PREVENTING CHRONIC DISEASE

PUBLIC HEALTH RESEARCH, PRACTICE, AND POLICY

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PREVENTING CHRONIC DISEASE
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ORIGINAL RESEARCH

Tobacco and Alcohol on Television: A Content Analysis of Male Adolescents' Favorite Shows

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PEER REVIEWED

Abstract

Introduction
Media tobacco and alcohol portrayals encourage adolescent substance use. Preventing adolescent initiation with these substances is critical, as they contribute to leading causes of morbidity and mortality in the United States. Television tobacco and alcohol portrayals have not been examined for more than 7 years. This study analyzed tobacco and alcohol portrayals on adolescents' favorite television shows and evaluated the rate of portrayals by parental rating.

Methods
Adolescent males (N = 1,220) from Ohio reported 3 favorite television shows and how frequently they watch them. For each of the 20 most-watched shows in the sample, 9 episodes were randomly selected and coded for visual and verbal tobacco and alcohol incidents. Demographics of characters who used or interacted with the substances were recorded. Negative binomial regression modeled rates of tobacco and alcohol incidents per hour by parental rating.

Results
There were 49 tobacco and 756 alcohol portrayals across 180 episodes. Characters using the products were mostly white, male, and adult. The rate of tobacco incidents per hour was 1.2 for shows rated TV-14 (95% CI, 0.4–3.6) and 1.1 for shows rated TV-MA (95% CI, 0.3–4.5). The estimated rate of alcohol incidents per hour was 20.9 for shows rated TV-14 (95% CI, 6.3–69.2) and 7.2 for shows rated TV-MA (95% CI, 1.5–34.1).

Conclusions
Adolescent males' favorite television shows rated TV-14 expose them to approximately 1 tobacco incident and 21 alcohol incidents per hour on average. Limiting tobacco and alcohol incidents on television could reduce adolescents' risk of substance use.

Introduction

Tobacco and alcohol use contribute substantially to the leading causes of morbidity and mortality in the United States (1,2). Adolescence presents an important window for preventing adult misuse of these products, as most adult tobacco users initiated use during adolescence (3) and alcohol misuse and dependence in adulthood are associated with alcohol use in adolescence (4). Although recent decreases have been observed in the prevalence of current combustible tobacco (5) and alcohol (6) use among adolescents, there is room for improvement. Decreases in combustible tobacco product use were offset by increases in electronic cigarette use (5) and current alcohol use among high school students had a prevalence of 32.8% in 2015 (6).

Exposure to media portrayals of tobacco and alcohol use leads to increased risk of adolescent tobacco and alcohol use (7–9). Whereas a substantial body of research has quantified the amount of tobacco and alcohol in movies, few studies have examined tobacco and alcohol portrayals on television. Although no studies have been conducted on the tobacco or alcohol content of television shows airing in the past 7 years, previous research indicates that tobacco and alcohol portrayals are numerous on broadcast television programs popular among adolescents (10,11). Moreover, parental ratings were not particularly useful in predicting whether a show contained tobacco or alcohol portrayals (10,11).

Adolescents in the United States watch approximately 2 hours of television per day, and the increased use of streaming services facilitates watching shows that no longer air, or never aired, on broadcast television (12). The lack of recent analysis of adolescents' favorite shows, across all television platforms, is an important gap in the literature. The primary objective of this study was to describe the frequency of tobacco and alcohol portrayals on adolescents' favorite television shows. A secondary objective was to examine whether the rates of tobacco and alcohol portrayals differed by parental rating.

Methods

Study population and design

Male adolescents aged 11 to 16 years (N = 1,220), from 1 urban and 9 Appalachian Ohio counties, were recruited into the Buckeye Teen Health Study between January 2015 and June 2016. Most subjects were recruited via address-based sampling (n = 991); the remainder were recruited via convenience sampling (n = 229). The survey-weighted mean age of study participants was 13.9 years (standard error = 0.06) and 68.2% were white non-Hispanic. Because an aim of the larger study (which includes boys only) was to identify predictors of smokeless tobacco use, girls were excluded. Additional details about the study procedures are provided elsewhere (13). This study was approved by The Ohio State University's institutional review board.

Trained interviewers asked youth to list their 3 favorite television shows and recorded programs. For each show, interviewers asked participants to recall how many episodes they watched in a typical week. Participants were asked not to list sporting events or sports programs, the news, movies on television, or special television events (eg, awards shows). A total of 1,068 (87.5%) participants listed at least 1 favorite show. Shows were weighted by the number of episodes participants watched in a typical week, and the 20 most-watched shows were selected for analysis. First, a sample of 3 seasons of each television show was randomly selected; seasons were excluded if any episodes within them first aired after January 1, 2015. This exclusion assured that we did not sample any episodes that aired after we started data collection. Next, 3 episodes were randomly selected from each season for content analysis, resulting in 9 total episodes analyzed from each show. Five shows had aired fewer than 3 seasons before 2015. In these cases, 9 episodes that had aired before 2015 were randomly selected. One television show (*Doctor Who*) had been airing since 1963; in this case, we excluded episodes that first aired before the show's 2005 reboot.

Television show coding procedures

A codebook and coding procedures were designed on the basis of prior television content analysis studies (11,14). The codebook was extensively pilot tested and revised through multiple iterations by the authors. Four undergraduate students were trained on coding procedures, which involved double-coding episodes, comparing results, and settling on final coding decisions in rotating pairs such that each student coded 6 episodes of every show.

The final coding instrument captured visual and verbal portrayals of tobacco and alcohol. All types of tobacco products (ie, cigarettes, electronic cigarettes, smokeless tobacco, cigars or cigarillos, hookah, pipes, or dissolvable tobacco) and alcoholic beverages were counted. Visual mentions were only counted once per character per scene, unless the character got a new product. For example, a group of 4 characters drinking beer in a bar would be coded as 4 instances of visual alcohol use regardless of how many times they drank from their glasses. If 1 character were to order and start drinking a second beer, a fifth instance would be added. Verbal mentions were also recorded as character- and scene-specific counts per episode. Thus, if 2 characters were to have a prolonged conversation about alcohol in one scene, it was coded as 1 verbal instance per character (as opposed to coding every single time alcohol is referenced by either character). If the characters resumed their conversation later in another scene, it was coded as 2 more verbal instances.

For visual portrayals, incidents were further classified as visual use (a character or crowd of characters using the product); visual nonuse (a character or crowd of characters interacting with the product but not using it, such as a bartender serving a drink or a character holding a drink but never drinking it); visual impairment (a character or crowd of characters observed clearly under the influence of the product, but not seen using the product [ie, hungover or drunk characters]); background portrayals (eg, bottles of wine on a kitchen counter); and visual cues to use the products (eg, ashtrays or empty wine glasses). Additionally, for all visual incidents, we recorded the associated character's sex (male, female, inconclusive, and mixed-sex crowd), race/ethnicity (non-Hispanic white, non-Hispanic black, Hispanic, Asian, mix of multiple race/ethnicities in a crowd, and other/unknown), and age (child or adolescent, young adult, adult, elderly, unknown, and crowd of mixed ages). Finally, we recorded whether visual use of the product was peer motivated (yes/no) and whether the character using the product was in an obviously positive/happy mood (yes/no).

Statistical analyses

We calculated descriptive statistics for characteristics of visual tobacco and alcohol incidents. Because we had no hypotheses related to the gender, age, race/ethnicity, peer motivation, or positive mood of tobacco or alcohol users on the television shows, hypothesis testing was not conducted.

We next estimated rates of visual and verbal tobacco and alcohol portrayals per hour (ie, not per episode) by using product-specific negative binomial regression models. The dependent variable was the sum of verbal and visual tobacco and alcohol incidents across all 9 episodes of each show. The offset term in the models was the log of the sum of minutes per show, summed across all 9 episodes. Episode length did not include commercials, and the range of episode lengths in our sample was 10 to 76 minutes. In models estimating the rate of tobacco and alcohol portrayals across all episodes, intercepts were exponentiated and multiplied by 60 to estimate rates per hour. Finally, we again used negative binomial regression to compare rates of visual and verbal tobacco and alcohol incidents by parental rating: TV-MA (mature audience only), TV-14 (parents strongly cautioned), and TV-PG/TV-Y7 (parental guidance suggested and directed to older children, respectively). Because there were zero tobacco or alcohol portrayals in shows rated TV-Y7, these shows were combined with the shows rated TV-PG to achieve stable estimates. The α for significance tests comparing rates of incidents by parental rating was .05. Analyses were completed with Stata version 14.2 (StataCorp).

Results

Adolescents listed 623 unique television shows. The list of sampled television shows, parental ratings of each show, and the number of visual and verbal tobacco and alcohol incidents summed across 9 episodes are shown in Table 1.

Characteristics of visual tobacco and alcohol portrayals

Most tobacco and alcohol portrayals were visual (Table 2). For visual tobacco portrayals, most incidents (89.3%) involved a character using the product. These characters were nearly all male, and most were white non-Hispanic adults. There were no cases of peer-motivated tobacco use, and characters had an obviously positive/happy mood in 14.3% of tobacco incidents.

For visual alcohol portrayals, a majority were instances of a character interacting with a product but not using it (55.7%). Like tobacco portrayals, most characters involved in visual alcohol portrayals were white non-Hispanic, male, and adult. Few cases of alcohol use were peer-motivated (4.2%) or associated with an obviously positive/happy mood (16.1%).

Rates of tobacco and alcohol portrayals per hour

A total of 49 visual and verbal tobacco portrayals appeared in our sample. Across all ratings, there was approximately 1 tobacco incident every 2 hours (Table 3). After conditioning on parental rating, shows rated TV-14 had more tobacco incidents per hour than shows rated TV-PG/TV-Y7 (rate ratio [RR] = 4.2; 95% confidence interval [CI], 1.003–17.7). The rate of tobacco incidents per hour for shows rated TV-MA did not differ from shows rated TV-14 (RR = 0.9; 95% CI, 0.2–5.7) or shows rated TV-PG/TV-Y7 (RR = 3.9; 95% CI, 0.7–21.0).

There were 756 visual and verbal alcohol portrayals in our sample of television shows, resulting in nearly 10 alcohol incidents per hour (Table 3). Rates of alcohol incidents did not differ by parental rating (results not shown), though the RR comparing the rate of alcohol incidents in shows rated TV-14 to shows rated TV-PG/TV-Y7 was marginally significant (RR = 3.8; 95% CI, 0.9–15.7).

Discussion

Television shows watched by adolescent males contained approximately 1 tobacco portrayal every 2 hours and 10 alcohol portrayals every hour. Characters who used or interacted with these products were largely white non-Hispanic, male, and adult. Television shows rated TV-14 had a higher rate of tobacco portrayals per hour than shows rated TV-PG/TV-Y7, but the rate did not differ from shows rated TV-MA. Our results are consistent with prior literature in finding that both substances are prevalent on television shows watched by adolescents, and that there is little evidence of different rates of substance portrayals according to parental rating (10,11).

With adolescents watching approximately 2 hours of television per day (12), the frequency of tobacco and alcohol portrayals is concerning. Cultivation theory (15) suggests that by shaping how they perceive the real world, frequent portrayals of tobacco and alcohol use on television may influence adolescents' health behaviors. Indeed, a substantial body of research has demonstrated that more (versus less) exposure to tobacco or alcohol in movies is associated with increased risk of adolescent use of those products (7–9). Further, social cognitive theory (16) describes the powerful effects that media portrayals of substance use may have on adolescents' health behaviors by teaching them about these behaviors through role models. Again, the literature supports this assertion, at least for tobacco use, by demonstrating that adolescents whose favorite movie stars smoke cigarettes are more likely to be cigarette smokers themselves (17,18).

It is unsurprising that most of the tobacco and alcohol portrayals in our sample of shows were by white non-Hispanic male characters, as our participants were all male and most were white non-Hispanic. One's media selections are related to gender and social identity, and thus our television shows largely had characters who looked like our participants (19). Additionally, the reinforcing spirals approach suggests that people select media content that portrays behaviors in which they are interested or engage, and that these selected media exposures in turn may reinforce these interests or behaviors (20). In our study, this approach would imply that youth who watch shows with high rates of tobacco or alcohol portrayals may be especially interested in these behaviors, and that watching such portrayals reinforces their interest in these substances. Furthermore, adolescent males who identify strongly with characters on television are more likely to learn from the behaviors modeled by those characters (21,22). Thus, the fact that our subjects were largely watching characters who looked like them portraying tobacco and alcohol use suggests that these exposures may be particularly persuasive.

One way to reduce adolescents' exposure to tobacco and alcohol portrayals on television would be to require that shows carry a TV-MA rating if they depict substance use. Currently, substance use is not considered when assigning television ratings in the United States (23). With parents giving increasing attention to the ratings of shows their children are allowed to watch (24), this presents an opportunity to markedly reduce youth exposure to substance use portrayals on television.

In addition to strengthening parental ratings, interventions to address how adolescents react to portrayals of substances on television may prove effective in reducing adolescent substance use. Potential interventions could involve improving adolescents' self-control and media literacy. By reducing positive expectancies of product use, good self-control modifies the effect of movie exposure to tobacco and alcohol on adolescent substance use behaviors (25), and interventions targeting self-control have been successful with other outcomes (26). Similarly, studies testing media literacy interventions have found them to be successful in both increasing adolescents' media literacy and reducing their susceptibility to smoking (27–29).

Our study had several strengths. First, rather than relying on current broadcast ratings to sample television shows, we sampled shows based on what adolescents actually watched, and how often they watched them. This resulted in our coding shows that adolescents continue to watch even after the series ends (eg, *The Office*). Additionally, shows appeared in our sample that air on cable and are not included in broadcast ratings (eg, *SpongeBob SquarePants*). Together, this approach led to a more valid estimation of the rate of tobacco and alcohol portrayals adolescent males are exposed to per hour of television watching than would have been achieved through older methods of television show sampling.

The following limitations should be considered when interpreting our study results. First, the present results pertain to adolescent males in Ohio and may not generalize to other samples. Although the shows reported by the youth in this study are also popular (or were at one time popular) nationwide, it is possible that regional preferences drove the sample of television shows. Indeed, although 11 of the top 20 shows in our sample were the most-watched among both urban and rural participants in our study, redrawing the sample of television shows after stratifying on urban/rural status would have led to different samples of shows. Similarly, a sample of adolescent girls would likely produce a somewhat different sample of shows displaying potentially different rates of tobacco and alcohol use. Second, because several hundred unique shows were listed by study youth, it was not feasible to analyze the content of each show; therefore, we were unable to estimate how exposure to tobacco and alcohol use on television is associated with adolescent use of these products in our study. Third, our coding scheme did not collect specific information about the type of tobacco product used, and thus we cannot describe whether the balance of tobacco products portrayed on television is similar to the balance of products used among adolescents. Finally, we observed substantial heterogeneity in rates of tobacco and alcohol portrayals across shows with the same parental rating in our sample; for example, the range of alcohol portrayals across 9 episodes of shows rated TV-14 was 10 to 107 portrayals. This heterogeneity contributed to large confidence intervals for our estimated rate ratios. It is possible that this is due in part to sampling only 9 episodes from each show. Future studies analyzing more episodes within each TV rating category could result in greater precision of estimated rates.

In conclusion, adolescents are exposed to high rates of tobacco and alcohol portrayals on television. Though rated as acceptable for underage youth (ie, aged 14 years and older), shows rated TV-14 depict at least 1 tobacco incident and nearly 21 alcohol incidents per hour on average. Evidence from the movie literature suggests that greater exposure to substance use in the media places adolescents at increased risk of tobacco and alcohol initiation (7–9). Future research should examine this association as it pertains to television exposures to inform interventions aiming to reduce adolescent tobacco and alcohol initiation. Consideration of substance portrayal on television shows when assigning parental ratings may help reduce adolescent tobacco and alcohol use.

