With continuous FACIT score as the outcome, stepwise selection determined the final set of variables in the linear regression analysis. Variables with more than 5% of missing data on income, age at cancer diagnosis, and education were excluded from analysis. We included an interaction term to test for moderation by age category. Then we generated an interaction plot to explore the relationship between physical activity and fatigue by age categories. Significance was set at $P < .05$ with a 2-sided test.

Results

Of 3,800 possible participants, 525 initiated the study, 307 completed the survey, and 267 had sufficient data on the variables used in this analysis. The mean FACIT score was 32.3, (Table 1). Participants in the sample were on average aged 54 years, had a mean BMI of 30.4 kg/m^2, which is considered obese, and had 1 comorbidity. Most participants worked for pay, did not smoke, were diagnosed with breast cancer at Stage II or higher, and had undergone adjuvant chemotherapy or adjuvant radiation; just under half received hormone therapy. The mean time since treatment completion was 7 years, and 16% had a recurrence. Compared with those not meeting physical activity guidelines (n = 150), participants meeting physical activity guidelines (n = 117) were significantly more likely to have higher FACIT scores ($P > .001$), to be younger ($P = .02$); to have lower BMI ($P = .007$); to have fewer comorbidities ($P = .009$); and had more time since completion of cancer treatment ($P = .04$).

The multiple linear regression model suggested that FACIT scores were 3.2 points higher for those meeting physical activity guidelines than for those not meeting guidelines ($P < .001$). Additionally, FACIT scores were about 4 points higher each for those aged 50 to 59 years ($P < .001$) and 60 years or older ($P = .03$) than for those younger than 50 years (Table 2). Another demographic factor significantly associated with FACIT score was employment status. Participants currently working for pay had on average a 2-point higher FACIT score than those not working for pay ($P = .03$). No other factors were significantly associated with CRF. However, without age in the model, more years since treatment was significantly associated with less fatigue, suggesting that age at time of study accounted for some of the variance associated with years since treatment and FACIT scores.

Age had a significant interaction with adherence to physical activity guidelines ($P < .001$). The relationship between FACIT score and physical activity compliance varied by age group (Figure). For participants aged under 50 years, those who met physical activity guidelines had higher FACIT scores. Among women aged 50 years or older, the relationship between physical activity and fatigue was not significant. Overlapping confidence intervals of predictive margins for each age category showed no difference between the upper 2 age categories (50–59 y: confidence interval [CI], 2.02–5.95; ≥60 y: CI, 1.33–6.19).

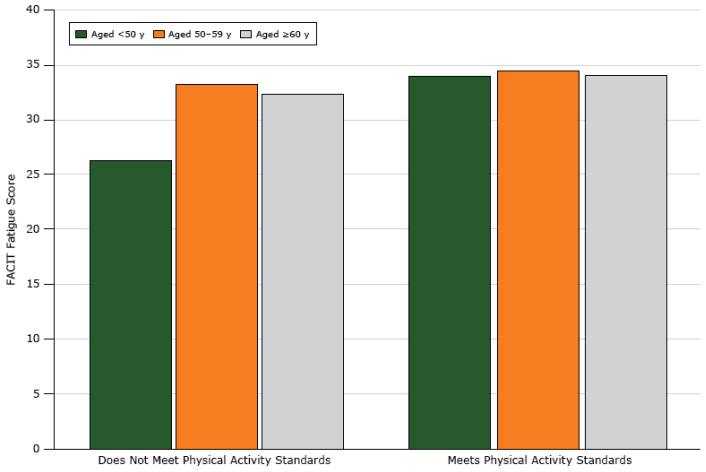

Figure 1. Relationship between FACIT (Functional Assessment of Chronic Illness Therapy) fatigue scores and physical activity, by age, among black female breast cancer survivors in the United States. Higher scores indicate less fatigue, with a score range of 4 to 52. The mean score for a similar age-matched population of women in the United States is 40 (23). Physical activity was assessed by a dichotomous (yes/no) variable: does not meet physical activity guidelines/meets physical activity guidelines.

Discussion

Meeting physical activity guidelines was associated with less CRF in this analysis of black women with a history of breast cancer. However, this association was most robust for women aged less than 50 years. As in previous studies (9–14), we found that older women had less CRF than younger women, and we also found no difference in fatigue score by physical activity level for women over 50. Study results strengthen the evidence of an association between fatigue and physical activity by age group and validate this observation for black women. Results further suggest that CRF may have more to do with a patient's age than with how long ago the patient underwent treatment. Although more information is needed to clarify relationships for women older than 50 years, our study results can inform the development of physical activity interventions designed to remedy the consequences of CRF for black women with a history of breast cancer.

The association between fatigue and physical activity was strongest among women aged under 50 years, which may reflect that younger women (ie, diagnosed before age 45 y) may have a poorer prognosis because of greater likelihood of fast-growing, high grade, and hormone-receptor–negative tumors (25), thereby requiring more aggressive treatment. (Although we did not have data on actual age at cancer diagnosis, women aged under 50 years completing a survey for cancer survivors can be assumed to have had cancer at an early age, because having a previous cancer diagnosis was a prerequisite for study participation.) Having more aggressive treatment may increase recovery time, which compromises regular physical activity habits (24) and could result in greater CRF. Furthermore, in black women breast cancer at a younger age is often accompanied by comorbid conditions, high-dose chemotherapy, physical inactivity, and abdominal obesity. The combination of these factors may contribute to persistent mild to severe fatigue. CRF may remain elevated as a result of residual effects on cardiac function from the aggressive treatment that is often required with early onset breast cancer, which often has a stronger effect on the younger woman's body and organ systems than on women aged 50 years or older (26).

Another possible explanation is that women under age 50 have unique demands on their time and resources that women over 50 do not and may have higher levels of CRF than older cancer survivors because of greater personal demands (ie, family and work) or greater (unrealistic) expectations for energy (9–14). More lifestyle stresses, such as demanding jobs, child care, or elder care may contribute to higher levels of fatigue (27. Younger women cite high social and environmental demands, such as working and caring for children, as a barrier to physical activity, and these demands are known to contribute to fatigue (9,28). These stresses may be exacerbated when a woman is unemployed, which was a significant factor in our sample. A possible reason is that fatigue itself may lead to an inability to work or that stress associated with lack of ability to work may contribute to fatigue. Thus, women who do engage in physical activity may be balancing existing stressors. Interventions that include educational and time-management strategies may provide women with skills to integrate physical activity into existing tasks and may serve to reduce CRF.

Randomized trials have indicated that engaging in physical activity is consistently associated with lowering CRF (7,18–21). Young female breast cancer survivors who engage in physical activity may be doing so to lower their levels of CRF. However, not all dimensions of fatigue can be remedied by physical activity alone. Fatigue may manifest itself differently in younger and older women. The impact of fatigue on learning and memory may be more relevant for younger women, because they are still actively engaged in the work force. Older women may not be bothered by or are aware of memory challenges and are more concerned with fatigue's physical consequences (9). Younger women may also be at higher risk for depressive symptoms, insomnia, anxiety, and fear of recurrence than older breast cancer survivors (14). Thus, our finding of no difference in the relationship between physical activity levels and fatigue for women aged over 50 years may indicate that physical activity is not as effective a treatment for the kinds of fatigue that women of this age experience. As a whole, this could suggest that emotional challenges may drive higher fatigue levels for younger women with a history of cancer. Physical activity alone may not remedy that emotional fatigue. Because black women have a greater likelihood of experiencing adverse social conditions, the compounding of physical and emotional fatigue may be especially problematic over time for those experiencing cumulative stress (29). Further research is warranted to address the cooccurring roles of stress, fatigue, and depression in black women with a history of breast cancer.

Our study has limitations. As a cross-sectional study, this analysis does not establish a causal relationship between fatigue and physical activity or differentiate between the domains of physical fatigue and emotional fatigue. For example, fatigue may cause people to be less active, or physical activity may be used to decrease fatigue. To broaden the understanding of the directionality of the associations, a longitudinal study design could be used. Nevertheless, ours is a first step in identifying the relationship between fatigue and physical activity for black women. Another limitation is that we used self-reported data on fatigue, cancer history, and physical activity. Self-reported data may be subject to recall bias; however, the recall period for fatigue in the last 7 days is relatively short, and self-report of breast cancer treatment factors was validated as over 90% accurate (30). All respondents took the

survey during the summer months of May, June, and July; thus, no seasonal variation in physical activity was expected to be observed. Future prospective studies could use objective measures of fatigue and physical activity. Although several FACIT scales are designed for breast cancer survivors, they focus on symptoms that are present during active cancer treatment. For this reason, those FACIT scales may not have been appropriate for this analysis of women who are further out from treatment completion. Thus, we used a general FACIT scale, which also allowed us to examine how participants compare with a similar age-matched population of women in the United States without cancer.

Our cross-sectional study explored the relationship between fatigue and physical activity by age group among black women with a history of breast cancer. Although the mean level of fatigue was slightly greater in our sample than for a similar age-matched population of women in the United States without cancer, women under 50 who met physical activity guidelines had lower levels of fatigue than those who did not meet physical activity guidelines. These results offer a platform to further examine the relationship of physical activity for black women younger than 50 years by using prospective and objective measures of fatigue and physical activity. Given our results, black women with a history of breast cancer may benefit from CRF interventions that offer physical activity options that can be integrated into existing tasks and that provide age-appropriate resources to address physical and emotional fatigue.