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Tables

Table 1. Portrayal of Tobacco and Alcohol on Male Adolescents' Most-Watched Television Shows[a], 10 Ohio Counties, 2015–2016

Parental Rating	Television Show	Popularity Ranking[b]	Percent of Youth Who Listed Show as a Favorite	Number of Tobacco Incidents[c]	Number of Alcohol Incidents[c]
TV-Y7					
	The Amazing World of Gumball	5	3.9	0	0
	Gravity Falls	15	2.7	0	0
TV-PG					
	SpongeBob SquarePants	1	10.8	1	0
	The Flash	6	5.1	0	63
	Teen Titans Go	8	3.0	0	0
	The Regular Show	9	3.6	0	0
	Adventure Time	10	3.5	0	2
	Modern Family	11	3.5	2	48
	The Office	12	3.1	0	40
	Doctor Who	14	3.4	1	41
	Ridiculousness	17	2.6	2	27
	The Middle	20	2.5	5	41
TV-14					
	Family Guy	3	8.0	9	103
	The Big Bang Theory	4	5.5	0	87
	American Dad	7	3.3	5	107
	Impractical Jokers	16	2.4	5	10
	Arrow	18	3.0	1	68
TV-MA					
	The Walking Dead	2	11.3	0	11
	South Park	13	2.9	5	32
	Breaking Bad	19	3.1	13	76

[a] Up to three favorite television shows were listed by adolescent males enrolled in the Buckeye Teen Health Study between January 2015 and June 2016. Shows were weighted by how many episodes adolescents reported watching in a typical week; the 20 most-watched shows were selected.
[b] Popularity ranking represents the frequency of how often the show was watched by adolescents in the study. For example, *SpongeBob SquarePants* was the most-watched show in our sample.
[c] Number of incidents includes verbal and visual product portrayals, summed across all 9 randomly selected episodes of television shows.

Table 2. Characteristics of 49 Tobacco and 756 Alcohol Portrayals Across 180 Episodes[a], 10 Ohio Counties, 2015–2016

Characteristic	Tobacco Portrayals[b] n (%)[c]	Alcohol Portrayals n (%)[c]
Type of portrayal		
Visual	36 (73.5)	534 (70.6)
Verbal	13 (26.5)	222 (29.4)
Type of visual portrayal[d]		
Individual	28 (77.8)	312 (58.4)
Crowd	0	49 (9.2)
Background	5 (13.9)	134 (25.1)
Visual cue	3 (8.3)	39 (7.3)
Type of visual use/nonuse[e]		
Use of product	25 (89.3)	147 (40.7)
Interaction with product, no use	3 (10.7)	201 (55.7)
Impairment, no use	0	13 (3.6)
Sex of character[e]		
Female	1 (3.6)	84 (23.3)
Male	27 (96.4)	241 (66.8)
Unknown/inconclusive	0	4 (1.1)
Mixed-sex crowd	0	32 (8.9)
Race/ethnicity of character[e]		
White non-Hispanic	18 (64.3)	268 (74.2)
Black non-Hispanic	2 (7.1)	22 (6.1)
Hispanic	5 (17.9)	9 (2.5)
Asian	0	18 (5.0)
Multiple race/ethnicities in crowd	0	26 (7.2)
Other/unknown	3 (10.7)	18 (5.0)
Age of character[e]		
Child/adolescent	1 (3.6)	9 (2.5)
Young adult	2 (7.1)	10 (2.8)
Adult	22 (78.6)	326 (90.3)
Elderly	1 (3.6)	0
Multiple ages in crowd	0	1 (0.3)
Unknown/inconclusive	2 (7.1)	15 (4.2)
Motivation of character[e]		
Peer motivated	0	15 (4.2)
Not peer motivated	28 (100.0)	346 (95.8)

[a] Three episodes from 3 seasons of each show were randomly selected for analysis. All episodes aired before January 1, 2015.

[b] Tobacco portrayals include portrayals of any tobacco product (ie, cigarettes, electronic cigarettes, smokeless tobacco, cigars or cigarillos, hookah, pipes, or dissolvable tobacco).

[c] Percentages may not sum to 100 due to rounding.

[d] This item was only coded for visual portrayals.

[e] These items were only coded for individual or crowd visual portrayal types.

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Table 2. Characteristics of 49 Tobacco and 756 Alcohol Portrayals Across 180 Episodes[a], 10 Ohio Counties, 2015–2016

Characteristic	Tobacco Portrayals[b] n (%)[c]	Alcohol Portrayals n (%)[c]
Mood of character[e]		
Positive/happy mood	4 (14.3)	58 (16.1)
Neutral/negative mood	24 (85.7)	303 (83.9)

[a] Three episodes from 3 seasons of each show were randomly selected for analysis. All episodes aired before January 1, 2015.

[b] Tobacco portrayals include portrayals of any tobacco product (ie, cigarettes, electronic cigarettes, smokeless tobacco, cigars or cigarillos, hookah, pipes, or dissolvable tobacco).

[c] Percentages may not sum to 100 due to rounding.

[d] This item was only coded for visual portrayals.

[e] These items were only coded for individual or crowd visual portrayal types.

Table 3. Rates of Tobacco and Alcohol Portrayals Per Hour of Television[a], 10 Ohio Counties, 2015–2016

Category	Tobacco Portrayals Rate (95% CI)	Alcohol Portrayals Rate (95% CI)
Overall rate per hour	0.6 (0.3–1.3)	9.6 (5.0–18.7)
Rate per hour by parental rating[b]		
TV-PG and TV-Y7	0.3 (0.1–0.7)	5.5 (2.5–12.1)
TV-14	1.2 (0.4–3.6)	20.9 (6.3–69.2)
TV-MA	1.1 (0.3–4.5)	7.2 (1.5–34.1)

Abbreviation: CI, confidence interval.

[a] A negative binomial regression was used to estimate rates of combined visual and verbal tobacco and alcohol portrayals during 60 min of television (excluding commercials).

[b] Rate ratios cited in the text are based on unrounded values and may differ from rate ratios calculated from this table, which were rounded values.

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ORIGINAL RESEARCH

Gestational Diabetes and Health Behaviors Among Women: National Health and Nutrition Examination Survey, 2007–2014

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PEER REVIEWED

Abstract

Introduction
Women with gestational diabetes are at 7 times greater risk of developing type 2 diabetes than are women without gestational diabetes. The objectives of this study were to examine recent changes in the prevalence of gestational diabetes mellitus among women of reproductive age in the United States and assess the prevalence of factors associated with participating in healthy lifestyle behaviors.

Methods
Data were from 4 waves of the National Health and Nutrition Examination Survey (2007–2014). Gestational diabetes was identified by participants' response to whether they were ever told by a health care professional that they had diabetes during pregnancy. The health behaviors were participation in physical activity, healthy dietary patterns (intake of cholesterol, sodium, and fiber within recommended guidelines), and smoking. The analytical sample included 3,034 women aged 20 to 44 years. Multivariate logistic regression was used to assess the association between gestational diabetes and health behaviors.

Results
The overall prevalence of gestational diabetes was 8.9% (95% confidence interval [CI], 7.6%–10.4%) during 2007–2014. The prevalence increased from 8.4% in 2007–2008 to 10.4% in 2013–2014, an increase of 24%, but the change was not significant (P = .28). The proportions of women meeting recommended guidelines for the health behaviors did not change significantly. We found no significant difference in practicing healthy behaviors between women with gestational diabetes and women without gestational diabetes.

Conclusion
The prevalence of gestational diabetes increased slightly in recent years, and women with the condition were generally not meeting guidelines for healthy behaviors. Coordinated interventions are needed to promote healthy lifestyle behaviors among women with gestational diabetes because they are at increased risk for diabetes.

Introduction

Gestational diabetes mellitus (hereinafter, gestational diabetes) is defined as any glucose intolerance diagnosed during pregnancy (1). An estimated 1% to 14% of pregnancies are affected by gestational diabetes in the United States (2,3). Women with gestational diabetes are at 7 times greater risk of developing type 2 diabetes than are women without gestational diabetes (4). Although most women with gestational diabetes return to normal glucose tolerance after delivery, as many as 10% to 50% can develop type 2 diabetes within 5 years (4). Yet, progression to type 2 diabetes can be prevented by adopting and maintaining a healthy weight through adopting healthy lifestyle behaviors (4,5).

Several studies have examined health behaviors among women with gestational diabetes. One analysis of data from the 2006 Behavioral Risk Factor Surveillance System found approximately 3% of women aged 18 to 44 had gestational diabetes, and levels of physical activity, fruit and vegetable consumption, or smoking did not differ significantly between women with gestational diabetes and women without gestational diabetes (5). Another study using data from the 2007–2010 National Health and Nutrition Examination Survey (NHANES) found that 7.7% of women aged 20 to 44 had gestational diabetes and that dietary quality among these women was lower than that among women without a history of gestational diabetes (6).

Information on trends in the prevalence of gestational diabetes is limited, and most of this information is based on hospital delivery data (7,8). Recent changes in health behaviors among women with a history of gestational diabetes in the United States have not been examined. Such information is needed to inform efforts to promote healthy lifestyles in this population. The objectives of our study were to 1) describe the prevalence and recent changes in the prevalence of gestational diabetes in the United States, 2) describe and compare changes in practicing healthy behaviors among women with and without gestational diabetes, and 3) assess the relationship between a diagnosis of gestational diabetes and practicing healthy behaviors.

Methods

We collected data for this analysis from 4 waves of NHANES: 2007–2008, 2009–2010, 2011–2012, and 2013–2014 (9). At the time of our analysis, in 2018, the most recent NHANES data available were from 2013–2014. NHANES consists of self-reported data collected from participants during an in-home interview and clinical examination data gathered in a mobile examination center. The survey provides estimates for health conditions and health behaviors that can be generalized to the entire US population. The question on gestational diabetes was first administered in 2007–2008. We collected measures of health behaviors from the questionnaires on physical activity, dietary recall, and smoking/cigarette use.

Our sample consisted of women aged 20 to 44 years. In the NHANES survey, women were asked, "During your pregnancy, were you ever told by a doctor or other health professional that you had diabetes, sugar diabetes or gestational diabetes?" As in previous research (6), women who responded yes to this question were classified as having gestational diabetes (n = 335); those who answered no or "borderline" were classified as not having gestational diabetes (n = 2,807). We excluded women who self-reported currently having diabetes (n = 108). Thus, the final study sample consisted of 3,034 women (287 with gestational diabetes and 2,747 without gestational diabetes): 802 women in 2007–2008, 833 women in 2009–2010, 625 women in 2011–2012, and 774 women in 2013–2014.

Measures

Physical activity. In the Physical Activity Questionnaire, women were asked, "In a typical week, on how many days do you do vigorous-intensity sports, fitness or recreational activities?," "How much time (minutes) is spent doing vigorous recreational activities?," "In a typical week, on how many days do you do moderate-intensity sports, fitness or recreational activities?," and "How much time (minutes) is spent doing moderate recreational activities?" To calculate the total minutes of physical activity, the number of minutes spent in vigorous-intensity physical activity was doubled (assuming that 1 minute of vigorous activity equals 2 minutes of moderate activity [10]) and added to the minutes of moderate-intensity physical activity (11). This variable was coded as binary: either meeting the guideline for physical activity (if ≥150 minutes per week) or not meeting the guideline (if <150 minutes per week).

Dietary behaviors. In the Dietary Recall Questionnaire, women were asked about their daily food consumption, and the amount of sodium, fiber, and cholesterol intake was estimated. According to the American Heart Association and the American Diabetes Association, a daily cholesterol intake of less than 300 mg, a daily fiber intake of more than 25 g, and a daily sodium intake of less than 1,500 mg meet the daily dietary guidelines (11). Daily intakes that met these guidelines were classified as meeting guidelines, and daily intakes that exceeded the guidelines (cholesterol or sodium) or did not reach the guideline (fiber) were classified as not meeting the guidelines. All 3 dietary behavior variables were coded as binary (yes or no) outcomes.

Smoking behavior. In the Smoking/Cigarette Questionnaire, women were asked, "Do you now smoke cigarettes?" and "Have you smoked at least 100 cigarettes in your entire life?" Women were classified as current smokers if they answered yes to both questions; otherwise, they were classified as noncurrent smokers (ie, former or never smokers).

On the basis of previous literature (5,12), we selected the following covariates: age, race/ethnicity (non-Hispanic white, non-Hispanic black, Mexican American, and other [other Hispanic people and other racial groups]), education (<high school graduate, high school graduate, ≥some college), ratio of family income to federal poverty level (<100%, 100%–199%, and ≥200%), marital status (married or living with partner, other), self-reported health (fair or poor; excellent, very good, or good), body mass index (normal/underweight [<25 kg/m^2], overweight [25 to <30 kg/m^2], and obese [≥30 kg/m^2], and the number of times a delivery resulted in live birth.

Statistical analysis

We calculated the overall prevalence of gestational diabetes during 2007–2014, and we examined differences in demographic characteristics between respondents with gestational diabetes and respondents without. For each survey period, we calculated the prevalence of gestational diabetes and the proportion of women who met the guidelines for healthy behaviors. We then assessed the changes (from 2007 through 2014) in gestational diabetes prevalence and proportions of women that met the guidelines for health behaviors, by regressing the prevalence rates and proportions of women who met the guidelines on time (ie, the survey period, coded as 1 for 2007–2008, 2 for 2009–2010, 3 for 2011–2012, and 4 for 2013–2014). Using the pooled data from 2007–2014, we ran multivariate logistic regression to assess the association between gestational diabetes and practicing the healthy behaviors, with the healthy behaviors being the outcome variables. We also tested the following interactions: gestational diabetes by year, gestational diabetes by race/ethnicity, gestational diabetes by income, and gestational diabetes by education. None of these interactions were significant. Thus, we did not include them in the final model. We used survey commands in SAS version 9.4 (SAS Institute Inc) in all analyses to account for the survey design of NHANES.

Results

Women with a history of gestational diabetes were older (35.2 vs 33.7 y), more likely to be obese (48.4% vs 35.8%), more likely to be married (77.9% vs 70.9%), and more likely to report poor or fair health (23.1% vs 14.8%), and had more live births delivered (2.3 vs 2.1) than women without gestational diabetes (Table 1).

The overall prevalence of gestational diabetes during 2007–2014 was 8.9% (95% confidence interval [CI], 7.6%–10.4%). The prevalence was 8.4% (95% CI, 6.2%–11.4%) in 2007–2008, 6.9% (95% CI, 4.7%–9.9%) in 2009–2010, 10.0% (95% CI, 7.8%–12.8%) in 2011–2012, and 10.4% (95% CI, 7.8%–13.9%) in 2013–2014. From 2007–2008 to 2013–2014, the prevalence of gestational diabetes increased 23.8%, but this increase was not significant (*P* = .28 according to linear regression model results).

Changes in the proportion of women with a history of gestational diabetes who met the guidelines for health behaviors varied by behavior (Figure 1). For physical activity, the proportion decreased from 70.4% in 2007–2008 to 58.6% in 2013–2014, a decrease of 16.7% (70.38% − 58.60%/70.38%); for cholesterol intake, the proportion increased from 69.8% in 2007–2008 to 73.2% in 2013–2014, an increase of 4.8% (73.16% − 69.82%/69.82%). Overall, trends were flat, with no significant increases or decreases. The estimates for sodium intake, fiber intake, and current smokers were not valid because the small sample size resulted in relative standard errors of more than 30%.

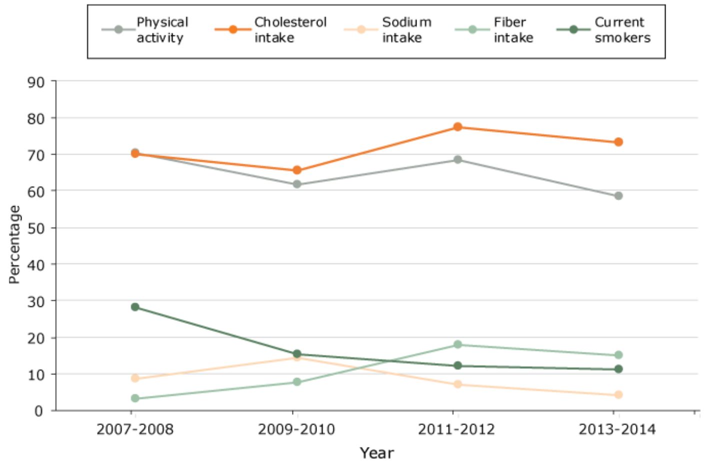

Figure 1. Proportions of women with gestational diabetes (n = 287) who met guidelines for health behaviors, National Health and Nutrition Examination Survey, 2007–2014. The estimates for fiber intake, sodium intake, and current smokers were not valid because the small sample size resulted in relative standard errors of more than 30%.

The pooled data for 2007–2014 showed that, among women with gestational diabetes, 64.2% (95% CI, 54.3%–73.0%) met the physical activity guideline, 71.8% (95% CI, 64.9%–77.8%) met the cholesterol intake guideline, 8.0% (95% CI, 4.9%–12.9%) met the sodium intake guideline, 11.3% (95% CI, 7.4%–17.0%) met the fiber intake guideline, and 16.5% (95% CI, 12.0%–22.2%) were current smokers.

In our examination of changes in the proportion of women without gestational diabetes who met guidelines for health behaviors (Figure 2), we found a significant trend only for fiber intake: the proportion increased from 8.7% in 2007–2008 to 13.7% in 2013–2014 (*P* = .04), according to linear regression results. We found no significant trends for the other health behaviors.

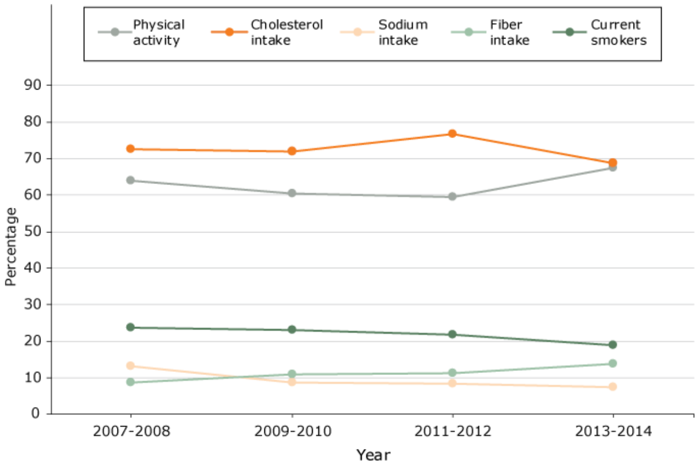

Figure 2. Proportions of women without gestational diabetes (n = 2,747) who met guidelines for health behaviors, National Health and Nutrition Examination Survey, 2007–2014.

In the multivariate logistic regression analysis, we found no significant difference in practicing the health behaviors between women with gestational diabetes and women without gestational diabetes (Table 2 and Table 3). Some covariates in the models, however, were significant. In the physical activity model, women who self-reported fair or poor health (adjusted odds ratio [AOR] = 0.59; 95% CI, 0.38–0.93) and women who were obese (AOR = 0.63; 95% CI, 0.43–0.92) were less likely to meet the physical activity guideline than were women who self-reported good, very good, or excellent health and women who were not overweight or obese (Table 2).

In the smoking status model, women were less likely (AOR = 0.59; 95% CI, 0.44–0.78) to smoke in 2013–2014 than in 2007–2008. Non-Hispanic black women, Mexican American women, and women in the “other” racial group were less likely to smoke than non-Hispanic white women ($P < .001$). Women with at least some college were less likely (AOR = 0.33; 95% CI, 0.25–0.45) to smoke than those who did not graduate from high school. Women whose annual household income was 100% or more of the federal poverty level were less likely to smoke than women with a lower household income (<100% of the federal poverty level) ($P < .006$). Women who were obese (AOR = 0.71; 95% CI, 0.52–0.98) were less likely to smoke than women who were not overweight or obese, and women who reported fair or poor health (AOR = 1.94; 95% CI, 1.42–2.66) were more likely to smoke than women who reported good, very good, or excellent health (Table 2).

In the cholesterol model, non-Hispanic black women (AOR = 0.57; 95% CI, 0.44–0.73), Mexican American women (AOR = 0.57; 95% CI, 0.45–0.73), women in the “other” racial group (AOR = 0.63; 95% CI, 0.48–0.82), and women who were obese (AOR = 0.75; 95% CI, 0.57–0.98) were less likely to meet the cholesterol intake guideline than the reference groups. In the fiber intake model, non-Hispanic black women (AOR = 0.54; 95% CI, 0.34–0.87) were less likely to meet the fiber intake guideline than non-Hispanic white women, but Mexican American women (AOR = 2.06; 95% CI, 1.44–2.94) were more likely. Women were less likely to meet the sodium intake guideline in 2011–2012 (AOR = 0.52; 95% CI, 0.32–0.86) and in 2013–2014 (AOR = 0.49; 95% CI, 0.31–0.75) than in 2007–2008. Women whose annual household income 200% or more of the federal poverty level were less likely to meet the sodium intake guideline, yet women having more birth deliveries (AOR = 1.14; 95% CI, 1.01–1.29) were more likely to meet this guideline (Table 3).

Discussion

Our study showed that the prevalence of gestational diabetes is trending upward, but not significantly. The trends for the proportions of women who met guidelines for health behaviors were flat during the study period for women with gestational diabetes and those without. The study period (2007–2014) may have been too short to detect a trend. We found no significant association between gestational diabetes status and practicing the health behaviors examined. Overall, we showed that a substantial number of women with gestational diabetes did not meet healthy behavior guidelines: 35.8% did not meet the guideline for physical activity; 28.2% did not meet the guideline for cholesterol intake; 92.0% did not meet the guideline for sodium intake, 88.7% did not meet the guideline for fiber intake; and 16.5% were current smokers.

Recent studies emphasize the importance of lifestyle interventions and education for women with gestational diabetes (13–15). To prevent the progression of type 2 diabetes, the American College of Obstetrics and Gynecology (16) and the American Diabetes Association (1) recommend that all women at high risk for diabetes receive healthy lifestyle education on diet, physical activity, and weight management. The Diabetes Prevention Program showed that lifestyle interventions reduced type 2 diabetes incidence by 35% in women with gestational diabetes (17).

Our study showed that during 2007–2014, 8.9% of women of reproductive age reported a history of gestational diabetes, which aligns with previous estimates of gestational diabetes prevalence (18,19). The 2007–2010 Pregnancy Risk Assessment Monitoring System, for example, showed that 9.2% of women delivering live births had a diagnosis of gestational diabetes (20).

Although the 2007–2014 NHANES data did not show a significant increasing trend in gestational diabetes prevalence, previous studies, mostly using inpatient data sets, did show such a trend. For example, one study of National Hospital Discharge Survey data reported that the rate of gestational diabetes increased significantly among females aged 15 to 49, from 0.3% in 1979–1980 to 5.8% in 2008–2010 (7). Another study analyzing data from the Agency for Healthcare Research and Quality's State Inpatient Databases found that the prevalence of gestational diabetes increased from 3.71 per 100 deliveries in 2000 to 5.77 per 100 deliveries in 2010 (8). The lack of a significant trend in gestational diabetes prevalence in our study may be due to the shorter time span — only 4 waves of data were available for our analysis. The trend should continue to be monitored.

Our results showed that women with gestational diabetes were not more likely or less likely to meet the guidelines for health behaviors than women without gestational diabetes. We expected that women with a history of gestational diabetes would have higher levels of healthy behaviors. Our findings are consistent with a 2006 study on health behaviors in women of childbearing age (5), which found no difference in physical activity and other health behaviors between women with and without gestational diabetes. Our study results suggest that more education efforts are needed to promote healthy behavior practices among these women.

Some studies found that women with gestational diabetes, citing concern for the health of the baby, did report making healthy behavior changes during pregnancy. After the birth, however, women reported obstacles, such as fatigue, lack of time, and lack of child support, to practicing healthy behaviors (21,22). Additionally, women with gestational diabetes typically are closely monitored by a team of medical providers during pregnancy. After pregnancy, healthy behaviors may be hard to sustain because of fragmentation of care (23). One study found that routine glucose tolerance testing after a gestational diabetes pregnancy was not practiced by physicians (24). Future research should investigate interventions to remove physician barriers to promoting women's health after pregnancy.

We found some racial differences in practicing health behaviors. Women in racial/ethnic minority groups were less likely to be current smokers and to meet cholesterol intake guidelines than non-Hispanic white women, and Mexican American women were more likely than non-Hispanic white women to meet fiber guidelines. One qualitative study found that Vietnamese women were most likely to follow diet and exercise plans while white women were least likely (25). Thus, understanding how various racial/ethnic groups interpret health messages may be important, and health educators may need to tailor their messages for these groups. Furthermore, we showed that a higher income level did not necessarily increase the odds of practicing healthy behaviors. For example, higher-income women were not more likely than low-income women to meet the sodium intake guideline. This finding is consistent with data from the Interdisciplinary Chronic Disease Collaboration survey, which found no significant difference in following behavioral change advice among various income groups (26). Thus, factors other than income may play a more important role in behavior change among reproductive-aged women. Higher income women were, however, more likely to be nonsmokers.

Our study found some differences over time in dietary behaviors and smoking. Women in 2013–2014 were less likely than women in 2007–2008 to meet the daily sodium intake guideline, which may reflect consumption of high-sodium fast food. A study found that the sodium content in 8 leading US fast-food restaurants increased by 23.4% from 1997–1998 to 2009–2010 (27). Studies also found that women aged 20 to 39 were more likely to consume fast food than women in other age groups (28). On a positive side, our study found that women were less likely to smoke in 2013–2014 than in 2007–2008 and were more likely to meet the fiber intake guideline in 2011–2012 and 2013–2014 than in 2007–2008. The decrease in smoking rate may be related to increases in state cigarette taxes (29). For fiber intake, changes in SNAP (Supplemental Nutrition Assistance Program) and WIC (Special Supplemental Nutrition Program for Women, Infants, and Children) may be a factor. A revision of the SNAP for WIC program in 2009 increased the availability and accessibility of high-fiber produce in WIC-certified vendors (30). These reforms allow mothers to more easily shop for healthy foods.

This study has limitations. First, the data are self-reported, and such data are subject to bias. Respondents may misreport or underreport gestational diabetes and may overreport healthy behaviors, thus affecting the accuracy of the estimates. Second, the short study period — only 4 waves of data — may not be sufficient for trend analysis. Our study provided an initial assessment of the changes from 2007 through 2014. Future research is needed to assess the trend when more data are available. Third, we did not include such factors as employment status in our model, which could have affected the estimates of the association between gestational diabetes status and health behaviors. We did not include the number of children in the home because these data were not available in 2007–2009 NHANES. Contextual variables were not included in the model because these data are not available in NHANES. Future study should investigate environmental barriers to adopting healthy life behaviors.

NHANES data showed that the prevalence of gestational diabetes did not change and the practice of healthy behaviors did not increase significantly from 2007–2008 to 2013–2014. Many women with gestational diabetes did not meet guidelines for healthy behaviors. Given the high risk of type 2 diabetes, practicing healthy behaviors is essential to preventing type 2 diabetes. Barriers to healthy behavior involve intrapersonal and interpersonal factors as well as system-level factors. Thus, coordinated intervention programs are needed to promote and assist women with a history of gestational diabetes in adopting health behaviors.

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Tables

Table 1. Characteristics of a Sample (n = 3,034) of Women Aged 20–44 With and Without Gestational Diabetes, National Health and Nutrition Examination Survey, 2007–2014[a]

Characteristic	Women With Gestational Diabetes (n = 287)	Women Without Gestational Diabetes (n = 2,747)	*P* Value[b]
Age, mean (95% CI), y	35.2 (34.3–36.1)	33.7 (33.3–34.0)	.001
Race/ethnicity			
Non-Hispanic white	53.3 (44.5–62.0)	58.3 (53.2–63.3)	.18
Non-Hispanic black	13.7 (10.0–18.4)	15.2 (12.7–18.1)	
Mexican American	14.7 (9.8–21.4)	12.3 (10.0–15.1)	
Other	18.3 (14.1–23.4)	14.1 (12.0–16.6)	
Married or living with partner	77.9 (72.0–82.9)	70.9 (68.7–73.0)	.02
Education level			
<High school graduate	22.5 (17.2–28.7)	17.7 (15.8–19.7)	.20
High school graduate	17.2 (12.0–24.0)	20.6 (18.7–22.6)	
≥Some college	60.3 (52.2–67.9)	61.8 (58.9–64.5)	
Ratio of family income to federal poverty level			
<100%	21.6 (17.6–26.3)	23.3 (21.0–25.7)	.73
100%–199%	24.9 (19.9–30.8)	23.2 (21.7–24.8)	
≥200%	53.5 (46.7–60.0)	53.6 (50.6–56.5)	
BMI, mean (95% CI)	30.5 (29.5–31.6)	28.8 (28.4–29.1)	.02
BMI category			
Not overweight or obese (<25 kg/m^2)	22.9 (18.6–27.8)	35.3 (32.9–37.8)	<.001
Overweight (25–30 kg/m^2)	28.7 (23.0–35.3)	28.9 (27.1–30.8)	
Obese (30 kg/m^2)	48.4 (41.3–55.5)	35.8 (33.8–37.8)	
Health status fair or poor	23.1 (18.1–29.0)	14.8 (13.2–16.7)	.001
No. of live births delivered, mean (95% CI)	2.3 (2.2–2.5)	2.1 (2.1–2.2)	.006

Abbreviations: BMI, body mass index, CI, confidence interval.

[a] All values are weighted percentage (95% CI) unless otherwise indicated. Means are weighted.

[b] Other Hispanic people and other racial groups.

Table 2. Logistic Regression Results of the Association Between Gestational Diabetes Status and Physical Activity and Cigarette Smoking in a Sample of Women Aged 20–44 (n = 3,034), National Health and Nutrition Examination Survey, 2007–2014

Variables	Physical Activity		Currently Smoking	
	Adjusted OR (95% CI)	*P* Value	Adjusted OR (95% CI)	*P* Value
Gestational diabetes	1.08 (0.67–1.74)	.74	0.79 (0.52–1.19)	.25
Year				
2007–2008	1 [Reference]		1 [Reference]	
2009–2010	0.92 (0.61–1.37)	.66	0.84 (0.61–1.15)	.28
2011–2012	0.82 (0.52–1.28)	.38	0.84 (0.65–1.08)	.18
2013–2014	1.12 (0.69–1.83)	.64	0.59 (0.44–0.78)	<.001
Age	1.00 (0.98–1.03)	.70	0.99 (0.91–1.01)	.56
Race/ethnicity				
Non-Hispanic white	1 [Reference]		1 [Reference]	
Non-Hispanic black	1.34 (0.88–2.02)	.16	0.54 (0.40–0.73)	<.001
Mexican American	1.15 (0.73–1.80)	.54	0.08 (0.05–0.13)	<.001
Other[a]	1.00 (0.67–1.51)	.99	0.35 (0.24–0.50)	<.001
Education level				
<High school graduate	1 [Reference]		1 [Reference]	
High school graduate	0.94 (0.59–1.48)	.78	0.82 (0.60–1.12)	.20
≥Some college	1.10 (0.80 - 1.51)	.54	0.33 (0.25–0.45)	<.01
Ratio of family income to federal poverty level				
<100%	1 [Reference]		1 [Reference]	
100%–199%	0.83 (0.54–1.27)	.39	0.66 (0.50–0.89)	<.001
≥200%	1.04 (0.69–1.56)	.85	0.26 (0.18–0.38)	.006
BMI category				
Not overweight or obese (<25 kg/m^2)	1 [Reference]		1 [Reference]	
Overweight (25–30 kg/m^2)	0.76 (0.52–1.12)	.17	0.90 (0.65–1.24)	.50
Obese (30 kg/m^2)	0.63 (0.43–0.92)	.02	0.71 (0.52–0.98)	.04
Health status				
Good, very good, or excellent	1 [Reference]		1 [Reference]	
Fair or poor	0.59 (0.38–0.93)	.02	1.94 (1.42–2.66)	<.001
No. of live births delivered	1.02 (0.88–1.18)	.84	0.97 (0.88–1.07)	.58

Abbreviations: BMI, body mass index; OR, odds ratio.

[a] Other Hispanic people and other racial groups.