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Tables

Table 1. Participant (N = 267) Characteristics, Study of Cancer-Related Fatigue and Physical Activity Among Black Female Breast Cancer Survivors in the United States, Overall and by Not Meeting or Meeting Physical Activity Guidelines[a], 2012

Characteristic	Overall Sample (N = 267)	Not Meeting Guidelines (n = 150)	Meeting Guidelines (n = 117)	*P* Value[b]
FACIT fatigue score[c], mean (SD)	32.3 (0.4)	30.7 (0.6)	34.2 (0.5)	<.001
Age, y				
<50	93 (35.0)	47 (31.0)	46 (39.0)	.02
50–59	90 (34.0)	50 (33.0)	40 (34.0)	
≥60	84 (31.0)	53 (35.0)	31 (26.0)	
Body mass index (kg/m^2), mean (SD)	30.4 (0.4)	31.3 (0.5)	29.3 (0.5)	.007
Number of comorbidities, mean (SD)	1.3 (1.1)	1.5 (1.1)	1.1 (1.1)	.009
Working for pay[d]	179 (67)	96 (64.0)	83 (70.9)	.23
Current smoker	11 (4.1)	10 (6.7)	1 (0.9)	.10
Cancer stage at diagnosis				
I	87 (32.6)	49 (32.7)	38 (32.5)	.77
II	131 (49.1)	75 (50.0)	56 (47.9)	
III or IV	49 (18.4)	26 (17.3)	23 (19.7)	
Treatment type				
Chemotherapy	186 (69.7)	105 (70.0)	82 (70.1)	.90
Radiation	181 (67.8)	104 (69.3)	77 (65.8)	.54
Hormone therapy	130 (48.7)	76 (50.7)	54 (46.2)	.47
Years since treatment	7 (1)	6 (1)	7 (1.0)	.04
Recurrence	43 (16.1)	29 (19.3)	14 (12.0)	.11

Abbreviations: FACIT, Functional Assessment of Chronic Illness Therapy; SD, standard deviation.

[a] Physical activities guidelines are from Centers for Disease Control and Prevention, current as of 2008 (24). Values are n (%) unless otherwise indicated. Percentages may not sum to 100 because of rounding.

[b] χ^2 test was used to determine *P* values to test the difference between women who met physical activity guidelines and those who did not.

[c] Lower FACIT scores indicate more fatigue; scores below 30 indicate severe fatigue. The mean FACIT score in a similar age-matched population of US women without cancer is 40 (23).

[d] Employed, or retired and working for pay.

Table 2. Multiple Linear Regression of Fatigue Based on FACIT (Functional Assessment of Chronic Illness Therapy) Fatigue Score[a], Participants (N = 267) in Study of Cancer-Related Fatigue and Physical Activity Among Black Female Breast Cancer Survivors in the United States, YEAR

Variable	β (SE) [95% CI]	*P* Value[b]
Physical activity[c]	3.20 (0.79) [1.62 to 4.77]	<.001
Age, y[d]		
50–59 (n = 90)	3.98 (0.99) [2.02 to 5.95]	<.001
≥60 (n = 84)	3.76 (1.23) [1.33 to 6.19]	.003
BMI (kg/m^2)	−0.074 (0.07) [−0.21 to 0.06]	.29
Number of comorbidities	−0.73 (0.40) [−1.52 to 0.06]	.07
Working for pay[e]	2.05 (0.91) [0.24 to 3.84]	.03
Current smoker	−0.39 (0.73) [−1.82 to 1.05]	.59
Stage[f]		
Stage II	0.37 (0.91) [−1.43 to 2.17]	.68
Stage III and IV	0.44 (1.21) (−1.94 to 2.82]	.71
Treatment		
Chemotherapy	−1.27 (0.94) [−3.12 to 0.57]	.18
Radiation	−1.41 (0.87) [−3.13 to 0.31]	.11
Hormone treatment	0.31 (0.77) [−1.21 to 1.83]	.69
Years since treatment	0.12 (0.08) [−0.03 to 0.27]	.12
Recurrence	−1.26 (1.12) [−3.46 to 0.94[	.26

[a] Lower FACIT scores indicate more fatigue.
[b] χ^2 test was used to determine *P* values to test the null hypothesis that the variable in question is not associated with a higher fatigue score.
[c] Reference is 1.0, not meeting physical activity guidelines of the Centers for Disease Control and Prevention (24).
[d] Reference is <50 y (n = 93).
[e] Employed, or retired and working for pay. Reference is unemployed/retired (1.0).
[f] Reference is stage I.

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ORIGINAL RESEARCH

Time-Varying Effects of Parental Alcoholism on Depression

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PEER REVIEWED

Abstract

Introduction
Children of alcoholic parents are at increased risk for lifetime depression. However, little is known about how this risk may change in magnitude across age, especially in mid-adulthood and beyond.

Methods
We used a nationally representative sample (N = 36,057) of US adults from the National Epidemiologic Survey on Alcohol and Related Conditions, wave III. After adjusting for demographic characteristics, we examined the relationship between parental alcoholism and outcomes of 1) major depressive disorder, Diagnostic and Statistical Manual of Mental Disorders-5th edition (DSM-5) and 2) DSM-5 persistent depressive disorder. To examine continuous moderation of this relationship across participants' age, we used time-varying effect models.

Results
Parental alcoholism was associated in general with a higher risk for both major depressive disorder (odds ratio [OR], 1.98, 95% confidence interval [CI], 1.85–2.11; $P < .001$) and persistent depressive disorder (OR, 2.28, 95% CI, 2.04–2.55; $P < .001$). The association between parental alcoholism and major depressive disorder was stable and positive across age, but the association with persistent depressive disorder significantly declined among older adults; respondents older than 73 years old were not at increased risk for persistent depressive disorder.

Conclusions
Findings from this study show that the risk of parental alcoholism on depression is significant and stable among individuals of a wide age range, with the exception of a decline in persistent depressive risk among older adults. These findings highlight the importance of screening for depression among adults with parental alcoholism.

Introduction

Parental alcoholism has various negative physical, mental, and social consequences. Chief among these is depression; offspring of alcoholics are at heightened risk of depressive mood symptoms (1,2). The evidence for heightened depression among those exposed to parental alcoholism is particularly strong among young, college-aged adults (3,4).

Much of the research on the association between parental alcoholism and depression focuses on the question of resilience among adult children of alcoholics; that is, whether these individuals are ever able to overcome the challenges of parental alcoholism. Although some evidence suggests that older adults (those in their late 20s and early 30s) are more resilient than are young adults (those aged 18 through their early 20s) (5), there is little research on the effects of parental alcoholism among offspring of alcoholics in mid- to late adulthood, making their longer-term resilience unknown. Furthermore, the question of increased resilience at older ages assumes that the magnitude of the effect of parental alcoholism changes with increasing age; however, such age-varying effects have not yet been examined.

This study examined 1) the association between parental alcoholism and lifetime outcomes of both major depressive disorder (MDD) and persistent depressive disorder (PDD) among a full range of adults after controlling for demographic characteristics and 2) the age-varying effects of these associations (ie, how they may change in strength across participants' ages). We used data from wave III of the National Epidemiologic Survey on Alcohol and Related Conditions (NESARC-III), a large nationally representative data set.

Methods

NESARC-III was sponsored, designed, and directed by the National Institute on Alcohol Abuse and Alcoholism (NIAAA) and conducted during 2012–2013. NESARC-III is a nationally representative sample of the civilian noninstitutionalized population of the United States aged 18 years or older; it had a 61.1% response rate and an original sample size of 36,309. The NIAAA collected information via questionnaires on alcohol and drug use and disorders, related risk factors, and associated physical and mental disabilities on the basis of NIAAA's Alcohol Use Disorder and Associated Disabilities Interview Schedule. This study excluded respondents with missing information on parental alcoholism; the final sample size for this study was 36,057. We used existing data from human participants in NESARC, and the study was approved by the University of North Dakota institutional review board. We completed the final analyses in May of 2016.

Measures

Parental alcoholism

Parental alcoholism was based on the self-reported answer to the question "Before you were 18, parent/other adult living in home was a problem drinker/alcoholic?" as a binary response variable (yes or no).

Depression

We analyzed 2 depressive disorders, lifetime MDD and lifetime PDD, as separate outcomes. Each outcome was derived from detailed self-reported responses to questionnaire items on the basis of corresponding criteria from the Diagnostic and Statistical Manual of Mental Disorders, 5th edition (DSM-5)(6). Briefly, lifetime MDD is characterized by one or more discrete episodes of at least 2 weeks during which respondents had either a depressed mood or a loss of interest in nearly all activities at some time during their adult lives (6). Lifetime PDD is a milder but more chronic form of depression and can be diagnosed when the mood disturbance continues for at least 2 years at some time during an adult's life (6). Both MDD and PDD exclude mood or anxiety disorders that are either substance-induced or due to a general medical condition.

Demographic characteristics

Age and sex were self-reported. Race/ethnicity was self-reported as white, black, Hispanic, American Indian, or Asian. Full-time employment was self-reported as working 35 or more hours per week or less than 35 hours per week.

Marital status was self-reported according to 6 response options, which were re-categorized as currently married (ie, married or living with someone as if married), not currently married (ie, widowed, divorced, or separated), and never married.