Table 3. Logistic Regression Results of the Association Between Gestational Diabetes Status and Dietary Behaviors in a Sample of Women Aged 20–44 (n = 3,034), National Health and Nutrition Examination Survey, 2007–2014

Variables	Cholesterol Intake		Sodium Intake		Fiber Intake	
	Adjusted OR (95% CI)	*P* Value	Adjusted OR (95% CI)	*P* Value	Adjusted OR (95% CI)	*P* Value
Gestational diabetes	1.05 (0.75–1.50)	.79	0.75 (0.41–1.37)	.34	0.94 (0.58–1.54)	.81
Year						
2007–2008	1 [Reference]		1 [Reference]		1 [Reference]	
2009–2010	0.88 (0.67–1.15)	.33	0.72 (0.50–1.04)	.08	1.38 (0.80–2.38)	.24
2011–2012	1.17 (0.87–1.57)	.28	0.52 (0.32–0.86)	.01	1.72 (0.97–3.06)	.06
2013–2014	0.81 (0.61–1.07)	.13	0.49 (0.31–0.75)	.002	2.03 (1.18–3.49)	.01
Age	0.99 (0.98–1.01)	.46	1.02 (0.99–1.05)	.11	1.01 (0.98–1.03)	.59
Race/ethnicity						
Non-Hispanic white	1 [Reference]		1 [Reference]		1 [Reference]	
Non-Hispanic black	0.57 (0.44–0.73)	<.001	1.15 (0.83–1.58)	.39	0.54 (0.34–0.87)	.01
Mexican American	0.57 (0.45–0.73)	<.001	0.96 (0.54–1.70)	.88	2.06 (1.44–2.94)	<.001
Other[a]	0.63 (0.48–0.82)	.001	0.76 (0.45–1.29)	.31	1.36 (0.87–2.13)	.18
Education level						
<High school graduate	1 [Reference]		1 [Reference]		1 [Reference]	
High school graduate	1.18 (0.86–1.62)	.29	0.99 (0.60–1.64)	.96	0.51 (0.28–0.91)	.02
≥Some college	0.98 (0.75–1.27)	.85	0.77 (0.48–1.24)	.27	1.19 (0.76–1.86)	.45
Ratio of family income to federal poverty level						
<100%	1 [Reference]		1 [Reference]			
100%–199%	1.00 (0.77–1.30)	>.99	1.09 (0.74–1.62)	.65	0.99 (0.63–1.57)	.97
≥200%	1.05 (0.79–1.38)	.74	0.44 (0.29–0.69)	<.001	1.36 (0.86–2.13)	.18
BMI category						
Not overweight or obese (<25 kg/m^2)	1 [Reference]		1 [Reference]		1 [Reference]	
Overweight (25–30 kg/m^2)	0.90 (0.68–1.19)	.44	1.09 (0.68–1.75)	.71	1.08 (0.74–1.58)	.67
Obese (30 kg/m^2)	0.75 (0.57–0.98)	.03	1.36 (0.89–2.07)	.15	0.85 (0.59–1.22)	.37
Health status						
Good, very good, or excellent	1 [Reference]		1 [Reference]		1 [Reference]	
Fair or poor	1.15 (0.91–1.47)	.24	1.19 (0.78–1.81)	.42	0.93 (0.58–1.49)	.77
No. of live births delivered	1.03 (0.94–1.12)	.54	1.14 (1.01–1.29)	.04	1.00 (0.87–1.16)	.98

Abbreviations: BMI, body mass index; OR, odds ratio.

[a] Other Hispanic people and other racial groups.

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ORIGINAL RESEARCH

Forecasting Participants in the All Women Count! Mammography Program

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PEER REVIEWED

Abstract

Introduction

The All Women Count! (AWC!) program is a no-cost breast and cervical cancer screening program for qualifying women in South Dakota. Our study aimed to identify counties with similar socioeconomic characteristics and to estimate the number of women who will use the program for the next 5 years.

Methods

We used AWC! data and sociodemographic predictor variables (eg, poverty level [percentage of the population with an annual income at or below 200% of the Federal Poverty Level], median income) and a mixture of Gaussian regression time series models to perform clustering and forecasting simultaneously. Model selection was performed by using Bayesian information criterion (BIC). Forecasting of the predictor variables was done by using an autoregressive integrated moving average model.

Results

By using BIC, we identified 5 clusters showing the groups of South Dakota counties with similar characteristics in terms of predictor variables and the number of participants. The mixture model identified groups of counties with increasing or decreasing trends in participation and forecast averages per cluster.

Conclusion

The mixture of regression time series model used in this study allowed for the identification of similar counties and provided a forecasting model for future years. Although several predictors contributed to program participation, we believe our forecasting analysis by county may provide useful information to improve the implementation of the AWC! program by informing program managers on the expected number of participants in the next 5 years. This, in turn, will help in data-driven resource allocation.

Introduction

An estimated 1 in 8 women will be diagnosed with breast cancer at some point in their lives (1). In 2014, breast cancer was the second leading cause of cancer death in women in South Dakota, and 608 women were newly diagnosed with the disease (2). More than half of the new breast cancers were diagnosed and reported at a localized (early) stage. Since 1997, South Dakota has administered mammograms and Papanicolaou (Pap) smears to women who qualify under the All Women Count! (AWC!) program (3). From 2012 through 2016, the AWC! program screened more than 3,914 eligible women for breast cancer (4).

AWC! is part of the National Breast and Cervical Cancer Early Detection Program (NBCCEDP), which has been the subject of ample research and reporting (5–8). *The Journal of Cancer Causes and Control* published an entire issue dedicated to the effects of NBCCEDP (7), and several studies have reported on the program, including the proportion of women reached and the program's impact on breast cancer mortality rates among low-income women (annual incomes at or below 200% of the Federal Poverty Level). Other articles did not discuss NBCCEDP but discussed disparities in cancer screening among various groups (9,10) with some specific to breast cancer screenings (11–13). To our knowledge, however, forecasting participation in NBCCEDP has not been done. Forecasting participation in AWC!, an NBCCEDP program, would assist with planning and resource allocation and thereby increase access to timely breast cancer screening among underserved women in South Dakota. The goals of our project were to forecast the number of participants for South Dakota's 66 counties and to identify county clusters within the state that share similar socioeconomic characteristics and that are rural with low populations. We fit a model within each cluster simultaneously by using a finite mixture of Gaussian regression time series models (14).

Methods

Data source

The AWC! data set consisted of patient sociodemographic information, residential information, date of visit to health care provider, and medical screenings from 1997 through 2017. Our analysis focused on breast cancer screening, both mammography and clinical breast examination (CBE). The data set did not include counts from other programs operating in South Dakota that offered free or reduced-cost mammograms, including those of the Indian Health Service. We counted only the first mammography visit per year. If a woman had abnormal results and required an additional mammogram, only the first mammogram was counted. Additional data sources were used to gather further predictors. Locations of participating mammography clinics in the state over a 10 year period (2005–2015) were also provided to us by the South Dakota Department of Health. We used the US Census Bureau's Small Area Income and Poverty Estimates (SAIPE) database to obtain the median income of residents and the percentage of the population with annual incomes at or below 200% of the Federal Poverty Level (hereinafter poverty percentage) for each county (15) and the census bureau's Population and Housing Unit Estimates database (16) for estimates by sex, race, and age group. We extracted the population of women aged 40 to 64 from the latter database at the county level by year and used this for our analysis.

The initial AWC! program screening data set contained 63,990 rows with 26,988 unique participants. At the time of our analysis, 2017 data were not complete and were removed, reducing our row count by 2,139 rows. Our analysis was concerned only with breast cancer screening (mammography and CBE). All participants who received either a CBE or a mammogram were kept. Next, we removed all participants from outside South Dakota, because our analysis included only South Dakota residents. Although women aged 30 to 39 are eligible under NBCCEDP to receive a CBE but not a mammogram, women in this age group were outside the scope of our study and were therefore excluded, reducing the data by 15,783 rows. Ninety-one percent of these of these removed rows contained data on women aged 30 to 39 who received only CBE. Our analysis was concerned only with the number of AWC! participants, defined as women aged 40 to 64 who received a CBE or mammogram at least once during a given year, regardless of their number of clinic visits in a given year. We then obtained counts of the number of participants per year by county. This yielded a total of 37,922 CBE or mammogram visits from 1997 through 2016. The SAIPE and Population and Housing Estimates data sets containing the 3 predictors (ie, population, poverty percentage, and median income) were joined to these counts on the basis of year and county.

Statistical analysis

Some South Dakota counties are very rural and thus had a small number of participants. By grouping these counties together into clusters, we increased the amount of data used to build our forecasting model, thereby increasing the model's robustness. The advantages of this were twofold. First, we could identify similar counties for future program modifications. Second, we took into account that the number of participants over the years for a given county were autocorrelated and not independent. These 2 procedures can be done simultaneously by using a finite mixture model of Gaussian regression time series. The model is given by

$$f(\mathbf{y}_i; \mathbf{X}_i, \boldsymbol{\Psi}) = \Sigma_k \tau_k \phi_T(\mathbf{y}_i; \mathbf{X}_i \boldsymbol{\beta}_k, \boldsymbol{\Sigma}_k),$$

where τ_k's for $k=1,\dots,K$ are mixing proportions and have the restrictions $0 < \tau_k \leq 1$ and must sum to 1. ϕ_T is a T-variate Gaussian distribution, and $\boldsymbol{X}_i \boldsymbol{\beta}_k$, and $\boldsymbol{\Sigma}_k$ are the mean vector and covariance matrix of the Gaussian distribution. Therefore, we model $\boldsymbol{y}_i$-$\boldsymbol{X}_i \boldsymbol{\beta}_k$ as a zero-mean autoregressive–moving average (ARMA) (p, q) time series, where $\boldsymbol{y}_i$ is a T-variate response vector and $\boldsymbol{X}_i$ is a $T \times m$ matrix of predictor variables, where m is the number of predictor variables in the regression model. The model parameters were estimated by using the Expectation Maximization algorithm (17). The result from the Expectation (E)-step, deals with identifying groups of similar counties that exist in the data and the Maximization (M)-step, provides the parameter estimates within each group identified from the E-step. These 2 steps are iterated until a convergence criterion is met indicating that the best solution was achieved. More details on this model are available (14). This mixture model is used to find similar counties and to build a single regression ARMA model within each cluster. In our work, the optimal number of clusters was determined by using the Bayesian information criterion (BIC) (18).

Once models were trained on the currently available data, forecasting was carried out. All the variables used as predictors in the models needed to be available for the forecast period. To accomplish this, we used a simple ARIMA (autoregressive integrated moving average) (p, d, q) model, which is an ARMA model, with I for Integrated, meaning y_t differenced to create a stationary time series. The model is given by $\Phi(B)(1- B)^{d} y_t = (1 + \theta(B))\varepsilon_t$ where $\Phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p$, $\theta(B) = \theta_1 B + \dots + \theta_q B^q$, and B is a backshift operator such that $B^j(y_t) = y_{t-j}$. ε_t is assumed to be white noise. The optimal orders for this model, p, q, and d, were found by using the Akaike information criterion (19). This model was fitted by using the R package forecast (20). After obtaining the best model for each county and forecast predictors, we forecast the next 5-year counts. Model assessment was done through the validation set approach. The data set was split into training and validation by using year. The first 17 years of data were used for the training set, and the remaining 3 years were used for the validation set. The validation mean squared error (MSE) was calculated to assess the accuracy of our forecasting algorithm. The MSE was calculated as follows: $MSE = 1/n\ \Sigma_i(Y_i - \hat{Y}_i)^2$. We define n as the total number of forecasts, Y_i as the observed count, and $\hat{Y}_i$ as the forecast for $i=1,\ldots,n$. All analysis was completed using R version 3.4.2 (R Corporation).

Results

The number of AWC! participants increased steadily from 1997 through 2011 and then sharply decreased in 2012. Since then, participation steadily decreased. Some counties had similar sociodemographic characteristics (average number of participants , median income, poverty percentage, and population) for the 1997–2016 time period (Figure 1). Minnehaha and Pennington were the most populated counties and had the largest number of AWC! participants (Table 1). Corson, Dewey, Buffalo, and Ziebach all had populations with a low median income and a high poverty percentage. Finally, Brown, Codington, and Lincoln had low poverty percentages and high populations. The mixture model described above was used and the optimal number of clusters was determined to be 5.

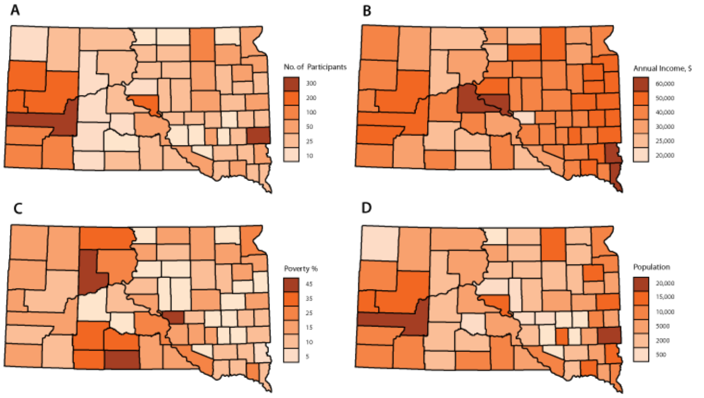

Figure 1. Average number of participants in the All Women Count! program (AWC!) by median income, poverty percentage (percentage of population with annual incomes at or below 200% of the Federal Poverty Level), and population for each South Dakota county,1997–2016.

We summarized the characteristics that pertain to the identified clusters and predictors and the number of participants for 2016 for the 5 clusters (Table 2). Cluster 1 contains the 3 counties with the largest populations, Minnehaha, Pennington, and Hughes counties. This cluster had the smallest average poverty percentage and the highest median income. Cluster 2 had the highest poverty percentage, an average of almost 25%. It also had the lowest median income of the clusters. The overall average number of participants for this cluster was the second-largest even though its average population size was the third largest. Cluster 3 was very similar to Cluster 1 in regard to poverty percentage and median income but had a much smaller population than Cluster 1. Cluster 4's predictors were in the middle of the other clusters. It had the third-largest poverty percentage and median income of the clusters and the second-smallest population. It contains the second-largest number of counties with 19 in the cluster. Cluster 5 has the smallest average population at only 500. It also had the second-highest number of people living in poverty as indicated by the higher poverty percentage and lower median income than the other clusters. In addition, it had the smallest number of participants, an average of 7 participants in the last 20 years, and the largest number of counties (N = 30), fewer than half of the 66 counties in South Dakota.

Analysis of forecasts over the next 5 years shows all 5 clusters with an increase in participants (Table 3). Cluster 2 is the only cluster with an expected decrease for a year, occurring in 2018. Cluster 1 is forecasted to have more than 1,000 participants in 2021. Individual county forecasts identified only 6 counties with an expected decrease in the number of participants, one county staying flat, and the rest of the counties with an increased number of participants. Sixteen counties had an observed decrease in participants over the last 5 years, but our model predicted them to have increased participation in the future.

Only two-thirds of clinics in these counties participated for all 10 years. Geographic patterns in county clusters varied (Figure 2). Most of South Dakota's population is concentrated in the eastern and western parts of the state with the central part sparsely populated. Cluster 1 contained the 2 largest counties on the east and west sides of the state. The counties in cluster 4 appear in groups of 2 to 3, mostly on the eastern side of the state. Most of the low population counties of the central and northwestern parts of the state belong to cluster 5 with the widest scatter. Also, most of the counties in cluster 5 do not have a participating clinic in their county.

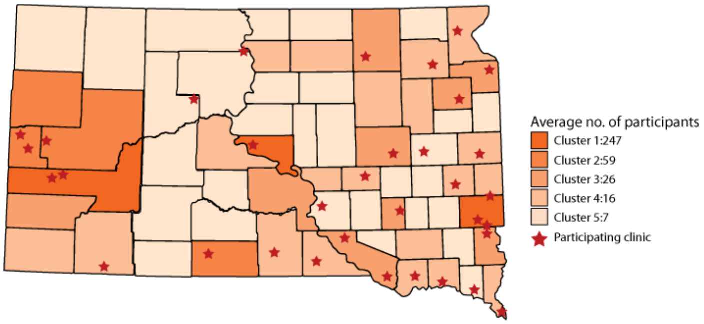

Figure 2. County clusters (groups of counties with similar sociodemographic characteristics [population, percentage of population with annual incomes at or below 200% of the Federal Poverty Level, median income] and AWC! participation) and the 20-year (1997–2016) average annual number of participants in the All Women Count! (AWC!) program in those counties. Red stars indicate that a clinic in that county participated in the AWC! program.

Our forecast of the average trend in AWC! participation for the identified clusters for the next 5 years, 2017 through 2022, (Table 3) showed that, if all the circumstances stay the same (eg, insurance coverage, policy, advertisement of the AWC! program) participation on average will increase at the cluster level. At the individual county level, forecasts showed that participation in some will increase and will decrease in others. The MSE of training data for years 1997 through 2013 for the state was 21.54, and for the validation data for years 2014 through 2016 was 43.80. The increased test MSE was expected because our training data contained only the first year of decrease from 2012 through 2013. However, when building the final forecasting model, all 20-year data were used; therefore, we expect the error rate on the forecasts to be less than the test MSE reported above.

Discussion

Our data contained only AWC! screening results. However, 2016 Behavioral Risk Factor Surveillance System (BRFSS) data (21) and Small Area Health Insurance Estimates (SAHIE) (22) data can be used to provide a general context to the AWC! program participation rate. BRFSS results showed that 68% of women in South Dakota aged 40 or older received a mammogram in 2015 and 2016. This is approximately 139,806 women. Of these, we estimated that about 1,926 women aged 40 to 64, about 2.17%, used the AWC! program during those 2 years. Based on the estimates provided in SAHIE data, this is approximately 33% of eligible women in South Dakota.

An exploratory analysis showed an initial increase followed by a decrease in the number of AWC! participants. This may be related to the termination of the WISEWOMEN program, a heart disease screening program that worked in conjunction with AWC! to perform mammography screenings, and the implementation of the Affordable Care Act (ACA). ACA led to an increase in the diagnosis of early-stage cancers, specifically colon and breast cancers, because of an increase in affordability and accessibility of cancer screening (23). Analysis of the effects of these programs or other possible factors on participation needs to be addressed in future work. For example, cluster 5 had a large poverty percentage but low AWC! participation, which may need additional analysis to determine why eligible women were not using the program. Cluster 1 had increased participation for 2016, and further analysis is needed to determine why. Likewise, counties with a large proportion of eligible women screened should be studied to determine factors that possibly contributed to this success. Finally, the model identifies the counties with increasing and decreasing expected participation.

Most forecasting articles we found were on drug use and prescription drug spending. Most of these carried out linear regression analyses. One performed linear regression analysis to aggregate sales data and forecast expected drug expenditures for a hospital (24). Four years of data were used to make predictions for the next 2 years. Similarly, we found another article forecasting resources for US Army health care (25). That study used ordinary least squares estimation, ridge regression, and robust regression and concluded that, although all the models produced nearly the same estimates, ordinary least squares was desirable because it had the simplest interpretations. We considered linear regression for our data. It was, however, too difficult to analyze 66 individual forecasting models for South Dakota counties. Moreover, a forecast for South Dakota as a whole did not provide enough granularity.

In contrast, a mixture of Gaussian regression time series models allowed us to identify, group, and fit models for groups of similar counties. Clustering, as opposed to evaluating single counties, enabled us to use more data when creating forecasts. In our study, we created 5 models from the available data set, as opposed to 66 models by county. If necessary, we can still obtain individual forecasts for each county for more granular analysis.

Several individual county forecasts displayed counter-intuitive trends. Some of these trends may be attributed to an expected increase in forecasted predictors, such as population or median income. This result may also be caused by other predictors, such as advertisement budget, participation through the WISEWOMAN program, or the start of ACA. Future work investigating travel time to the mammography clinic and how that affects participation could also be conducted. Forecasting efforts would also benefit from more comprehensive data sets that include data related to other state programs (eg, Indian Health Services) to show the total number of women participating in screening programs. Forecasting projects for similar cancer screening programs in other states will help both to validate our methodology and to improve models for screening programs in general.

The identification of county clusters may assist the South Dakota Department of Health to allocate and manage resources more effectively. The results of our study indicate which counties may see an increase in number of AWC! participants. Hence resource allocation decisions could be tailored on the basis of need, which would lead ultimately to an increase in breast cancer screening rates and early detection of breast cancer. In addition, our results may help the South Dakota Department of Health determine which counties would benefit more from a mobile mammography unit, which would reduce barriers to mammography screening, reach underserved populations, and thus address breast cancer disparities in rural areas. This aligns with the goals and objectives of AWC! and the South Dakota Comprehensive Cancer Control State Plan (26).

Our study identified clusters and forecasted the trend in AWC! participation for the next 5 years. According to our model, the number of participants will increase in some counties and decrease in others. Forecasting is a complex analysis; though our analysis was limited by the number of predictors, this is the first forecasting study among cancer screening programs. Our work provides information for AWC! managers engaged in budgeting and planning strategies to increase screening rates among underserved women in South Dakota.

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Tables

Table 1. All Women Count! Participants in South Dakota Counties by Demographic Characteristics and Population, 1997–2016

County	Average No. Participants	Average of US Census Median County Income	Average Poverty Percentage[a]	Average Population
Aurora	8.11	38,045.11	12.03	423.58
Beadle	31.79	38,372.68	12.76	2,729.05
Bennett	5.89	29,334.05	33.16	465.11
Bon Homme	15.89	37,045.16	14.22	970.74
Brookings	23.37	43,479.53	12.96	3,573.16
Brown	56.16	43,380.11	10.26	5,724.32
Brule	12.68	38,580.37	13.35	821.63
Buffalo	15.42	18,621.58	37.84	247.95
Butte	55.26	35,539.00	14.57	1,611.05
Campbell	5.16	35,874.68	11.68	264.68
Charles Mix	24.47	32,096.42	23.52	1,335.95
Clark	8	38,030.89	13.36	595.90
Clay	11.32	35,241.79	19.90	1,491.63
Codington	34.53	42,772.37	10.36	4,120.21
Corson	5.47	25,238.32	36.26	549.90
Custer	29.79	42,883.42	11.02	1,620.42
Davison	33.58	40,754.84	11.95	2,900.42
Day	21.42	35,252.32	14.96	966.32
Deuel	6.47	41,027.05	9.80	700.37
Dewey	6.26	29,018.05	28.47	759.68
Douglas	9.16	37,780.53	12.25	501.05
Edmunds	9.95	42,557.42	11.26	669.63
Fall River	27.16	34,455.47	15.26	1315.79
Faulk	7.79	37,505.05	12.56	384.00
Grant	23.21	41,414.11	9.97	1,254.32
Gregory	14.79	29,423.26	18.78	723.00
Haakon	4.05	37,711.05	12.06	337.37
Hamlin	8.74	42,841.47	10.66	786.42
Hand	9.16	39,506.63	10.56	575.58
Hanson	5.79	46,690.63	9.41	518.53
Harding	2.47	35,922.89	13.27	227.32
Hughes	104.89	50,532.42	9.91	2,927.84
Hutchinson	13.42	38,143.26	12.16	1,120.53
Hyde	5.63	38,027.74	12.33	232.26
Jackson	5.32	27,982.11	30.75	420.26

[a] Defined as percentage of population with incomes at or below 200% of the Federal Poverty Level.

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(continued)

Table 1. All Women Count! Participants in South Dakota Counties by Demographic Characteristics and Population, 1997–2016

County	Average No. Participants	Average of US Census Median County Income	Average Poverty Percentage[a]	Average Population
Jerauld	6.63	37,255.47	13.63	348.79
Jones	4.11	35,868.05	13.72	180.11
Kingsbury	10.16	40,054.53	9.77	855.21
Lake	14.74	42,858.11	10.47	1,767.90
Lawrence	61.16	38,855.68	13.05	3,807.58
Lincoln	22.95	64,288.58	4.51	5,370.79
Lyman	18.42	33,327.53	21.60	552.26
Marshall	6.37	38,048.26	12.52	720.63
McCook	10.84	43,111.26	9.76	859.16
McPherson	7.05	30,467.37	15.35	401.00
Meade	63.58	44,720.05	10.35	3,878.26
Mellette	3.95	27,075.84	32.48	279.42
Miner	4.84	36,984.84	12.06	378.68
Minnehaha	353.21	48,054.37	9.74	24,749.32
Moody	10.68	43,968.21	10.04	1,062.84
Pennington	337.79	42,919.42	13.43	15,432.26
Perkins	13.53	32,988.74	15.15	528.74
Potter	7.95	39,537.84	11.15	412.16
Roberts	16.32	34,492.37	19.67	1,526.11
Sanborn	9.89	38,997.47	13.05	413.05
Oglala Lakota	19.37	24,610.68	43.54	1,472.63
Spink	12.63	38,332.11	12.66	1,101.32
Stanley	11.05	48,299.53	9.15	523.95
Sully	3.47	44,233.63	8.66	239.84
Todd	11.95	23,713.84	41.91	1,102.79
Tripp	15.21	34,837.95	18.42	958.58
Turner	9.58	43,770.89	9.31	1,377.63
Union	16.47	56,129.68	6.64	2,260.11
Walworth	11.11	34,310.42	16.17	933.79
Yankton	28.68	41,454.42	11.94	3,433.47
Ziebach	2.32	23,472.53	46.33	357.42

[a] Defined as percentage of population with incomes at or below 200% of the Federal Poverty Level.

Table 2. Average of Predictors, All Women Count! Program Participants and Number of Counties for Each Cluster[a], 2017–2021

Cluster[a] No.	Average Population	Average Poverty Percentage[b]	Average of US Census Median County Income	No. of 2016 Participants	No. of Counties
5	550.71	16.65%	36,917.73	6.14	30
4	1,272.55	14.76%	38,828.68	13.49	19
2	2,395.26	24.93%	33,814.49	50.42	5
3	2,876.77	12.90%	42,656.58	30.56	9
1	14,493.21	11.09%	47,420.31	370.76	3

[a] A cluster is a group of counties with similar sociodemographic characteristics (population, percentage of population with incomes at 200% or below the Federal Poverty Level, median income).

[b] Defined as the percentage of the population with an annual income at or below 200% of the Federal Poverty Level.

Table 3. Forecasted Average of the Number of Particicapnts in the All Women Count! Program for Each County Cluster[a], 2017–2021

Cluster[a], No.	2017	2018	2019	2020	2021
1	374.18	529.31	707.60	898.70	1,098.41
2	41.80	40.67	42.57	43.34	44.66
3	34.46	40.38	46.54	52.96	59.65
4	13.48	15.83	18.36	20.97	23.69
5	5.67	6.69	7.93	9.18	10.51

[a] A cluster is a group of counties with similar sociodemographic characteristics (population, percentage of population with annual income at or below 200% of the Federal Poverty Level, median income). These calculations are obtained under the assumption that all circumstances stay the same (eg, health care coverage, insurance coverage) over the next 5 years.

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ORIGINAL RESEARCH

Educational Attainment, Health Status, and Program Outcomes in Latino Adults With Arthritis Participating in a Walking Program

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PEER REVIEWED

Abstract

Introduction

Latinos are disproportionately likely to lack a high school diploma, compared with non-Hispanic whites, a trend associated with worse outcomes in arthritis and indicating a need for health interventions. *Camine Con Gusto* (CCG) is the Spanish version of the evidence-based Walk With Ease program for arthritis. This study compared baseline health status and examined differences in program efficacy and adherence among Latino adults with and without a high school diploma enrolled in a pre−post evaluation of CCG.

Methods

CCG participants (n = 233) were classified into 2 groups: high school diploma or more (n = 129) and less than high school diploma (n = 104). We used logistic regression to estimate odds ratios (ORs) and 95% confidence intervals (CIs) for associations of education with measures of baseline health and program adherence. We computed effect sizes for the difference between education groups by using mean change scores for arthritis symptoms, physical function, and psychosocial variables.

Results

The group without a high school diploma was more likely to report worse general health (OR = 2.40; 95% CI, 1.28–4.53) and lower levels of arthritis self-efficacy (OR = 1.95; 95% CI, 1.05–3.63) than the group with a high school diploma. CCG improved outcomes for both groups, with no significant between-group differences. The group without a high school diploma was less likely to read most of the program workbook (OR = 0.51; 95% CI, 0.27–0.97), but we found no significant differences in the amount of walking between the 2 groups.

Conclusion

CCG was equally effective among Latinos with and without a high school diploma; however, education did affect participants' engagement with the program workbook. Adaptation of interventions for Latinos should consider how information can best be conveyed to those with lower levels of formal education.

Introduction

Arthritis is the most common cause of disability in the United States, affecting 54.4 million adults (1). Although Latinos have a lower rate of arthritis (15.4%) compared with non-Hispanic white adults (22.6%) and black adults (22.2%), they report higher levels of disability from arthritis (1,2).

Fewer years of formal education is associated with greater pain, disability, and activity limitations due to arthritis (3–5). Because 30.0% of Latinos living in the United States lack a high school diploma, compared with 7.1% of non-Hispanic whites, interventions for Latinos who have arthritis and low levels of education must be specially designed to be appropriate and efficacious (6).

The Walk With Ease program is a 6-week, evidence-based intervention for people with arthritis. Both the instructor-led group format and the workbook-guided self-directed format can reduce arthritis symptoms and increase physical performance up to 1 year after the program (7,8). With the exception of a secondary analysis of African American participants, at least 70% of all participants in evaluations of Walk With Ease have had at least a high school education (7–10). Although studies acknowledge education differences in preferred format (those with more education prefer the self-directed format), ours is the first study to evaluate possible differences in the program's efficacy based on educational attainment (8,10).

This study was a secondary analysis of data from a pre–post evaluation of *Camine Con Gusto* (CCG), the Spanish translation and adaptation of Walk With Ease (11). The parent study, which evaluated CCG among 233 Latino adults with arthritis, found the program feasible, safe, acceptable, and efficacious at improving symptoms, physical function, and psychosocial measures in this population (11). The objectives of our study were to 1) compare baseline health status among participants with and without a high school diploma; and 2) examine arthritis outcomes and program adherence at follow-up to determine whether CCG's efficacy differed between education groups.

Methods

We analyzed data from baseline and 6-week follow-up assessments of 233 participants in the parent study of CCG (11), which was conducted from May through September 2014 in the area surrounding Chapel Hill, North Carolina. A bilingual team recruited participants from the rheumatology, gastrointestinal, geriatric, and internal medicine clinics in the University of North Carolina Hospitals Center for Latino Health (CELAH) program, a CELAH-sponsored health fair, the Mexican consulate, and 3 churches with Hispanic ministries. Recruitment is detailed elsewhere (11). Participants self-identified as Hispanic/Latino, were aged 21 years or older; reported arthritis, joint pain, or a diagnosis of arthritis by a health care professional; and were able to walk unassisted but were currently walking on average less than 150 minutes per week.

The parent study evaluated the CCG program only in the self-directed format. During recruitment, participants received a copy of the CCG workbook, which is written at a 6th-grade reading level and guides participants through developing a walking plan, getting started walking, overcoming barriers, and staying motivated. The workbook has 6 chapters and 183 pages, which participants are encouraged to read during the first 2 weeks and then reference throughout the 6-week program and beyond. The design of the CCG workbook is interactive, containing self-tests for participants to score pain, fatigue, and physical limitations and then suggesting different strategies for differing scores.

During recruitment, the bilingual team gave participants a brief explanation (approximately 5 minutes) of the program goals (walking 5 times/week for 30 minutes, or 150 minutes/week) and highlights of the workbook, including the self-test assessments, summary of information contained in each chapter, and warm-up and cool-down exercises. Participants completed baseline surveys in person or over the telephone and then completed a follow-up survey by mail or telephone after 6 weeks. All study procedures were approved by the Biomedical Institutional Review Board of the University of North Carolina at Chapel Hill.

Measures

Demographic characteristics. We collected demographic information on race, age, education, sex, marital status, health status, comorbid conditions, and acculturation measures. Age was measured as a continuous variable based on date of birth. Education was assessed with the question, "What is the highest level of education you have finished in school? Please check." Responses included grades 1 through 8, grades 9 through 11, high school graduate, some college, junior college diploma, college degree, some post-college work, or advanced degree. Body mass index (BMI, measured as weight in kilograms divided by weight in meters squared [kg/m^2]) was calculated as a continuous measure by using self-reported height and weight. To measure number and type of comorbid conditions, participants self-reported nonarthritis conditions by using a 13-item checklist (cancer, fibromyalgia, glaucoma, emphysema, high blood pressure, heart disease, circulation problems, diabetes, stomach or intestinal disorders, osteoporosis, chronic liver or kidney disease, stroke, or depression). A short-form acculturation scale for Hispanics was used to record country of birth; parent's county of birth; language spoken in childhood; language in which one thinks, reads, and writes; and language spoken at home and with friends (12). Because of the large proportion of respondents who were born in Mexico, we categorized answers to this question on country of birth as born in Mexico or born in another country. For the questions on language, the options were Spanish only, Spanish more than English, both English and Spanish, English more than Spanish, or English only.