Education was self-reported with 14 response levels ranging from "no formal schooling" to "completed Master's degree or higher," and we re-categorized these into 3 levels: less than a high school diploma, high school diploma, and some college or more.

Annual household income was self-reported with 21 response categories ranging from less than $5,000 to $200,000 or more. We recoded these into a new numeric variable on the basis of midpoints of each category up to level 20; level 21 (≥$200,000) was recoded as $250,000, which is approximately the median income among households earning $200,000 or more (7).

Statistical analyses

We conducted weighted regressions using the statistical software R (The R Foundation) and its survey package to examine the association between parental alcoholism and outcomes of MDD and PDD, after adjusting for demographic characteristics.

We used time-varying effect models (TVEMs), an extension of regression modeling that allows coefficients to vary continuously over time (8), to assess how the association between parental alcoholism and depression outcomes varied across age of participants. In other words, TVEMs examine moderation across some continuous measure of time (eg, historical time, age, time from event). TVEMs are spline-based regression models, which estimate a lower-order polynomial trend within equal intervals on the basis of user-specified number of knots, k. On the basis of established standards for this methodology (9), 10 knots were specified, and P-spline estimation, which automatically finds the most parsimonious model ($k \leq 10$), was used. We ran separate logistic TVEM models for outcomes of MDD and PDD after controlling for demographic characteristics. Each model included a time-varying intercept (to adjust for the overall prevalence of depression across age) and the time-varying predictor of age (to examine continuous moderation of the effect of parental alcoholism across ages). We performed TVEM analyses in SAS 9.3 (SAS Institute Inc) using a publicly available SAS macro (9), version 3.1.0. TVEM analyses were interpreted with respect to 1) overall significance of the effect at a given value of age (ie, whether the confidence bands overlap the odds ratio (OR) of 1.0), and 2) the change in the effect across different ages (ie, whether the confidence bands exclude each other at different ages). Although these methods of establishing significance are more conservative than conventional significance tests, we did this because P values were available only for time-invariant covariates.

Results

Approximately 23% of respondents (n = 8,407) reported parental alcoholism. Respondents who reported parental alcoholism were significantly more likely than adults who did not report parental alcoholism to meet DSM-5 criteria for both MDD (29.6% vs 17.7%, $P < .001$) and PDD (9.3% vs 4.4%, $P < .001$) (Table). People who reported parental alcoholism were slightly but significantly younger (mean age, 44.8 y vs 45.9 y, $P < .001$); were more likely to be female (59.4% vs 55.4%, $P < .001$); had lower annual household incomes (median $32,500 vs $37,500, $P < .001$); were less likely to be never married (25.8% vs 28.4%, $P < .001$); were more likely to be not currently married (27.6% vs 25.4%, $P < .001$); were more likely to be white (57.8% vs 51.4%) or American Indian (2.1% vs 1.2%); and were less likely to be black (18.2% vs 22.3%) or Asian (1.9% vs 5.9%). The 2 groups did not significantly differ by education level (approximately 15% had <high school diploma, 22% high school diploma, and 62% some college or more), or full-time employment status (approximately 43%).

Additionally, compared with respondents who did not report parental alcoholism, those who reported parental alcoholism were slightly but significantly younger when they first had the first episode of MDD (median age, 27.8 y vs 30.5 y, $P < .001$) and PDD (median age, 27.9 y vs 30.6 y, $P < .001$) and had a significantly higher number of MDD episodes (median no., 4.6 vs 3.5, $P < .001$) and a nonsignificantly higher number of PDD episodes (median no., 2.1 vs 1.9). Respondents who reported parental alcoholism also talked to any health professional or therapist significantly more often to help improve their mood caused by MDD (63% vs 58%, $P < .001$) and nonsignificantly more often to help improve their mood caused by PDD (68% vs 64%) compared with respondents who did not report parental alcoholism. Respondents who reported parental alcoholism were significantly more likely to have symptoms of suicidal ideation (13% vs 8%, $P < .001$) and also meet DSM-5 criteria for other mental comorbidities such as anxiety (21% vs 11%, $P < .001$), personality disorders (27% vs 12%, $P < .001$), eating disorders (3% vs 1.5%, $P < .001$), substance use disorders (57% vs 37%, $P < .001$), and posttraumatic stress (12% vs 5%, $P < .001$).

Weighted regression analyses showed that parental alcoholism was associated with an approximately twofold increase in the odds of both MDD (OR, 1.84; 95% confidence interval [CI], 1.72–1.96; $P < .001$) and PDD (OR, 2.11; 95% CI, 1.88–2.37; $P < .001$), after controlling for demographics.

Parental alcoholism had a positive and stable effect on MDD across individuals throughout most of the age range of respondents aged 18 to 85 years (Figure 1). Participants between these ages were approximately 2 times as likely to have MDD as were participants who reported no parental alcoholism. Because of the small sample size of participants older than 85 years and the resulting widening of the confidence band (ie, the lower limit of the confidence band is less than the OR of 1), the relationship was no longer significant among these individuals, even though the point estimate remained stable.

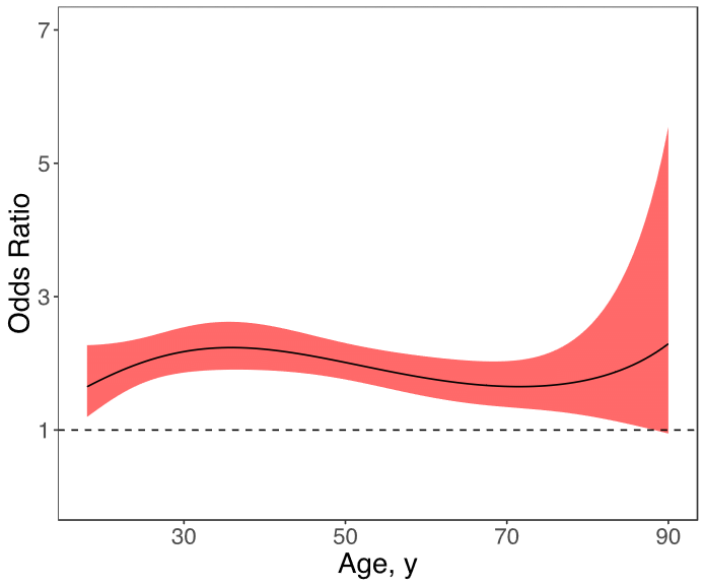

Figure 1. Age-varying effects of parental alcoholism on lifetime major depressive disorder for respondents aged 18–90 years, National Epidemiologic Survey on Alcohol and Related Conditions, Wave III, 2012–2013. Age-varying effects are presented as odds ratios (ORs) across ages; the solid line represents the OR point estimates, and the surrounding shading represents 95% confidence intervals. The horizontal line represents an OR of 1.00.

Similarly, parental alcoholism had a positive effect on PDD across a wide age range (Figure 2). Participants aged 18 to 73 years were approximately 2 times as likely to have PDD as were participants who reported no parental alcoholism. The association was nonsignificant for those aged 74 years and older. Additionally, the effect of parental alcoholism among older individuals (eg, OR of 0.8 for participants aged 80 y) was significantly weaker than the effect among younger individuals (eg, OR of 2.3 for participants aged 60 y).

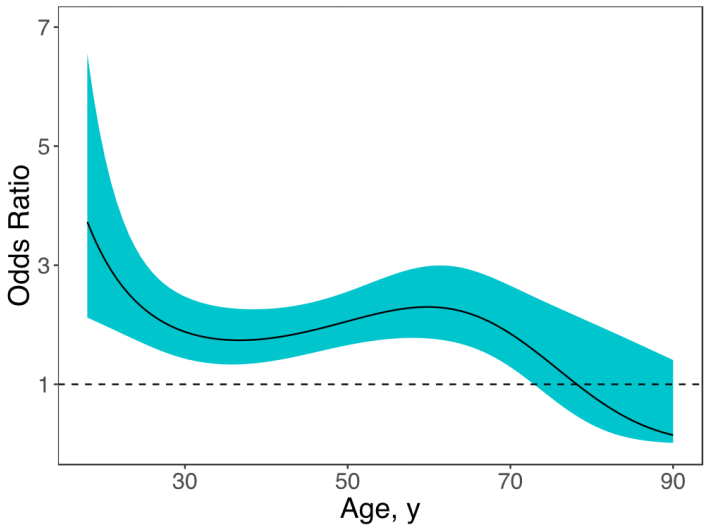

Figure 2. Age-varying effects of parental alcoholism on lifetime persistent depressive disorder for respondents aged 18–90 years, National Epidemiologic Survey on Alcohol and Related Conditions, Wave III, 2012–2013. Age-varying effects are presented as odds ratios (ORs) across ages; the solid line represents the OR point estimates, and the surrounding shading represents 95% confidence intervals. The horizontal line represents an OR of 1.00.

Discussion

This study examined how the relationship between parental alcoholism and depression outcomes may change across individuals of different ages. Respondents who reported being exposed to parental alcoholism as children had approximately twice the risk of meeting criteria for lifetime MDD and PDD. Parental alcoholism had a positive and stable effect on the odds of lifetime MDD throughout most of the age range of the participants, although this association was no longer significant for those aged 85 years old or older. However, although the association with PDD was positive and stable across individuals in early and late adulthood, it significantly decreased in strength for those older than 73, such that parental alcoholism was no longer associated with a heightened risk for PDD.