Primary outcome measures. Primary outcome measures were physical function and arthritis symptoms. Physical function was assessed with the validated Spanish-modified Health Assessment Questionnaire scale, which measures difficulty in performing activities of daily living. The Health Assessment Questionnaire has 8 items with scores ranging from 0 (without any difficulty) to 3 (unable to do) (13). Arthritis symptoms (pain, fatigue, and stiffness) were assessed with visual numeric scales (range 0–10, with 0 being "none" and 10 being "pain/fatigue/stiffness as bad as can be") (13). Pain and fatigue were assessed by using the validated Visual Numeric Pain scale and the Visual Numeric Fatigue scale, respectively (13,14). A visual numeric scale for stiffness was adapted from the Visual Analog Scale for stiffness to resemble the fatigue and pain scales (15,16).

Secondary outcome measures. Secondary outcomes were self-reported general health status and psychosocial measures. Self-reported general health status was measured by asking participants to rate their health status as excellent, very good, good, fair, or poor (17). Psychosocial measures were arthritis self-efficacy, measured by the 11-item short form Spanish-modified Arthritis Self-Efficacy Scale, and perceived helplessness, measured by the Spanish-modified helplessness subscale of the Rheumatology Attitudes Index (15,18,19).

Program adherence measures. Adherence with program objectives was assessed at 6 weeks by asking about walking behaviors and use of the CCG workbook. Participants were asked if they did any walking (yes, no), and if they did, how many days and minutes per week they walked (1 or 2 days [referent], 3 or 4 days, ≥5 days; <15 minutes [referent], 15–30 minutes, 30–45 minutes, >45 minutes). Workbook usage was assessed with the question, "How much of the *Camine Con Gusto* Workbook did you read?" (none [referent], a little, some [2 or 3 chapters], most [4 or 5 chapters], other ways [an open-response option, eg, "read about exercises in back of book"]). Although self-reported measurements of walking are subject to recall and social desirability bias and are not as reliable as objective measures, such as a wearable device, the parent study used self-reported measures. This choice was made because walking was not a primary outcome measure and because the study team interacted with participants only once and very briefly, precluding the provision of adequate instructions on how to use the device and collection of the device after the study (20).

Analysis

We computed descriptive statistics for covariates at baseline, stratified by education (≥high school diploma, <high school diploma). High school diploma served as a binary cut-off point because roughly half of our participants were on each side of the cut-off. We tabulated continuous variables as mean and standard deviation and categorical variables as frequency and percentage. All tests were 2-sided and considered significant at $P \leq .05$. All analyses were carried out in SAS software version 9.4 (SAS Institute Inc).

Baseline data were missing for BMI (21.0%) and marital status (13.7%). Analyses to explore whether data were missing at random did not find any significant associations between predictors and missingness of data. We used Markov Chain Monte Carlo methods with all covariates to impute missing covariate values in 40 data sets in SAS PROC MI. Markov Chain Monte Carlo methods are a class of algorithms that allow approximation of the posterior distribution by random sampling values from the distribution to fill in missing data.

Mixed effects logistic regression accounting for clustering by recruitment site was used to estimate the odds ratios (ORs) and 95% confidence intervals (CIs) for the association between education level with baseline values of binary health status measures, amount of workbook read, and days of walking. Cut-off points were selected for binary variables by using medians for all health status variables except visual numeric score scales and comorbidities. Medians for pain, fatigue, and stiffness visual numeric scale scores were all between 50 and 60, so 60 was conservatively selected as a cut-off point for all 3 scales to preserve consistency. For number of comorbidities, 2 comorbidities was used as a cut-off point because data for most participants clustered at 1 comorbidity, which was also the median.

We used multivariate linear mixed regression models with recruitment site as a random effects variable to calculate mean changes between baseline and 6-week follow-up scores, controlling for baseline outcome score and covariates. Mean change scores were used to estimate effect sizes, expressed as Cohen *d*, which was calculated by comparing the mean change scores from baseline to 6 weeks divided by the pooled standard deviation (21). We calculated mean change scores for all CCG participants for changes from baseline to follow-up, and we calculated effect sizes that compared mean change scores between those who did not complete high school and those who did. Covariates were age, sex, marital status, obesity, country of origin, primary language spoken, and number of comorbidities.

Results

Educational attainment was generally low, with 44.2% (103 of 233) of study participants lacking a high school diploma (Table 1). Of participants who lacked a high school diploma, 95 of 103 (92.2%) reported having less than a 9th-grade education, and a significantly higher percentage were female (78.6%), born in Mexico (78.6%) and spoke only Spanish (79.6%) than in the group with a high school diploma (female, 76.9%; born in Mexico, 61.5%; speak only Spanish, 42.3%). A smaller percentage of the group without a high school diploma was obese (39.8% vs 48.5%); however, because a greater percentage (33%, n = 34) of this group had a very high BMI (≥40), compared with the percent- age of the group with a high school diploma (15%, n = 20), mean BMI did not differ significantly between the 2 groups. Finally, a greater proportion of the group without a high school diploma were single (19.4% vs 16.2%), although the proportion of single participants was low in both groups.

About half of all participants rated their general health status as fair or poor, but the group without a high school diploma was significantly more likely to report their general health as fair or poor compared with their more educated counterparts (OR = 2.40; 95% CI, 1.28–4.53) in analyses adjusted for sex, age, obesity, marital status, language spoken, and country of origin (Table 2). They also had a higher mean number of comorbidities (1.6 vs 1.0; *P* = .005) (Table 1) and had greater odds of having more than 2 comorbid conditions, although these odds ratios were not significant (Table 2).

In measures of arthritis symptoms, the group without a high school diploma was approximately 60% to 90% more likely to report high scores (≥60) for arthritis pain, stiffness, and fatigue at baseline (odds ratios range, 1.59–1.88), although none of these variables were significant in adjusted analyses (Table 2). Surprisingly, the group without a high school diploma had higher mean arthritis symptom scores despite lower rates of obesity. In measures of psychosocial factors, the group without a high school diploma was significantly more likely to report low scores (≤7) for arthritis self-efficacy (OR = 1.95; 95% CI, 1.05–3.63), although not for physical function (Health Assessment Questionnaire score ≥0.5: OR = 1.01; 95% CI, 0.55–1.85) or helplessness (Rheumatology Attitudes Index score ≥2: OR = 1.71; 95% CI, 0.87–3.36).

Both groups improved in arthritis symptoms, physical function, and psychosocial variables at 6-week follow-up (Table 3); therefore, the program seemed to be effective regardless of educational attainment. In fact, the change in primary and secondary outcome measures from baseline to follow-up was slightly greater for most outcome measures in the group without a high school diploma, although none of the effect sizes were significant.

Unlike outcome measures, program adherence measures did differ by education. The group without a high school diploma was significantly less likely to have read some or most of the CCG workbook than they were to have read none or a little, in analyses adjusted for sex, age, obesity, marital status, country of origin, and language spoken (OR = 0.51; 95% CI, 0.27–0.97). The group without a high school diploma was also less likely than the group with a high school diploma to report walking 3 or 4 days (OR = 0.58; 95% CI, 0.21–1.55) and 5 or more days (OR = 0.75; 95% CI, 0.28–2.06) per week compared with 1 or 2 days. These odds ratios were not significant in analyses adjusted for sex, age, obesity, marital status, country of origin, and language spoken.

Discussion

In this study, almost half (44.2%) of participants reported not having a high school diploma. Participants with less than a high school diploma were more likely to report high scores for arthritis pain, fatigue, and stiffness, low levels of arthritis self-efficacy, and poorer general health during baseline assessment. The enhanced burden of arthritis on this group of participants highlights the importance of ensuring that arthritis interventions for Latinos are appropriate for those with less formal educational attainment.

The *Camine Con Gusto* program evaluated in the parent study was a self-directed program based on a workbook. Because engaging with the workbook requires a certain degree of literacy, we expected that the program might be less effective among those without a high school diploma than among those who had graduated from high school. Contrary to expectations, our study showed no differences in primary or secondary measures of program efficacy based on education. However, the group without a high school diploma did report reading less of the workbook compared with the group with the high school diploma. One possible explanation for the lack of difference in follow-up variables is that during recruitment, program staff verbally reviewed the workbook and explained the main objectives of the walking program. This recruitment method may have reduced the need for participants to read the entire workbook to benefit from the program and could explain why no significant differences emerged in the number of days that participants reported walking during the program. Additionally, being involved in a research study may have motivated participants to walk independently of whether or not they read the book. However, the program's efficacy regardless of educational level suggests that a program dependent on written materials, like CCG, could still hold promise for those with lower educational attainment, especially when paired with another medium of communication, such as a short verbal introduction to the program like the one the recruitment team provided.

The difference in participants' engagement with the workbook could also suggest a need to adapt the peripheral elements (for example, program information presented in workbook format) of the program so that they better support the core elements (for example, walking). Implementation science emphasizes the importance of implementing evidence-based programs with fidelity to the core components of the program but also allowing for adaptations to peripheral elements to improve the program's fit within new contexts and populations (22). In our study, the CCG program was effective at improving arthritis outcomes among those with both higher and lower educational attainment — and both groups reported walking similar amounts while participating in the program. Walking may therefore be the most important core element of this program, directly influencing the desired arthritis outcomes. Future research could explore whether the method by which information about walking safely and effectively is conveyed (for example, by book vs in-person communication) could be altered to fit populations with different levels of formal educational attainment.

Our study has several strengths, including a large number of participants and a good distribution of educational levels; the use of validated, participant-reported outcome measures for Latinos; and the inclusion of measures of acculturation (language and birthplace) as covariates in adjusted analyses. Our study also has several limitations. All outcome measures were self-reported, and no performance measures for health status or physical activity were included. In addition, all participants were recruited from the same geographic location in North Carolina.

Our study supports previous research showing that low educational attainment is associated with worse symptoms and health outcomes for Latinos with arthritis (3–5). Although baseline health status differed according to level of education, we found no differences in the extent to which health outcomes changed after the CCG intervention. However, participants without a high school diploma engaged with the program differently than did participants with a high school diploma in that they were less likely to read the program workbook. Given the high percentage of Latinos in the United States that lack a high school diploma, the appropriateness of interventions for populations with low educational attainment should be considered in the process of translation and cultural adaptation.

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Tables

Table 1. Baseline Characteristics of Participants in the *Camine Con Gusto* (Walk With Ease) Program[a] Who Completed 6-Week Follow-Up, by Level of Education, North Carolina, May–September, 2014

Baseline Characteristic	All Participants (N = 233)	<High School Diploma (n = 103)	≥High School Diploma (n = 130)	*P* Value[b]
Age, mean (SD), y	47.0 (11.0)	48.1 (11.8)	46.1 (10.6)	.17
Female, no. (%)	181 (77.7)	81 (78.6)	100 (76.9)	.04
Marital status, no. (%)				
Single	41 (17.6)	20 (19.4)	21 (16.2)	<.001
Married	160 (68.7)	73 (70.9)	88 (67.7)	
Other	32 (13.7)	11 (10.7)	21 (16.0)	
Body mass index, mean (SD), kg/m^2	30.2 (6.8)	30.0 (6.6)	30.3 (7.1)	.76
Obese, no. (%)[c]	104 (44.6)	41 (39.8)	63 (48.5)	<.001
Acculturation, no. (%)				
Born in Mexico	161 (69.1)	81 (78.6)	80 (61.5)	<.001
Speak Spanish only	137 (59.8)	82 (79.6)	55 (42.3)	<.001
Self-reported health status				
Fatigue score[d], mean (SD)	48.9 (30.5)	52.8 (30.7)	45.7 (30.3)	.08
Pain score[d], mean (SD)	57.5 (25.1)	62.1 (25.3)	53.9 (24.9)	.01
Stiffness score[d], mean (SD)	47.5 (29.5)	49.3 (32.0)	46.2 (27.7)	.43
Arthritis Self-Efficacy Scale score, mean (SD)[e]	7.1 (2.2)	6.8 (2.2)	7.4 (2.2)	.03
Health Assessment Questionnaire score, mean (SD)[f]	0.5 (0.5)	0.5 (0.5)	0.4 (0.4)	.20
Rheumatology Attitudes Index score, mean (SD)[g]	1.4 (1.0)	1.6 (1.0)	1.3 (1.0)	.01
General health[h] (fair/poor), no. (%)	113 (48.5)	65 (63.1)	48 (36.9)	<.001
Comorbidities[i]				
No. of comorbidities, mean (SD)	1.3 (1.6)	1.6 (1.9)	1.0 (1.3)	.005
High blood pressure, no. (%)	64 (27.5)	35 (34.0)	29 (22.3)	<.001
Heart disease, no. (%)	10 (4.3)	7 (6.8)	3 (2.3)	<.001
Circulation problems, no. (%)	58 (24.9)	33 (32.0)	25 (19.2)	<.001

Abbreviation: SD, standard deviation.

[a] *Camine con Gusto* is a 6-week Spanish-language walking program for adults with arthritis, which participants complete on their own using a workbook.

[b] χ^2 test for categorical variables; *t* test for continuous variables.

[c] Obesity defined as having a body mass index (kg/m^2) ≥30.0.

[d] Pain, fatigue, and stiffness were measured by using 10-point visual analogue scales, with 0 being "none" and 10 being "pain/fatigue/stiffness as bad as can be." Scores were converted to a 100-point scale for analysis.

[e] The Arthritis Self Efficacy Scale has 11 items that characterize confidence in managing arthritis pain and symptoms. Options range from 1 (very uncertain) to 10 (very certain), with the average of the 11 items used in analysis.

[f] The Health Assessment Questionnaire measures perceived level of difficulty performing activities of daily living. It has 8 items on common activities, with each item ranging from 0 (without any difficulty) to 3 (unable to do). The average of the 8 items was used in analysis.

[g] The Rheumatology Attitudes Index is a 5-item subscale that measures perceived helplessness. Each item is scored from 0 to 4 (least to greatest amount of helplessness), and the average was used for analysis.

[h] Participants were asked to rate their general health as excellent, very good, good, fair, or poor.

[i] Participants reported each condition they had from a list of 13 common conditions (cancer, fibromyalgia, glaucoma, emphysema, high blood pressure, heart disease, circulation problems, diabetes, stomach or intestinal disorders, osteoporosis, chronic liver or kidney disease, stroke, or depression).

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Table 1. Baseline Characteristics of Participants in the *Camine Con Gusto* (Walk With Ease) Program[a] Who Completed 6-Week Follow-Up, by Level of Education, North Carolina, May–September, 2014

Baseline Characteristic	All Participants (N = 233)	<High School Diploma (n = 103)	≥High School Diploma (n = 130)	*P* Value[b]
Stroke, no. (%)	4 (1.7)	1 (1.0)	3 (2.3)	.001
Diabetes, no. (%)	33 (14.2)	23 (22.3)	10 (7.7)	<.001
Depression, no. (%)	45 (19.3)	23 (22.3)	22 (16.9)	<.001

Abbreviation: SD, standard deviation.

[a] *Camine con Gusto* is a 6-week Spanish-language walking program for adults with arthritis, which participants complete on their own using a workbook.

[b] χ^2 test for categorical variables; *t* test for continuous variables.

[c] Obesity defined as having a body mass index (kg/m^2) ≥30.0.

[d] Pain, fatigue, and stiffness were measured by using 10-point visual analogue scales, with 0 being "none" and 10 being "pain/fatigue/stiffness as bad as can be." Scores were converted to a 100-point scale for analysis.

[e] The Arthritis Self Efficacy Scale has 11 items that characterize confidence in managing arthritis pain and symptoms. Options range from 1 (very uncertain) to 10 (very certain), with the average of the 11 items used in analysis.

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[g] The Rheumatology Attitudes Index is a 5-item subscale that measures perceived helplessness. Each item is scored from 0 to 4 (least to greatest amount of helplessness), and the average was used for analysis.

[h] Participants were asked to rate their general health as excellent, very good, good, fair, or poor.

[i] Participants reported each condition they had from a list of 13 common conditions (cancer, fibromyalgia, glaucoma, emphysema, high blood pressure, heart disease, circulation problems, diabetes, stomach or intestinal disorders, osteoporosis, chronic liver or kidney disease, stroke, or depression).