Results of this study also showed that 23% of adults had a parent with alcohol problems before the age of 18; the 1988 National Health Interview Survey estimated that 18.1% of adults had a parent with alcohol problems before the age of 18 (10). Although there is a large gap in timeline, the prevalence of adults growing up with a parent with alcohol problems seems comparable. Although current data on the prevalence of adults who grew up with a parent with alcohol problems are not available, it is estimated that an annual average of 7.5 million US children (10.5% of all children) live with a parent who had an alcohol use disorder in the past year (11). Although this figure is lower than we report here, it includes only past-year alcohol use disorder, a severe form of problem drinking. Hence, assuming that this prevalence will increase under NESARC's inclusion of other, less severe forms of problem drinking, the current prevalence rates are more consistent with those of previous reports.

Our findings confirm those of previous research that established that parental alcoholism is associated with an increased risk of depression among offspring (2,12,13). This study also extends this research in 2 important ways, given that many previous studies are limited to younger adults (2,3). Here, we examined the effects of parental alcoholism on depression among adults across a wide age range, and we rigorously examined the age-varying effects of parental alcoholism, showing that its effect is largely stable across individuals from early to late adulthood.

This study has limitations. First, the measure of parental alcoholism is limited in several ways. The single question that assessed parental alcoholism was proxy-reported by offspring. As a result, both the timing and the nature of the question may have created recall bias, in which those with depression are more likely to remember the drinking of their parents as problematic than those with no depression. Additionally, the wording of the question included parents as well as non-parental adults living in the household, although most participants reported living only with one or more biological parents. Thus, the wording of this question may have affected the results in unknown ways. Second, this study used cross-sectional data and thus cannot conclude that parental alcoholism causes depression among offspring.

Third, because we used cross-sectional data, the findings do not distinguish between true age and cohort when considering the age-varying effect of parental alcoholism. A true age-varying effect would capture data on the change in the effect of parental alcoholism as an individual ages, but these analyses examined the effect across individuals of different ages. This analysis introduces a cohort effect: the association between parental alcoholism and depression may change across individuals born in different years as a result of differences across time periods in, for example, the prevalence of parental alcoholism, the threshold at which participants consider alcohol consumption "problem drinking," the prevalence of depression, or other associated risk and protective factors. It is likely that both an age effect (5) and a cohort effect (14,15) contribute to our findings, but this study cannot distinguish between them. Thus, the findings should not be interpreted as effects for a given individual across time. Future studies using longitudinal data are needed to separate true age-varying effects from cohort effects.

Strengths of this study include the large, nationally representative sample, the use of rigorous and well-validated DSM-5 measures of MDD and PDD, and the use of TVEMs, an innovative methodology for examining continuous moderation across age.

Parental alcoholism is stably associated with depression outcomes among offspring across a range of ages from early to late adulthood, with a decline in PDD among older adults. This finding implies that the effect of parental alcoholism on PDD may weaken among older adults (aged ≥60 y), making them more resilient than middle-aged and younger adults for PDD. Conversely, we found no evidence of resilience to MDD, as shown by a similar effect across ages. Despite this long-term effect of parental alcoholism, many adults with depression do not seek treatment because of a desire for self-reliance and the perceived stigma of mental health difficulties (16). Children of alcoholics often desire secrecy about their parents' alcoholism (17), and this additional stigma may further compound the lack of treatment seeking among adult offspring of alcoholics. Our findings highlight the importance of screening for depression among offspring of alcoholics in health care settings to provide them with services and support to ultimately manage this mental health burden.

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Table

Table. Descriptive Statistics of Sample (N = 36,057), Study on Effects of Parental Alcoholism on Depression, National Epidemiological Survey on Alcohol and Related Conditions, Wave III, 2012–2013

Measure	Parental Alcoholism[a]	
	Yes	No
Major depressive disorder[b]	29.6	17.7
Persistent depressive disorder[b]	9.3	4.4
Median (IQR), age, y[c]	44.0 (32–56)	44.0 (30–59)
Sex[b]		
Female	59.4	55.4
Male	40.6	44.6
Education		
<High school diploma	15.7	14.8
High school diploma	22.4	22.7
Some college or more	61.9	62.4
Median (IQR) annual household income, $[c]	32,500 (17,500–65,000)	37,500 (17,500–65,000)
Full-time employment (≥35 h/wk)	43.2	44.2
Marital status		
Currently married	46.6	46.2
Not currently married[b]	27.6	25.4
Never married[b]	25.8	28.4
Race/ethnicity		
White[b]	57.8	51.4
Black[b]	18.2	22.3
American Indian[b]	2.1	1.2
Asian[b]	1.9	5.9
Hispanic	19.9	19.2

Abbreviation: IQR, interquartile range.

[a] Numeric variables presented as median (IQR), and categorical variables presented as percentages.

[b] χ^2 significant in parental alcoholism status at $P < .05$. MDD is characterized by discrete episodes of at least 2 weeks during which respondents experienced either depressed mood or a loss of interest in nearly all activities in adults at some time in their lives. Lifetime PDD is a milder but more chronic form of depression and can be diagnosed when the mood disturbance continues for at least 2 years in adults at some time in their lives (6).

[c] Analysis of variance significant in parental alcoholism status at $P < .05$.

UNDERGRADUATE CATEGORY

PREVENTING CHRONIC DISEASE
PUBLIC HEALTH RESEARCH, PRACTICE, AND POLICY
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ORIGINAL RESEARCH

Telemedicine in the Management of Type 1 Diabetes

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Accessible Version: www.cdc.gov/pcd/issues/2018/17_0168.htm

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PEER REVIEWED

Abstract

Background
Veterans with type 1 diabetes who live in rural Alabama and Georgia face barriers to receiving specialty diabetes care because of a lack of endocrinologists in the Central Alabama Veterans Health Care System. Telemedicine is a promising solution to help increase access to needed health care. We evaluated telemedicine's effectiveness in delivering endocrinology care from Atlanta-based endocrinologists.

Methods
We conducted a retrospective chart review of patients who were enrolled in the Atlanta VAMC Endocrinology Telehealth Clinic from June 2014 to October 2016. Outcomes of interest were hemoglobin A1c levels, changes in glycemic control, time savings for patients, cost savings for the US Veterans Health Administration, appointment adherence rates, and patient satisfaction with telehealth.

Results
Thirty-two patients with type 1 diabetes received telehealth care and in general received the recommended processes of diabetes care. Patients trended toward a decrease in mean hemoglobin A1c and glucose variability and a nonsignificant increase in hypoglycemic episodes. Patients saved 78 minutes of travel time (one way), and the VA saved $72.94 in travel reimbursements per patient visit. Patients adhered to 88% of scheduled telehealth appointments on average, and 100% of surveyed patients stated they would recommend telehealth to other veterans.

Conclusions
Specialty diabetes care delivered via telemedicine was safe and was associated with time savings, cost savings, high appointment adherence rates, and high patient satisfaction. Our findings support growing evidence that telemedicine is an effective alternative method of health care delivery.

Introduction

The diabetes epidemic is continuously growing in America and affects 29.1 million Americans (9.3% of the US population) (1). The burgeoning prevalence of diabetes has created an increase in demand for specialty diabetes care. However, there is a nationwide shortage of approximately 1,500 full-time endocrinologists (2), creating a disparity between diabetes care and specialty diabetes providers.

Patients who live in rural areas, approximately 20% of the US population, have more barriers to receiving specialty care. Barriers such as long travel distances and costly expenses to urban areas where specialty care is often available (3,4) create challenges for these patients to achieve good health (4). Telemedicine, the exchange of medical information via electronic communications such as clinical video telehealth (CVT) (real-time videoconferencing between patients and providers), has emerged as a promising solution (5,6). The US Veterans Health Administration (VHA) created the Telehealth Services Program to increase access to specialty medical care for veterans with limited access (7). In 2014, the Atlanta Veterans Affairs Medical Center (VAMC) Endocrinology Telehealth Clinic was established to deliver specialty diabetes care to patients with type 1 diabetes in the Central Alabama Veterans Health Care System (CAVHCS); because the CAVHCS serves rural communities in Alabama and west Georgia, specialty diabetes care is often inaccessible for these patients.

We characterized the effectiveness of the Atlanta VAMC Endocrinology Telehealth Clinic in improving diabetes outcomes for patients with type 1 diabetes and increasing their access to specialty diabetes care. We studied patients with type 1 diabetes because the Atlanta VAMC Endocrinology Telehealth Clinic was

created to increase access to specialty care for type 1 diabetes patients who manage their condition with insulin pump therapy. We hypothesized that management of type 1 diabetes via CVT leads to improvements in glycemic control, saves costs for the VHA, saves time for patients, and is associated with high appointment adherence and patient satisfaction.

Methods

CAVHCS serves more than 134,000 veterans in 43 counties of Alabama and Georgia but does not employ a local endocrinologist. In 2014, the Atlanta VAMC Endocrinology Telehealth Clinic was established to increase access to specialty care for type 1 diabetes for CAVHCS patients. Without telehealth, CAVHCS patients have to travel to the Veterans Affairs (VA) medical centers in either Birmingham, Alabama, or Atlanta, Georgia, to receive in-person specialty care. With telehealth, patients travel to local community-based outpatient clinics for their telehealth appointment, where they check in as they would for a regular face-to-face appointment; they have their vital signs checked, go to a patient care room with a webcam or dedicated telehealth monitor, and have a CVT consultation from an Atlanta-based endocrinologist with in-person assistance from a telehealth pharmacist. Visits typically last 30 to 60 minutes.

We conducted a retrospective chart review of patients with type 1 diabetes who received care through the Atlanta VAMC Endocrinology Telehealth Clinic from June 2014 to October 2016. We collected data about changes in glycemic control, telemedicine's capacity to save costs for the VHA and time for patients, patient adherence to telemedicine appointments, and patient satisfaction with telemedicine. Data were stored in REDCap, a secure web-based database application. Our use of REDCap was sponsored by the Atlanta Clinical and Translational Science Institute. This study was approved by the Emory institutional review board and the Atlanta VA Research and Development Committee.

To assess diabetes management, we collected data on recommended processes of diabetes care: blood pressure management, eye screening, urine microalbumin-to-creatinine ratio, and lipid panels (triglycerides, high-density lipoprotein cholesterol, low-density lipoprotein cholesterol). We also assessed whether patients received drug prescriptions for which they were eligible, specifically statins and aspirin.

To assess diabetes outcomes, we collected data on change in glycemic control, specifically hemoglobin A1c levels, 2-week frequency and severity of hypoglycemia, 2-week frequency and severity of hyperglycemia, and plasma glucose variability. Hemoglobin A1c indicates average plasma glucose concentration over 2 to 3 months and predicts diabetes complications (8,9). Hypoglycemia is defined as low plasma glucose concentration, and severe hypoglycemia may lead to unconsciousness (9). We defined hypoglycemia as a plasma glucose level of less than 70 mg/dL and severe hypoglycemia as less than 40 mg/dL. Hyperglycemia is defined as high plasma glucose concentration, which may lead to long-term complications such as diabetic retinopathy, nephropathy, and neuropathy (10). We defined hyperglycemia as a plasma glucose level of more than 250 mg/dL and severe hyperglycemia as more than 300 mg/dL. We reviewed patients' insulin pump downloads or patients' glucose logs over a 2-week period to determine frequency of hypoglycemia and hyperglycemia. Lastly, average glucose variability was defined as the standard deviation (SD) of all plasma glucose levels in the 2-week period. Data on glycemic control were collected at baseline visits, 6 month follow-up visits (±1 month), and 12 month follow-up visits (±1 month).

Cost savings for the VHA were calculated on the basis of the difference between patient travel reimbursement costs associated with in-person visits at VA medical centers in either Birmingham, Alabama, or Atlanta, Georgia, and costs associated with telemedicine visits at community-based outpatient clinics. Travel reimbursements were calculated using reimbursement rates published by the VHA's Beneficiary Travel Benefits program, which was 41.5 cents per mile with a $6 patient deductible (11). Patients who traveled more than 75 miles one way were eligible for VA-reimbursed overnight lodging, and lodging costs of $75 were added to the travel cost for an in-person visit. Time savings for patients were calculated using Google Maps (Google Inc) and were based on the difference in estimated time to travel to community-based outpatient clinics versus the nearest VA medical center in either Atlanta, Georgia, or Birmingham, Alabama.

To evaluate telemedicine appointment adherence, we recorded the number of CVT appointments missed (patient did not show up), cancelled, and scheduled. Telemedicine appointment adherence was reported as the ratio of the number of CVT appointments in which the patient showed up to the number of CVT appointments scheduled, excluding the number of appointments cancelled by the patient in advance. To assess patient satisfaction with telemedicine, we administered via telephone a satisfaction survey published by the VA Telehealth Services Program. Patients were surveyed about telemedicine's usability and convenience, and their satisfaction was measured using a Likert Scale with scores ranging from 1 through 5 (1 = "strongly agree" and 5 = "strongly disagree").

Data analysis was performed using Microsoft Office Excel 2010 (Microsoft Corporation), SPSS version 23.0 (IBM Corp), and SAS version 9.4 (SAS Institute Inc). To analyze changes in diabetes

outcomes, we conducted paired *t* tests from baseline data, 6-month follow-up data, and 12-month follow-up data. Significance was set at $P < .05$. To analyze patient satisfaction survey results, we calculated the median, mean, and SDs of patient responses to each survey question.

Results

Demographic characteristics

Among 54 patients enrolled in the Atlanta VAMC Endocrinology Telehealth Clinic, 32 patients had type 1 diabetes (Figure). Of the 32 patients with type 1 diabetes, 17 had follow-up visits at 6 months, and 9 had follow-up visits at 12 months. Telehealth patients with type 1 diabetes were predominately male (n = 29, 91%) and white (n = 27, 84%) (Table 1). Mean age was 53.5 years and mean body mass index was 27.6 kg/m^2. Comorbidities and diabetes complications were highly prevalent at baseline in this patient population; most patients had hyperlipidemia (n = 26, 81%) and diabetic neuropathy (n = 23, 72%).

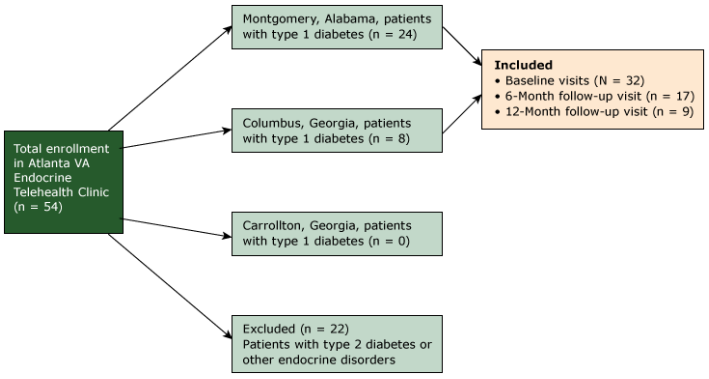

Figure. Diagram showing criteria for inclusion in a study of patients (N = 32) enrolled in the Atlanta VA Telehealth Endocrine Clinic, June 2014 to October 2016. Abbreviation: VAMC, Veterans Affairs Medical Center.

Telehealth patients generally received the standard processes of diabetes care (Table 2) (12). At baseline, 94% patients (30 of 32) had a diabetic retinopathy eye screening within the preceding 2 years, and 100% (9 of 9) received the recommended eye screening at 12-month follow-up. Furthermore, 81% of patients (26 of 32) had their urine microalbumin-to-creatinine ratio measured at baseline, which increased to 89% (8 of 9) at 12-month follow-up. Of patients who were eligible for statin use, 89% (24 of 27) were prescribed a statin, and 64% patients who were eligible for aspirin use (14 of 22) were prescribed aspirin. At 12-month follow-up, 88% of eligible patients (7 of 8) were prescribed a statin, and 50% of eligible patients (1 of 2) were prescribed aspirin. When seen at baseline visits and at 6-month and 12-month follow-up visits, all patients had received the recommended blood pressure measurements and lipid panels.

Diabetes outcomes and glycemic control

Mean hemoglobin A1c levels decreased overall from baseline (8.7%) to 6-month (8.2%) and 12-month (8.1%) follow-up, although the change was not significant. After 6 months and 12 months, patients also had a mean increase in average frequency of hypoglycemia per 2 weeks of blood glucose levels less than 70 mg/dL and less than 40 mg/dL, although these trends were not significant. The mean frequency of hypoglycemia of glucose less than 70 mg/dL was 3.3 hypoglycemic episodes per 2 weeks at baseline, 3.3 at 6-month follow-up, and 6.2 at 12-month follow-up. The average frequency of hypoglycemic episodes per 2 weeks of glucose less than 40 mg/dL was 0.2 at baseline, 0.2 at 6-month follow-up, and 0.6 at 12-month follow-up. Clinically, the difference in severe hypoglycemia (<40 mg/dL) was insignificant, but hypoglycemia of glucose less than 70 mg/dL increased overall.

The average frequency of hyperglycemia every 2 weeks increased from baseline to 6-month follow-up but was stable after 12 months. This trend was observed in hyperglycemic episodes of glucose greater than 250 mg/dL and greater than 300 mg/dL but was not significant. The mean frequency of hyperglycemia greater than 250 mg/dL was 16.3 at baseline, 22.5 at 6-month follow-up, and 16.2 at 12-month follow-up. For hyperglycemic episodes greater than 300 mg/dL, the mean frequency was 4.0 at baseline, 5.4 at 6-month follow-up, and 3.8 at 12-month follow-up.

Lastly, there was a nonsignificant trend toward a decrease in mean 2-week blood glucose levels at 6-month and 12-month follow-up. Mean daily blood glucose level was 79.2 mg/dL (SD, 20.4 mg/dL; n = 27) at baseline, 76.2 mg/dL (SD, 15.7 mg/dL; n = 16) at 6 months, and 76.4 mg/dL (SD, 19.7 mg/dL; n = 9) at 12 months.

Time and cost savings

Patients saved a median of 78 minutes of one-way traveling time, and the VHA saved a median of $72.94 per patient visit in travel reimbursement. If Atlanta VAMC Endocrinology Telehealth patients received follow-up appointments every 3 months as recommended, each patient would save 624 minutes of traveling time per year, which corresponds with VHA savings of $9,336.32 per year in reimbursements to the 32 patients with type 1 diabetes.

Telehealth appointment adherence and patient satisfaction with telemedicine

Telehealth patients had a median of 5 scheduled appointments (range, 1–10 scheduled appointments). Patients were adherent to their telehealth appointments; at least half of the patients attended 100% of their appointments, and mean adherence rate was 87.8% (SD, 17.8%; range, 50.0%–100%).