Table 2. Association Between Having <High School Diploma[a] and Health Status Measures at Baseline Among Participants in the *Camine Con Gusto* (Walk With Ease) Program[b] Who Completed 6-Week Follow-Up, North Carolina, May–September, 2014

Characteristic	<High School Diploma[a,c], OR (95% CI)	*P* Value
Self-reported health status		
Fatigue score[d] ≥60	1.88 (1.00–3.54)	.05
Pain score[d] ≥60	1.61 (0.86–3.01)	.14
Stiffness score[d] ≥60	1.59 (0.87–2.92)	.13
Arthritis Self-Efficacy Scale score[e] ≤7	1.95 (1.05–3.63)	.04
Health Assessment Questionnaire score[f] ≥0.5	1.01 (0.55–1.85)	.97
Rheumatology Attitudes Index score[g] ≥2	1.71 (0.87–3.36)	.12
General health[h] is fair/poor	2.40 (1.28–4.53)	.01
Comorbidities[i]		
No. of comorbidities ≥2	1.08 (0.56–2.08)	.81
High blood pressure	1.37 (0.67–2.78)	.39
Heart disease	3.07 (0.57–16.52)	.19
Circulation problems	1.38 (0.68–2.81)	.37
Stroke	0.22 (0.02–2.64)	.23
Diabetes	2.22 (0.90–5.50)	.08
Depression	1.39 (0.64–3.02)	.40

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

[a] Compared with having an education ≥high school; data were multiply imputed for missing covariates and predictors.

[b] *Camine con Gusto* is a 6-week Spanish-language walking program for adults with arthritis, which participants complete on their own using a workbook.

[c] Adjusted for sex, age, obesity, marital status, language spoken, and country of origin; study site adjusted for as a random effect.

[d] Pain, fatigue, and stiffness were measured by using 10-point visual analogue scales, with 0 being "none" and 10 being "pain/fatigue/stiffness as bad as can be." Scores were converted to a 100-point scale for analysis.

[e] The Arthritis Self Efficacy Scale has 11 items that characterize confidence in managing arthritis pain and symptoms. Options range from 1 (very uncertain) to 10 (very certain), with the average of the 11 items used in analysis.

[f] The Health Assessment Questionnaire measures perceived level of difficulty performing activities of daily living. It has 8 items on common activities, with each item ranging from 0 (without any difficulty) to 3 (unable to do). The average of the 8 items was used in analysis.

[g] The Rheumatology Attitudes Index is a 5-item subscale that measures perceived helplessness. Each item is scored from 0 to 4 (least to greatest amount of helplessness), and the average was used for analysis.

[h] Participants were asked to rate their general health as excellent, very good, good, fair, or poor.

[i] Participants reported each condition they had from a list of 13 common conditions (cancer, fibromyalgia, glaucoma, emphysema, high blood pressure, heart disease, circulation problems, diabetes, stomach or intestinal disorders, osteoporosis, chronic liver or kidney disease, stroke, or depression).

Table 3. Baseline and 6-Week Follow-Up Scores, Mean Change Scores[a], and Effect Sizes[b] for Participants in *Camine Con Gusto* (Walk With Ease) Program[c], by Level of Education, North Carolina, May–September, 2014

Outcome Measures	<High School Diploma	≥High School Diploma	Effect Size[b]
Arthritis Symptoms[d]			
Pain			
No. of respondents	100	127	—
Baseline score, mean (SD)	64.5 (57.3)	58.6 (58.0)	—
Follow-up score, mean (SD)	44.5 (58.5)	41.5 (59.3)	—
Mean change (95% CI) [*P* value][a]	−20.0 (−26.1 to −13.9) [<.001]	−17.1 (−22.6 to −11.7) [<.001]	−0.05 (−0.31 to 0.21) [.71]
Fatigue			
No. of respondents	99	123	—
Baseline score, mean (SD)	52.3 (65.6)	46.6 (65.7)	—
Follow-up score, mean (SD)	36.4 (64.9)	31.0 (65.0)	—
Mean change (95% CI) [*P* value][a]	−15.9 (−22.7 to −9.1) [<.001]	−15.6 (−21.7 to −9.4) [<.001]	0 (−0.26 to 0.27) [.97]
Stiffness			
No. of respondents	97	122	—
Baseline score, mean (SD)	40.6 (60.1)	41.8 (60.6)	—
Follow-up score, mean (SD)	27.7 (58.9)	21.9 (59.5)	—
Mean change (95% CI) [*P* value][a]	−13.0 (−20.0 to −6.0) [<.001]	−19.8 (−26.1 to −13.5) [<.001]	0.11 (−0.15 to 0.38) [.40]
Physical Function			
Health Assessment Questionnaire[e]			
No. of respondents	99	123	—
Baseline score, mean (SD)	0.5 (1.0)	0.5 (1.0)	—
Follow-up score, mean (SD)	0.3 (1.0)	0.3 (1.0)	—
Mean change (95% CI) [*P* value][a]	−0.1 (−0.2 to −0.03) [.01]	−0.19 (−0.28 to −0.10) [<.001]	0.06 (−0.20 to 0.33) [.65]
Psychosocial Factors			
Rheumatology Attitudes Index[f]			
No. of respondents	97	117	—
Baseline score, mean (SD)	1.5 (1.9)	1.2 (1.8)	—
Follow-up score, mean (SD)	1.3 (1.8)	1.0 (1.8)	—

[a] We used multivariate linear mixed regression models with recruitment site as a random effects variable to calculate mean changes between baseline and 6-week follow-up scores, controlling for baseline outcome score and covariates (sex, age, marital status, body mass index, language spoken, country of origin, and comorbidities). Analysis included only participants who completed 6-week follow-up. Missing values for variables multiply imputed.
[b] Mean change scores were used to estimate effect sizes, expressed as Cohen *d*, which was calculated by comparing the mean change scores from baseline to 6 weeks divided by the pooled standard deviation (21).
[c] *Camine con Gusto* is a 6-week Spanish-language walking program for adults with arthritis, which participants complete on their own using a workbook.
[d] Pain, fatigue, and stiffness were measured by using 10-point visual analogue scales, with 0 being "none" and 10 being "pain/fatigue/stiffness as bad as can be." Scores were converted to a 100-point scale for analysis.
[e] The Health Assessment Questionnaire measures perceived level of difficulty performing activities of daily living. It has 8 items on common activities, with each item ranging from 0 (without any difficulty) to 3 (unable to do). The average of the 8 items was used in analysis.
[f] The Rheumatology Attitudes Index is a 5-item subscale that measures perceived helplessness. Each item is scored from 0 to 4 (least to greatest amount of helplessness), and the average was used for analysis.
[g] The Arthritis Self Efficacy Scale has 11 items that characterize confidence in managing arthritis pain and symptoms. Options range from 1 (very uncertain) to 10 (very certain), with the average of the 11 items used in analysis.

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Table 3. Baseline and 6-Week Follow-Up Scores, Mean Change Scores[a], and Effect Sizes[b] for Participants in *Camine Con Gusto* (Walk With Ease) Program[c], by Level of Education, North Carolina, May–September, 2014

Outcome Measures	<High School Diploma	≥High School Diploma	Effect Size[b]
Mean change (95% CI) [*P* value][a]	−0.23 (−0.42 to −0.03) [.02]	−0.23 (−0.41 to −0.05) [.01]	0 (−0.27 to 0.27) [.98]
Arthritis Self Efficacy[g]			
No. of respondents	101	121	—
Baseline score, mean (SD)	6.6 (4.5)	7.4 (4.5)	—
Follow-up score, mean (SD)	7.6 (4.5)	8.0 (4.4)	—
Mean change (95% CI) [*P* value][a]	0.94 (0.48 to 1.41) [<.001]	0.65 (0.22 to 1.08) [.003]	0.07 (−0.20 to 0.33) [.62]

[a] We used multivariate linear mixed regression models with recruitment site as a random effects variable to calculate mean changes between baseline and 6-week follow-up scores, controlling for baseline outcome score and covariates (sex, age, marital status, body mass index, language spoken, country of origin, and comorbidities). Analysis included only participants who completed 6-week follow-up. Missing values for variables multiply imputed.

[b] Mean change scores were used to estimate effect sizes, expressed as Cohen *d*, which was calculated by comparing the mean change scores from baseline to 6 weeks divided by the pooled standard deviation (21).

[c] *Camine con Gusto* is a 6-week Spanish-language walking program for adults with arthritis, which participants complete on their own using a workbook.

[d] Pain, fatigue, and stiffness were measured by using 10-point visual analogue scales, with 0 being “none” and 10 being “pain/fatigue/stiffness as bad as can be.” Scores were converted to a 100-point scale for analysis.

[e] The Health Assessment Questionnaire measures perceived level of difficulty performing activities of daily living. It has 8 items on common activities, with each item ranging from 0 (without any difficulty) to 3 (unable to do). The average of the 8 items was used in analysis.

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ORIGINAL RESEARCH

Obesity Among High School Students in the United States: Risk Factors and Their Population Attributable Fraction

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PEER REVIEWED

Abstract

Introduction

The prevalence of obesity among children and adolescents in the United States is high. The aim of this study was to assess the association between modifiable risk factors and obesity and to estimate the population attributable fractions (PAFs) of modifiable risk factors among high school students in the United States.

Methods

For this retrospective study, we used a nationally representative sample of 15,624 students who participated in the 2015 Youth Risk Behavior Survey (YRBS). Obesity was defined as body mass index at or above the 95th percentile, based on sex- and age-specific data from the Centers for Disease Control and Prevention. We examined unhealthy dietary behaviors, physical inactivity, and other modifiable risk factors (tobacco use, alcohol consumption, and sleep). We used multivariable logistic regression, accounting for the complex survey design of YRBS, to assess the association between risk factors and obesity and to calculate PAFs. Confidence intervals of PAFs were estimated by using the jackknife repeated replication method.

Results

Among all students included in the study, 13.9% were classified as obese. Not being on a sports team (odds ratio [OR], 1.61; 95% confidence interval [CI], 1.31–1.98), current tobacco use (OR, 1.42; 95% CI, 1.14–1.77), and watching television for 3 hours or more per day (OR, 1.38; 95% CI, 1.09–1.76) were significantly correlated with obesity. The combined PAF for all modifiable risk factors was 34.80% (95% CI, 32.09%–37.51%). The single modifiable risk factor with the largest PAF was not participating on a sports team (PAF, 16.57%; 95% CI, 15.30%–17.84%).

Conclusion

Findings about PAFs help demonstrate the importance of promoting physical activity, healthy diet, and other healthy lifestyles in reducing obesity among high school students in the United States.

Introduction

The prevalence of obesity among children and adolescents in the United States increased from 10.6% to 13.9% during 1999 through 2015 (1). Obesity can lead to serious adverse consequences such as asthma, obstructive sleep apnea, joint problems, hypertension, hypercholesterolemia, low self-esteem, and depression (2–7). Furthermore, children with obesity are 5 times more likely to be obese in adulthood, leading to long-term morbidity and mortality (8). The common risk factors of obesity may or may not be modifiable. Factors such as genetic variation, ethnic origin, and birth weight are not modifiable, whereas other factors such as dietary intake, physical activity, and sedentary behaviors (eg, watching television or using other screen devices) are modifiable (5–7,9–11).

Although it is challenging to determine the exact cause of obesity in any individual, efforts aiming to quantify the contribution of modifiable risk factors to childhood and adolescent obesity would help to prioritize prevention and treatment strategies to reduce such obesity. This evidence can be generated by using population attributable fractions (PAFs), defined as the proportion of disease or condition (eg, obesity) that could be prevented if a risk factor (eg, sedentary lifestyle) were removed from the population (12–15). Childhood and adolescent obesity prevalence is usually estimated through national surveys that employ complex survey designs (1,4,16), but statistical packages such as SAS (SAS Institute Inc) or Stata (StataCorp LLC) do not support the estimation of PAF in complex survey designs (13,17). To overcome this challenge, we used a statistical tool with a SAS macro developed by Heeringa et al (17) to estimate PAFs from complex sample survey data to assess the association between modifiable risk factors and determine the PAFs of modifiable risk factors of obesity in a nationally representative sample of high school students in the United States.

Methods

Study design and data

This study was a retrospective cross-sectional analysis of national data from the 2015 Youth Risk Behavior Survey (YRBS) of high school students (18). The national high school YRBS is conducted by the Centers for Disease Control and Prevention (CDC) to estimate the prevalence of health risk behaviors among US high school students. To achieve a nationally representative sample of students in public and private schools in grades 9 through 12, YRBS employs a complex sample scheme and a 3-stage cluster sample design with oversampling of certain subgroups such as black and Hispanic students. To protect students' privacy, survey participation is anonymous and voluntary (1).

The 2015 YRBS public data file contains 15,624 usable questionnaires; the survey had an overall response rate of 60%. Weighting procedures were applied to each record in the national YRBS to adjust for nonresponse and oversampling, making the weighted estimates representative of all US students in grades 9 through 12 attending public and private schools (1). The 2015 YRBS data used for this study were de-identified and publicly available; therefore, a review by the institutional review board was waived.

Measures

The individual student's obesity status was the dependent variable in this study. Obesity was defined as having a body mass index calculated from self-reported height and weight (ie, weight in kilograms divided by height in meters squared) at or above the 95th percentile based on sex- and age-specific reference data from the 2000 CDC growth charts (19). We treated respondent's obesity status as a dichotomous variable (obese or not obese).

The selection of modifiable risk factors for this study was informed by literature and the availability of information in YRBS data (1,6,9,20,21). We categorized the identified risk factors as being related to diet, physical activity, or other lifestyle behaviors. The presence of dietary-related modifiable risk factors was operationalized by using 6 indicators: students who did not eat breakfast, did not drink milk, did not eat vegetables, did not eat fruit or drink 100% fruit juice, did not drink sports drinks, and did not drink a can, bottle, or glass of soda or pop during the 7 days before the survey. The presence of physical activity–related risk factors was identified by using 5 indicators: students who did not attend physical education classes during the past week, did not participate in at least 60 minutes of physical activity on at least 1 day during the 7 days before the survey, did not play on at least 1 sports team during the past school year, played video or computer games or used computers 3 or more hours per day on an average school day, and watched television for 3 hours or more per day on an average school day. In addition, 3 other lifestyle-related risk factors were included as independent variables: students who currently drank alcohol (defined as at least 1 drink of alcohol on at least 1 day during the 30 days before the survey), currently used cigarettes, cigars, or smokeless tobacco (defined as use on at least 1 day during the 30 days before the survey), and slept 8 hours or less on an average school night (22).

Individual respondent's demographic factors — age (in years), sex (male or female), and race/ethnicity (non-Hispanic black, non-Hispanic white, Hispanic, and other) — were used as covariates.

Analysis

Data management and statistical analyses were performed by using SAS version 9.4. We conducted bivariate analyses by using χ^2 tests to assess demographic and health behavior characteristics among students in grades 9 through 12. PAF and variance estimation were conducted in a 4-step procedure by using a SAS macro developed by Heeringa et al for estimating PAFs by using complex survey design data (17). In the first of the 4 steps, the risk model was identified and its parameters were estimated by using multivariable logistic regression. As part of this multivariable model, all hypothesized modifiable and nonmodifiable risk factors were entered into the model in the same step to calculate adjusted parameter estimates and odds ratios (ORs). In the second step, population-weighted PAFs were constructed. In estimating PAFs for individual modifiable risk factors, mutually exclusive scenarios were created by assuming a path in which each risk factor is the first and only one to be eliminated (23). However, students with more than 1 risk factor could prevent obesity in more than one way. Therefore, PAFs for individual risk factors often overlap and add up to more than the overall PAF estimate for all risk factors combined (23,24). In the third step, the jackknife repeated replication method was used to estimate the sampling variability of PAF point estimates, taking into account the properties of the sample design. The fourth step was to calculate confidence intervals (CIs) for PAFs. This method shows an unbiased sampling error from a complex sample survey and can account for all hypothesized confounders (17). We accounted for individual respondents' demographic variables in all statistical models.

The YRBS complex survey design features and sampling weights were applied in all analyses to account for its complex sample design and nonresponse from schools and students. The results were also weighted to represent the total high school student population in the United States.

Results

The final sample for analysis was a weighted sample of 15,624 respondents: 7,955 (51.3%) boys and 7,551 (48.7%) girls. Most of our study sample was non-Hispanic white (54.5%), followed by Hispanic (22.3%) and non-Hispanic black (13.6%) (Table 1). Among all respondents, 2,005 (13.9%) had obesity. A greater proportion of boys (16.8%) than girls (10.8%) had obesity. A significant proportion of high school students engaged in unhealthy dietary, physical activity, or other lifestyle behaviors. About 24.7% of students watched television for 3 hours or more per day on an average school day; 42.4% did not play on any sports team during the past school year; 18.5% currently used cigarettes, cigar, or smokeless tobacco; and 72.7% slept 8 hours or less on an average school night.