Twenty-two (69%) telehealth patients with type 1 diabetes completed the survey about their satisfaction with telehealth care. Patients perceived the endocrinology care they received during their telemedicine appointments favorably; 100% of respondents agreed or strongly agreed that they were satisfied with telehealth (Table 3). Furthermore, 90.9% respondents strongly agreed with the statement that they would recommend telehealth to other veterans, and 90.9% respondents agreed or strongly agreed that they would rather use telehealth than travel long distances to see their providers. Two patients who preferred in-person care over telehealth stated that seeing their physician face-to-face was important to them.

Discussion

Our findings suggest that telemedicine is a safe method of delivering type 1 diabetes care to rural patients. Telehealth patients in our study experienced improvements overall in diabetes outcomes, although our findings were not significant. Patients also had an increased mean frequency of hypoglycemia. Our observation of increased hypoglycemic episodes is consistent with literature that suggests improved glycemic control, indicated by lower hemoglobin A1c levels, is correlated with an increased frequency of hypoglycemia (13).

Our findings are in line with those of other studies that suggest that diabetes care via telemedicine is comparable to in-person diabetes care. For example, in a recent randomized controlled trial of 282 diabetes patients, those who received telemedicine consultation had a −1.01% decrease in hemoglobin A1c compared with a −0.68% decrease in hemoglobin A1c in those receiving in-person consultation, although the change was nonsignificant (14). Our findings, which demonstrated a 0.6% decrease in hemoglobin A1c at 12 months of telemedicine follow-up consultation, complement this study's findings and growing evidence that suggests that telemedicine is a viable alternative for in-person care.

Previous studies also demonstrated telemedicine's effectiveness in delivering diabetes care to rural patients. Wood et al described telemedicine's use in pediatric type 1 diabetes care for patients in rural Wyoming, demonstrated equivalency between telemedicine and in-person visits, and found that patients received more follow-up visits after telemedicine's implementation (15). Similarly, Wagnild et al described the use of telecommunications for diabetes patients in Montana and found that patients showed improvements in hemoglobin A1c levels, blood pressure, and diabetes knowledge (16). Our findings are consistent with literature that suggests that telemedicine may effectively deliver diabetes care to rural patients.

Our study has limitations. First, the referring diabetes specialty provider at CAVHCS also independently manages the diabetes treatment of many of the patients enrolled in the telehealth clinic, in some cases just before referral to the telehealth clinic but mostly with select patients between telehealth visits as needed. Thus, telehealth patients' glycemic control before baseline visits and afterward may have been better than that of patients who receive care only from primary care providers (17). However, use of midlevel providers such as pharmacists and nurses is common across the VA health system, is an integral part of the VA-established Patient Aligned Care Team model, and may represent the patient-centered care model in use (18).

Another limitation was significant loss of follow-up. Many patients had follow-up visits that did not meet our study criteria of 6- and 12-month follow-up points. This apparent loss of follow-up may have been because the Atlanta VA Telehealth Endocrinology Clinic is available only once per week. As more patients enrolled in the clinic over time, the intervals between follow-up appointments necessarily increased. Therefore, some patients did not have an appointment scheduled at the 6-month point (5–7 months after baseline) or the 12-month point (11–13 months after baseline). Thus, if a patient had an appointment before 11 months or over 13 months after their initial appointment, they would not have been included for the 12-month follow-up analysis. Our follow-up data may have been further confounded by the possibility that patients with worse glycemic control needed more frequent follow-up and thus were more likely to have 12-month follow-up data.

Additionally, our study used convenience sampling of patients enrolled in the Atlanta VAMC Endocrinology Telehealth Clinic. Our findings may not accurately represent patients with type 1 diabetes in the general population because all our patients were veterans seen at the VA and most had insulin pumps, which are associated with better glycemic control compared with insulin injections (19). Furthermore, our evaluation of aspirin use may have been limited by inconsistent documentation of its use, because many patients purchase it over-the-counter at local drug stores, leading to an underestimation of its use.

Lastly, our limitations include self-selection bias and small sample size. Self-selection bias may have affected our satisfaction survey results because patients who prefer telemedicine may be more

likely to enroll in telehealth clinics, whereas patients who prefer in-person care may be more likely travel to VA medical centers to receive treatment. Furthermore, our small sample size limited our statistical power and generalizability. However, these limitations were inherent in our study design, because we conducted a retrospective review of only patients enrolled in our telehealth clinic.

One of telemedicine's most important benefits is its ability to increase access to health care. Distance is a significant factor for many veterans living in remote and rural areas seeking health care, because travel distance is negatively correlated with use of outpatient services (20). The VA has mitigated this issue by providing travel reimbursement and bus services for patients, but telemedicine further promotes health care accessibility for rural patients. Another important aspect of telemedicine is its acceptance by patients and providers. Our study demonstrates that most patients are satisfied with telemedicine care, believe that telemedicine appointments are convenient, and would recommend telemedicine to other veterans. Our findings are consistent with those of studies that report that both patients and providers are highly satisfied with telemedicine (21–24).

Lastly, our findings suggest that telemedicine leads to substantial cost savings and complement findings from studies that demonstrate telemedicine's cost-saving capacity in larger health care systems. For example, the use of telemedicine in 7 rural hospital emergency departments in Mississippi decreased the hospitals' expenditures from $7.6 million to $1.1 million during a 5-year period with no apparent effect on clinical outcomes (25). If the VHA implements telemedicine on a broader scale, veterans could receive more accessible patient-centered care, and the VHA could benefit from significant cost savings.

Our findings suggest that telemedicine delivers safe diabetes care to rural veterans and supports growing evidence that suggests that telemedicine is an effective alternative method of health care delivery. Additionally, telemedicine is associated with cost savings for the VHA, time savings for patients, high appointment adherence, and high patient satisfaction. Future studies with larger, more representative samples of patients with type 1 diabetes are needed to elucidate telemedicine's effectiveness in providing health care to broader patient populations.

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Tables

Table 1. Demographic Characteristics of Patients, Study of Patients (N = 32) Enrolled in the Atlanta VA Telehealth Endocrine Clinic, June 2014 to October 2016

Characteristic	Telehealth Patients With Type 1 Diabetes at Baseline (N = 32)[a]
Mean (SD) age, y	53.5
Sex	
Male	90.6
Female	9.4
Race	
White	84.4
Black	15.6
Primary care location	
Montgomery, Alabama	75.0
Columbus, Georgia	25.0
Carrollton, Georgia	0
Mean (SD) body mass index, kg/m^2	27.6
Mean (SD) duration of diabetes, y	24.7
Insulin pump use	75.0
Continuous glucose monitor use	18.8
Hypertension	46.9
Hyperlipidemia	81.3
Hypothyroidism	28.1
Tobacco use	21.9
Microvascular diseases	
Neuropathy	71.9
Nephropathy	21.0
Retinopathy	40.6
Macrovascular diseases	
Coronary Artery disease	25.0
Cerebrovascular disease	12.5
Peripheral vascular disease	3.1

[a] Values are percentages unless otherwise indicated.

Table 2. Maintenance of Standard Processes of Diabetes Care, Study of Patients (N = 32) Enrolled in the Atlanta VA Telehealth Endocrine Clinic, June 2014 to October 2016

American Diabetes Association 2016 Guideline	Monitoring	Percentage[a] of Patients With Recommended Care at Baseline	Percentage[a] of Patients With Recommended Care at 6 Months	Percentage[a] of Patients With Recommended Care at 12 Months
Blood pressure	Every routine visit	100 (32 of 32)	100 (17 of 17)	100 (9 of 9)
Diabetic retinopathy eye exam	Every 1 year	93.7 (30 of 32)	94.1 (16 of 17)	100 (9 of 9)
Urine microalbumin-to-creatinine ratio	Every 1 year	81.3 (26 of 32)	88.2 (15 of 17)	88.9 (8 of 9)
Lipid panel (triglyceride, HDL, and LDL levels)	Every 1 year	100 (32 of 32)	100 (17 of 17)	100 (9 of 9)
Statin use	Eligibility: aged >40 y or history of CVD	88.9 (24 of 27)	100 (15 of 15)	87.5 (7 of 8)
Aspirin use	Eligibility: aged >50 or history of CVD	63.6 (14 of 22)	69.2 (9 of 13)	50.0 (1 of 2)

Abbreviations: CVD, cardiovascular disease; HDL, high-density lipoprotein cholesterol; LDL, low-density lipoprotein cholesterol.
[a] Values in parentheses are number of patients who adhered to recommendation out of total number.

Table 3. Patient Responses to Telehealth Satisfaction[a] Survey, Study of Patients With Type 1 Diabetes (N = 32) Enrolled in the Atlanta VA Telehealth Endocrine Clinic, June 2014 to October 2016

Telehealth Patient Satisfaction Survey Question	Median	Mean (SD)
I felt comfortable with the equipment used.	5.00	4.91 (0.29)
I was able to see the clinician clearly.	5.00	4.95 (0.21)
I was able to hear the clinician clearly.	5.00	5.00 (0)
There was enough technical assistance for my meeting with the clinician.	5.00	4.95 (0.21)
My relationship with the clinician was the same during this session as it is in person.	5.00	4.18 (1.01)
The location of the telehealth clinic is convenient for me.	5.00	4.68 (0.65)
My needs were met during the session.	5.00	4.95 (0.21)
I received good care during the session.	5.00	4.95 (0.21)
The telehealth clinic provided the care I expected.	5.00	4.95 (0.21)
Overall, I am satisfied with the telehealth session.	5.00	4.91 (0.29)
I would recommend this type of session to other veterans.	5.00	4.77 (0.75)
I would rather use telehealth to receive this service than travel long distance to see my provider.	5.00	4.59 (1.05)

[a] Patient satisfaction was measured using a Likert Scale (from 1 through 5), where 1 indicated “strongly agree” and 5 indicated “strongly disagree.”

HIGH SCHOOL CATEGORY

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ORIGINAL RESEARCH

Differences by Sex in Association of Mental Health With Video Gaming or Other Nonacademic Computer Use Among US Adolescents

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PEER REVIEWED

Abstract

Introduction

Although numerous studies have examined the association between playing video games and cognitive skills, aggression, and depression, few studies have examined how these associations differ by sex. The objective of our study was to determine differences by sex in association between video gaming or other nonacademic computer use and depressive symptoms, suicidal behavior, and being bullied among adolescents in the United States.

Methods

We used data from the 2015 Youth Risk Behavior Survey on 15,624 US high school students. Rao–Scott χ^2 tests, which were adjusted for the complex sampling design, were conducted to assess differences by sex in the association of mental health with video gaming or other nonacademic computer use.

Results

Approximately one-fifth (19.4%) of adolescents spent 5 or more hours daily on video gaming or other nonacademic computer use, and 17.9% did not spend any time in those activities. A greater percentage of female adolescents than male adolescents reported spending no time (22.1% and 14.0%, respectively) or 5 hours or more (21.3% and 17.5%, respectively) in gaming and other nonacademic computer use ($P < .001$). The association between mental problems and video gaming or other nonacademic computer use differed by sex. Among female adolescents, prevalence of mental problems increased steadily in association with increased time spent, whereas the pattern for male adolescents followed a J-shaped curve, decreasing initially, increasing slowly, and then increasing rapidly beginning at 4 hours or more.

Conclusion

Female adolescents were more likely to have all 3 mental health problems than male adolescents were. Spending no time or 5 hours or more daily on video gaming or other nonacademic computer use was associated with increased mental problems among both sexes. As suggested by the J-shaped relationship, 1 hour or less spent on video gaming or other nonacademic computer use may reduce depressive symptoms, suicidal behavior, and being bullied compared with no use or excessive use.

Introduction

According to the Entertainment Software Association, in 2016, 63% of American households had at least one person who played video games regularly for 3 or more hours per week, and 27% of players were aged 18 years or younger (1). The average number of hours spent playing games continues to increase. According to Nielsen, time spent playing video games increased from 5.1 hours per week per person in 2011 to 6.3 hours in 2013 (2).

Internet use among adolescents has increased exponentially in the last decade (3). According to Common Sense Media, in 2015, American teenagers aged 13 to 18 spent an average of 3.5 hours per day on the Internet playing mobile games, watching online videos, using social network sites, chatting, and browsing websites. Moreover, 67% of teenagers owned a smartphone in 2015 (4). Growing ownership of smartphones has influenced the increase in Internet use over time.

Many studies showed that playing video or computer games and using the Internet for nonacademic purposes are associated with social behavior and have examined related health implications for adolescents; however, study results were contradictory. Some studies found that playing games was helpful in improving personality and networks of academic friendships, improving mood, and decreasing stress (5–11). Meta-analytic reviews found that playing violent video games was linked to aggressive behavior and decreased empathy (12–14). Playing violent video games was significantly associated with numerous symptoms of depression among pre-adolescents (15,16). Internet addiction among adolescents, including addiction to social network sites, was also related to sadness, suicide, distress, functional impairment, and cyberbullying (3,17–19).

Researchers and health professionals are concerned about depression, suicide and suicidal behavior, and bullying among children and adolescents (20–22). Being bullied is related to depression, mental illness, violent and aggressive behavior, and suicidal ideation (23–25). Adolescent depression and other mental disorders are chronic health conditions that can continue into adulthood (26). Depression is associated with suicide, and suicide among people aged 15 to 24 years was the third leading cause of death in United States in 2015 at a rate of 12.5 per 100,000 (27).

Although numerous studies have assessed the association between playing video games or other nonacademic computer use and aggression and depression, few studies have examined differences by sex in the relationship between playing video games or other nonacademic computer use and mental health among children and adolescents. Thus, the purpose of this study was to determine how the association between playing video or computer games or other nonacademic computer use (watching online videos, using social network sites, chatting, and browsing websites) and mental health (depressive symptoms, suicidal behavior, being bullied at school or cyberbullied) differs by sex among US adolescents.

Methods

We used data on 15,624 adolescents from the 2015 Youth Risk Behavior Survey (YRBS), administered by the Centers for Disease Control and Prevention. YRBS, which has been conducted biennially since 1991, uses a 3-stage cluster-sampling design to monitor priority health-risk behaviors among nationally representative samples of private school and public school students in grades 9 through 12 in the United States. In 2015, the sample size was 15,624, the school response rate was 69%, the student response rate was 81%, and the overall response rate was 60%.

Depressive symptoms were defined as the presence of feelings of sadness or hopelessness in response to the question, "During the past 12 months, did you ever feel so sad or hopeless almost every day for two weeks or more in a row that you stopped doing some usual activities?"

Students were questioned on 2 types of bullying: school bullying and cyberbullying. The school bullying question was "During the past 12 months, have you ever been bullied on school property?" with a yes/no answer option. The cyberbullying question was "During the past 12 months, have you ever been electronically bullied? (Include being bullied through e-mail, chat rooms, instant messaging, Web sites, or texting)," also with a yes/no answer option. Being bullied was defined as either being bullied at school or being cyberbullied.

Students were also asked 3 questions related to suicide: had they considered suicide, made a suicide plan, or attempted suicide. The question about considering suicide was "During the past 12 months, did you ever seriously consider attempting suicide?" with a yes/no answer option. The question about making a suicide plan was "During the past 12 months, did you make a plan about how you would attempt suicide?" also with a yes/no answer option. The question about attempting suicide was "During the past 12 months, how many times did you actually attempt suicide?" with response category options of 0 times, 1 time, 2 or 3 times, 4 or 5 times, or 6 or more times. Suicidal behavior was defined as answering yes to the questions about considering suicide or making a suicide plan or if the respondent reported having attempted suicide at least once in the past 12 months.

Engaging in video gaming or other nonacademic computer use was assessed with the question, "On an average school day, how many hours do you play video or computer games or use a computer for something that is not school work? (Count time spent on things such as Xbox, PlayStation, an iPod, an iPad or other tablet, a smartphone, YouTube, Facebook or other social networking tools, and the Internet)." Response options were none, 1 hour or less, 1 hour, 2 hours, 3 hours, 4 hours, and 5 or more hours.

Adjusted and weighted prevalence rates were measured by using a weighting factor in the YRBS to provide nationally representative estimates and by using PROC SURVEYFREQ in SAS version 9.4 (SAS Institute, Inc) to account for the complex 3-stage cluster sampling design. A weighting factor in YRBS data adjusted for school and student nonresponse, sex, grade, and race/ethnicity. Rao–Scott χ^2 tests, which were adjusted for the complex sampling design by using PROC SURVERYFREQ, were conducted to assess any differences by sex in time spent on video gaming or other nonacademic computer use, depressive symptoms, suicidal behavior, and being bullied and any differences by sex in the associ-

ation between time spent on video gaming or other nonacademic computer use with depressive symptoms, suicidal behavior, and being bullied. A 2-sided *P* value of <.05 was considered significant.

Results

Among the sample of 15,624 adolescents, 51.3% were male and 48.7% were female. One in 5 adolescents spent 5 hours or more per day playing video or computer games or used a computer for something unrelated to school work. Almost one-fifth (17.9%) did not engage in playing videos or computer games or other nonacademic computer use. A greater percentage of female adolescents than male adolescents reported no time or 5 hours or more spent in gaming or other nonacademic computer use ($P < .001$) (Table 1).

A significantly higher prevalence of depressive symptoms, suicidal behavior, and being bullied was observed among female adolescents than male adolescents (Table 1). Approximately 1 in 3 adolescents had depressive symptoms; 1 in 5 had considered suicide, made a suicide plan, or attempted suicide; and 1 in 4 had been bullied at school or had been cyberbullied. The prevalence of depressive symptoms, suicidal behavior, and being bullied differed significantly by sex ($P < .001$ for each mental health problem). Female adolescents were nearly twice as likely to have depressive symptoms, suicidal behavior, and to have been bullied than male adolescents.

A pattern of change in the prevalence of depressive symptoms, suicidal behavior, and being bullied in relation to time spent on video gaming or other nonacademic computer use had a J-shaped curve (Figure). Prevalence decreased initially, then increased slowly, and then increased rapidly from 4 hours or more. Those spending 5 or more hours per day on video games or other nonacademic computer use had the highest prevalence of depressive symptoms (43.1%), suicidal behavior (32.4%), and being bullied (31.5%). The lowest prevalence of depressive symptoms (22.8%) and being bullied (21.9%) was among those spending less than 1 hour, and the lowest prevalence of suicidal behavior was among those spending 1 hour (15.7%).

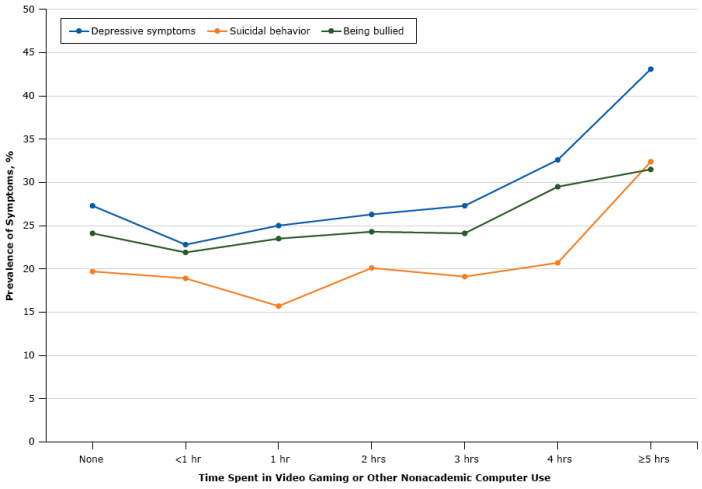

Figure. Prevalence of depressive symptoms, suicidal behavior, and being bullied in relation to time spent on video gaming or other nonacademic computer use among male and female adolescents, Youth Risk Behavior Survey, 2015.

The relationship between mental health and hours spent in video gaming or other nonacademic computer use varied by sex and type of mental health problems (Table 2). The percentage of female adolescents experiencing depressive symptoms with no time spent in video gaming or other nonacademic computer use was 32.7%, rose to 33.3% for less than 1 hour spent, fell to 32.7% for 1 hour spent, and then rose steadily to a peak of 53.8% at 5 or more hours spent ($P < .001$). Prevalence among male adolescents was 19.0% for no time spent in video gaming or other nonacademic computer use, fell to 16.1% for less than 1 hour, than rose to 30.3% for 5 hours or more ($P < .001$). For suicidal behavior among female adolescents, prevalence was 22.5% at no hours spent and rose to 37.8% at 5 or more hours spent. For male adolescents, prevalence was 14.9% for no hours spent and rose to 25.1% for 5 or more hours spent. Female adolescents who spent no time in video gaming or other nonacademic computer use had a prevalence of 27.3% of being bullied and 36.8% at 5 or more hours spent. For male adolescents, the prevalence of being bullied was 19.0% at no time spent, fell to 15.3% for less than 1 hour spent, and then rose to 25.5% for 5 or more hours spent. For all mental health problems and both sexes, prevalence fluctuated up and down between less than 1 hour and 5 or more hours and generally increased beginning at 4 hours.

Discussion

Our study examined differences between male and female adolescents in time spent video gaming or other nonacademic computer use, depressive symptoms, being bullied, and suicidal behavior

and any differences by sex in the association of time spent in video gaming or other nonacademic computer use with depressive symptoms, being bullied, and suicidal behavior. Our study provided evidence of the J-shaped relationship between video gaming or other nonacademic computer use and depressive symptoms, suicidal behavior, and being bullied among US adolescents. Adolescents who spent 5 hours or more in video gaming or other nonacademic computer use had the highest rates of depressive symptoms, suicidal behavior, and being bullied. The lowest rates were among adolescents spending less than 1 hour or 1 hour. Adolescents who did not play video or computer games or use the computer for nonacademic reasons had higher rates than those who spent 1 hour or less per day. However, female adolescents were almost twice as likely to experience depressive symptoms, suicidal behavior, or being bullied in relation to time spent playing video games or in other nonacademic computer use than male adolescents.

One study found similar results about the relationship between video gaming or other nonacademic computer use and suicide by using the 2007 and 2009 YRBS (19). That study found that 5 hours or more of daily video gaming or other nonacademic computer use was associated with higher risk of sadness, suicidal ideation, and suicidal planning than no time spent. The same study also found that 1 hour or less of daily video gaming had potentially protected against 2-week sadness compared with no video gaming. However, that study did not investigate differences by sex in the associations. It also did not investigate the association between being bullied and daily video gaming or other nonacademic computer use. Because Internet technologies have developed rapidly, adolescents are able to easily acquire information, and they have many ways, such as social network sites, to communicate with others online, which may suggest that adolescents are more likely to be at risk of being bullied, especially of being cyberbullied. Our study consistently showed that adolescents who spent 4 hours or more daily on video games or other nonacademic computer use were 1.5 times more likely to be bullied than those who spent 3 hours or less.

Two studies, Belanger et al and Kim, found a U-shaped association between Internet use for nonacademic purposes and mental health among Swiss and Korean adolescents, respectively (28,29). Both studies suggested that health professionals should be alert to heavy Internet use (≥2 h/d) and to no use as indicators of high risk for mental disorders. However, both studies defined heavy use as spending 2 hours or more daily on the Internet. Because Belanger et al used data from 2002 and Kim used data from 2009, their categories for intensity of Internet use are not relevant to recent trends, which were reported in 2015 at 3.5 hours per day on average for US adolescents, including playing mobile games, watching online videos, using social network sites, chatting, and browsing websites (4).

Although YRBS data have the advantage of being a nationally representative sample of adolescents, our study has several limitations. First, because YRBS consists of cross-sectional data, assessing the cause–effect relationship between video gaming or other nonacademic computer use and mental problems was not possible. Second, investigating the association of mental problems with video gaming or other nonacademic computer use separately was not possible. Although video gaming and other nonacademic computer use are different measures, YRBS uses a single variable for the 2 activities. However, studies have demonstrated differences between the 2 measures. For example, in one study, 62% of male adolescents enjoyed playing video games, compared with 20% of female adolescents, and 44% of female adolescents enjoyed using social media, compared with 29% of male adolescents (4). Moreover, on average, female adolescents spent about 40 minutes more on social network sites than male adolescents (4). Further research is warranted for establishing a separate measure each for video gaming and other nonacademic computer use to determine their relation to mental health.

Our study found that video gaming or other nonacademic computer use among US adolescents for 5 hours or more daily was significantly associated with increases in depressive symptoms, suicidal behavior, and being bullied. The prevalence of each of the 3 mental health problems was higher among female adolescents than among male adolescents. As suggested by the J-shaped relationship, 1 hour or less of playing video games or other nonacademic computer use may reduce the prevalence of these mental health problems whereas nonuse or excessive use may increase them. Therefore, sex-specific intervention programs should be developed. Furthermore, because our data show that some video gaming and other nonacademic computer use may reduce the prevalence of depressive symptoms, suicidal behavior, and being bullied, public health professionals may want to shift mindfulness intervention programs toward eHealth or mHealth technologies rather than completely dismissing the activities. Use of technology for health promotion and disease prevention has advanced rapidly through the emergence of eHealth and mHealth technologies. Both technologies offer several advantages over traditional, in-person methods of health promotion and disease prevention interventions. Both are cost efficient and interactive and can automate delivery of interventions, thereby enabling real-time assessments, personalizing and tailoring content, and reaching larger

populations and hard-to-reach subgroups than conventional methods (30). Sex-specific mindfulness intervention programs that use these technologies in conjunction with video games and other nonacademic computer use may be well received by adolescents as well as by their parents and teachers.

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Tables

Table 1. Prevalence of Time Spent in Video Gaming and Other Nonacademic Computer Use[a] and Mental Problems Among Students (N = 15,624), by Sex, 2015 Youth Risk Behavior Survey

Variable[b]	Total, %	Female, %	Male, %	*P* Value[c]
Time spent, h				
None	17.9	22.1	14.0	<.001
<1	13.8	10.9	16.5	
1	10.8	10.4	11.2	
2	15.8	13.8	17.7	
3	13.4	12.8	14.0	
4	8.9	8.7	9.1	
≥5	19.4	21.3	17.5	
Mental problems				
Depressive symptoms	29.9	39.8	20.3	<.001
Suicidal behavior	21.7	27.3	16.1	<.001
Being bullied	25.7	32.2	19.6	<.001

[a] Nonacademic computer use includes playing mobile games, watching online videos, using social network sites, chatting, and browsing websites.
[b] Values are adjusted and percentages are weighted unless otherwise noted.
[c] Calculated by using the Rao–Scott χ^2 test.

Table 2. Prevalence of Mental Problems by Time Spent in Video Gaming and Other Nonacademic Computer Use[a] Among Students (N = 15,624), by Sex, 2015 Youth Risk Behavior Survey

Variable	No. of Hours Spent, %[b]							*P* Value[c]
	None	<1	1	2	3	4	≥5	
Depressive symptoms								
Female	32.7	33.3	32.7	36.1	38.4	45.9	53.8	<.001
Male	19.0	16.1	18.1	18.9	17.3	20.6	30.3	
Suicidal behavior								
Female	22.5	25.9	19.5	26.1	25.4	28.5	37.8	<.001
Male	14.9	14.3	12.5	15.3	13.5	13.7	25.1	
Being bullied								
Female	27.3	32.2	30.4	33.0	29.3	37.4	36.8	<.001
Male	19.0	15.3	17.3	17.7	19.6	22.3	25.5	

[a] Nonacademic computer use includes playing mobile games, watching online videos, using social network sites, chatting, and browsing websites.
[b] Values are adjusted and percentages are weighted unless otherwise noted.
[c] Calculated by using the Rao–Scott χ^2 test.