Results of the multivariable logistic regression model show the associations between obesity and each dietary, physical activity, and other lifestyle-related risk behavior in the study sample after confounding all other variables (Table 2). After adjusting for respondents' demographic characteristics, we found that not playing on a sports team (OR, 1.61; 95% CI, 1.31–1.98), currently using tobacco products (OR, 1.42; 95% CI, 1.14–1.77), and watching television for 3 hours or more per day (OR, 1.38; 95% CI, 1.09–1.76) were all significantly positively associated with having obesity.

After controlling for respondents' demographics, the single modifiable risk factor with the largest PAF was not playing on at least 1 sports team during the past school year, with a PAF of 16.57% (95% CI, 15.30%–17.84%) (Table 3). Other modifiable risk factors with large PAFs were watching television for 3 hours or more per day (PAF, 7.13%; 95% CI, 6.89%–7.36%), and playing video or computer games or using a computer 3 hours or more per day (PAF, 6.27%; 95% CI, 4.21%–8.32%), and currently using tobacco products (PAF, 5.73%; 95% CI, 5.07%–6.39%). In models controlling for the respondents' age, sex, and race/ethnicity, the full PAF for all modifiable dietary, physical activity, and other lifestyle-related risk factors was 34.80% (95% CI, 32.09%–37.51%) (Table 3).

Discussion

In the United States, data on childhood obesity and potential correlates are primarily collected in 2 cross-sectional surveys, the National Health and Nutrition Examination Survey (NHANES) and YRBS, both of which employ complex probability sample designs (1,4,16). Although statistical methodologies for computing point estimates and variances of PAFs by using cross-sectional surveys with complex sample designs have continued to develop in recent decades (13,17), major statistical software packages such as SAS and Stata still do not have the capacity to estimate PAF and variance from complex sample survey data. Our study used a methodology developed to provide useful insights into the association between modifiable risk factors and obesity among students in grades 9 through 12 in the United States (17). To our knowledge, ours is the first study to quantify the association of modifiable risk factors and childhood and adolescent obesity in the United States by using a nationally representative sample of high school students. PAFs provide a useful way to quantify the burden of obesity associated with various modifiable or nonmodifiable risk factors; however, their use in research has been limited.

Our findings were consistent with previous research showing that several unhealthy behaviors, including not playing on a sports team, watching television for 3 hours or more per day, and using tobacco were associated with obesity in high school students (20,21). Many risk factors of obesity, such as genetically determined traits (eg, age, sex, race/ethnicity) and parental factors, are not easily modifiable, so we focused on the more readily modifi- able risk factors. We found that the combination of all modifiable unhealthy dietary, physical activity, and other lifestyle risk factors is associated with 34.8% of obesity in this population. This finding is striking because it shows that if all students became physically active, ate healthy foods, and adopted healthy lifestyles (such as not using tobacco and sleeping ≥8 hours per day), the prevalence of obesity in this population could be substantially reduced. We found that 42.4% of students did not participate in at least 1 sports team during the past school year; this modifiable risk factor had the most substantial contribution to obesity, with a PAF of 16.57%. Interventions coordinated at the student's home or at high schools may start with involvement in sports teams before other risk factors are addressed.

In our study, physical activity–related risk factors combined were associated with 27.96% of the prevalence of obesity in this population, indicating that being physically active and limiting sedentary behavior in general is important in preventing obesity among high school students. A meta-analysis found that youths who participate in sports are more likely to be physically active than nonparticipants (25), but further research is needed to provide clear evidence as to what types of sports are beneficial in preventing childhood and adolescent obesity. Because of the wide variety of sports, the prevalence of obesity also varies among sports (25).

The relationship between participation in various types of sports teams and the development of obesity should be carefully examined before an intervention is implemented to engage youths in sports teams.

Too much screen time, including television viewing, computer use, and videogame playing, is considered sedentary activity; television viewing, in particular, is associated with obesity among children and adolescents (21). We found that watching television or using a computer or videogame for 3 hours or more per day is linked with obesity in high school students, with a PAF of 7.1%. Children and adolescents with too much screen time may consume less energy, have less time for physical activity, and eat excessively while viewing, all of which lead to energy surplus and obesity. The results of this study help establish the priority of physical activity interventions to prevent obesity among high school students.

The benefits of physical activity in reducing obesity can be realized only when students also adopt healthy dietary habits so that they do not overcompensate for increased physical activity by eating more junk food or consuming more sugary drinks (25). Therefore, the combination of balancing caloric intake with physical activity and limiting sedentary behaviors is essential to maintaining normal growth and preventing obesity in children and adolescents (26). Although none of the dietary factors were significant in the multivariable risk estimation model used in this study, we found that dietary factors were associated with 2.3% of obesity in this population.

We observed negative PAFs for a few risk factors. According to the literature, a negative PAF indicates that the factor is protective or preventive (24,27,28). In our study, not drinking milk during the 7 days before the survey showed a negative association with having obesity, with a PAF of −3.73% (95% CI, −3.83% to −3.63%). A possible explanation is that the consumption of milk, especially whole milk or milk that contains high levels of saturated fat, may lead to childhood and adolescent obesity, because such milks contain more calories than reduced-fat or fat-free milks (26). This hypothesis is corroborated by the American Academy of Pediatrics' recommendation that children aged 2 years or older consume skim or 1% milk rather than 2% or whole milk (26). In addition, not eating vegetables also showed a negative PAF (−1.00%; 95% CI, −1.26% to −0.74%), indicating that vegetable intake may not have weight control benefits in this population. In YRBS, the definition of vegetable includes "green salad, potatoes (excluding French fries, fried potatoes, or potato chips), carrots, and other vegetables" (22). YRBS data do not indicate the types and quantities of vegetables eaten by survey respondents. The negative association found in our study may have been caused by respondents' consuming vegetables with a high glycemic index, such as potatoes, which are associated with weight gain (29). Nevertheless, this finding should be interpreted with caution and further research is needed on the types of vegetables consumed and their effect on childhood obesity.

Two other risk factors, the consumption of sports drinks and alcohol, also showed negative PAFs, but the confidence intervals included 0, indicating that the evidence is insufficient to determine the association between these factors and obesity in our population (13,17,30).

Among the other lifestyle-related factors evaluated in this study, we found that both tobacco use (PAF, 5.73%) and lack of sleep (PAF, 1.95%) were associated with the prevalence of obesity. However, no single modifiable behavior risk alone can explain the obesity status of children and adolescents. Comprehensive interventions that promote healthy diet, physical activity, reduced screen time, adequate sleep, and not drinking alcohol or smoking should therefore be implemented to reduce childhood obesity. The importance of a healthy lifestyle for the overall health of children and adolescents cannot be overstated. School, family, and community should share the responsibility to help promote healthy lifestyles and prevent obesity in children and adolescents.

Our study had several limitations. First, YRBS is a cross-sectional survey, and respondent's behavioral risk factors and height and weight information were collected in 1 survey questionnaire. Therefore, the PAFs of modifiable risk factors of obesity are indicators of association, not cause and effect. Second, we did not consider all potential risk factors of obesity; we focused only on readily modifiable risk factors at the respondent level. Other risk factors, such as parental and environmental factors, may also be modifiable but were not examined in our study because such information was not available in YRBS data. Additionally, respondents' height, weight, health behavior, and lifestyle factors were self-reported through questionnaires and thus are subject to such biases as social desirability bias and recall bias. The data were not validated by medical records, food diaries, or school records.

Physical activity, dietary, and other lifestyle factors (alcohol, tobacco, and sleep habits) were associated with over one-third of the obesity among high school students in the United States. Our study provides evidence that a substantial proportion of obesity in this population could be prevented through changes in unhealthy diet, sedentary lifestyle, and other harmful lifestyle behaviors. School, family, and community interventions focusing on promoting physical activity, healthy eating, and other healthy behaviors are important for reducing obesity and many chronic diseases in children and adolescents.

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Tables

Table 1. Demographic Characteristics and Modifiable Risk Factors of Obesity Among High School Students, United States (N = 15,624), 2015 Youth Risk Behavior Survey

Characteristic or Modifiable Risk Factor[a]	Total, No. (%) (N = 15,624)[b]	Obese, No. (%) (n = 2,005 [13.9])	Not Obese, No. (%) (n = 12,415 [86.1])	*P* Value[c]
Age, y				
≤15	5,666 (36.4)	697 (15.4)	4,513 (84.6)	.28
>15	9,895 (63.6)	1,308 (14.2)	7,902 (85.8)	
Sex				
Male	7,955 (51.3)	1,248 (16.8)	6,168 (83.2)	<.001
Female	7,551 (48.7)	757 (10.8)	6,247 (89.2)	
Race/ethnicity				
Non-Hispanic white	8,336 (54.5)	982 (12.4)	6,940 (87.6)	<.001
Non-Hispanic black	2,078 (13.6)	311 (16.8)	1,542 (83.2)	
Hispanic	3,142 (22.3)	509 (16.4)	2,589 (83.6)	
Other[d]	1,482 (9.7)	173 (12.8)	1,176 (87.2)	
Did not eat fruit or drink 100% fruit juices[e]				
Yes	793 (5.2)	132 (19.0)	564 (81.0)	.02
No	14,541 (94.8)	1,836 (13.6)	11,656 (86.4)	
Did not eat vegetables[e]				
Yes	1,022 (6.7)	131 (14.7)	762 (85.3)	.58
No	14,210 (93.3)	1,826 (13.8)	11,401 (86.2)	
Did not drink a can, bottle, or glass of soda or pop[e]				
Yes	4,011 (26.2)	442 (11.8)	3,289 (88.2)	.01
No	11,306 (73.8)	1,525 (14.6)	8,927 (85.4)	
Did not eat breakfast[e]				
Yes	2,081 (13.8)	293 (15.9)	1,548 (84.1)	.04
No	12,951 (86.2)	1,634 (13.5)	10,434 (86.5)	
Did not drink milk[e]				
Yes	3,140 (21.5)	350 (12.3)	2,505 (87.7)	.04
No	11,433 (78.5)	1,530 (14.4)	9,114 (85.6)	
Drank a can, bottle, or glass of a sports drink[e]				
Yes	7,390 (57.6)	969 (14.1)	5,894 (85.9)	.10
No	5,437 (42.4)	644 (12.9)	4,343 (87.1)	

[a] Percentages are based on weighted data to represent all students in grades 9 through 12 attending public and private schools in the United States. Source: Centers for Disease Control and Prevention (18).
[b] Sum of categories in each variable does not always add up to a total sample size of 15,624 because of missing values.
[c] *P* values were calculated by using χ^2 tests.
[d] Other race included American Indian or Alaska Native, Asian, Native Hawaiian or Other Pacific Islander, and multiple races.
[e] During the 7 days before the survey.
[f] Defined as at least 1 drink of alcohol on at least 1 day during the 30 days before the survey.
[g] Defined as use on at least 1 day during the 30 days before the survey.

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Table 1. Demographic Characteristics and Modifiable Risk Factors of Obesity Among High School Students, United States (N = 15,624), 2015 Youth Risk Behavior Survey

Characteristic or Modifiable Risk Factor[a]	Total, No. (%) (N = 15,624)[b]	Obese, No. (%) (n = 2,005 [13.9])	Not Obese, No. (%) (n = 12,415 [86.1])	*P* Value[c]
Did not participate in at least 60 minutes of physical activity on at least 1 day[e]				
Yes	2,182 (14.3)	304 (15.8)	1,621 (84.2)	.07
No	13,086 (85.7)	1,661 (13.6)	10,550 (86.4)	
Did not attend physical education classes on ≥1 days during the past week				
Yes	7,332 (48.4)	940 (13.9)	5,845 (86.1)	.89
No	7,828 (51.6)	1,011 (14.0)	6,224 (86.0)	
Did not play on at least 1 sports team during the past school year				
Yes	6,111 (42.4)	937 (17.1)	4,545 (82.9)	<.001
No	8,311 (57.6)	925 (11.8)	6,929 (88.2)	
Watched television ≥3 hours per day on an average school day				
Yes	3,720 (24.7)	592 (17.5)	2791 (82.5)	<.001
No	11,309 (75.3)	1,345 (12.8)	9,164 (87.2)	
Played video or computer games or used a computer ≥3 hours per day on an average school day				
Yes	6,317 (41.7)	905 (15.6)	4,909 (84.4)	<.001
No	8,826 (58.3)	1,039 (12.7)	7,151 (87.3)	
Currently drink alcohol[f]				
Yes	4,646 (32.8)	592 (13.6)	3,765 (86.4)	.90
No	9,553 (67.2)	1,207 (13.7)	7,606 (86.3)	
Currently use cigarettes, cigars, or smokeless tobacco[g]				
Yes	2,762 (18.5)	448 (17.8)	2,062 (82.2)	<.001
No	12,129 (81.5)	1,469 (13.1)	9,775 (86.9)	
Had ≤8 hours sleep on an average school night				
Yes	10,824 (72.7)	1,398 (13.9)	8,661 (86.1)	.80
No	4,065 (27.3)	529 (14.2)	3,208 (85.8)	

[a] Percentages are based on weighted data to represent all students in grades 9 through 12 attending public and private schools in the United States. Source: Centers for Disease Control and Prevention (18).
[b] Sum of categories in each variable does not always add up to a total sample size of 15,624 because of missing values.
[c] *P* values were calculated by using χ^2 tests.
[d] Other race included American Indian or Alaska Native, Asian, Native Hawaiian or Other Pacific Islander, and multiple races.
[e] During the 7 days before the survey.
[f] Defined as at least 1 drink of alcohol on at least 1 day during the 30 days before the survey.
[g] Defined as use on at least 1 day during the 30 days before the survey.

Table 2. Multivariable Logistic Regression Determining the Odds of Having Obesity Among High School Students, United States (N = 15,624), 2015 Youth Risk Behavior Survey[a]

Modifiable Risk Factors[b]	Odds Ratio (95% Confidence Interval)
Did not eat fruit or drink 100% fruit juices[c]	
Yes	1.45 (0.97–2.15)
No	1 [Reference]
Did not eat vegetables[c]	
Yes	0.83 (0.58–1.19)
No	1 [Reference]
Drank a can, bottle, or glass of soda or pop[c]	
Yes	1.04 (0.8–1.34)
No	1 [Reference]
Did not eat breakfast[c]	
Yes	1.23 (0.97–1.57)
No	1 [Reference]
Did not drink milk[c]	
Yes	0.80 (0.62–1.02)
No	1 [Reference]
Drank a can, bottle, or glass of a sports drink[c]	
Yes	0.99 (0.86–1.16)
No	1 [Reference]
Did not participate in at least 60 minutes of physical activity on at least 1 day[c]	
Yes	1.06 (0.84–1.32)
No	1 [Reference]
Did not attended physical education classes on ≥1 days during the past week	
Yes	1.03 (0.86–1.31)
No	1 [Reference]
Did not play on at least 1 sports team during the past school year	
Yes	1.61 (1.31–1.98)
No	1 [Reference]
Watched television ≥3 hours per day on an average school day	
Yes	1.38 (1.09–1.76)
No	1 [Reference]
Played video or computer games or used a computer ≥3 hours per day on an average school day	
Yes	1.19 (0.98–1.43)

[a] Odds ratios were estimated after accounting for the nonmodifiable risk factors age, sex, and race/ethnicity in the multivariable logistic regression model.
[b] Results are based on weighted data to represent all students in grades 9 through 12 attending public and private schools in the United States. Source: Centers for Disease Control and Prevention (18).
[c] During the 7 days before the survey.
[d] Defined as at least 1 drink of alcohol on at least 1 day during the 30 days before the survey.
[e] Defined as use on at least 1 day during the 30 days before the survey.

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Table 2. Multivariable Logistic Regression Determining the Odds of Having Obesity Among High School Students, United States (N = 15,624), 2015 Youth Risk Behavior Survey[a]

Modifiable Risk Factors[b]	Odds Ratio (95% Confidence Interval)
No	1 [Reference]
Currently drink alcohol[d]	
Yes	0.99 (0.83–1.18)
No	1 [Reference]
Currently use cigarettes, cigars, or smokeless tobacco[e]	
Yes	1.42 (1.14–1.77)
No	1 [Reference]
Had ≤8 hours sleep on an average school night	
Yes	1.03 (0.87–1.23)
No	1 [Reference]

[a] Odds ratios were estimated after accounting for the nonmodifiable risk factors age, sex, and race/ethnicity in the multivariable logistic regression model.
[b] Results are based on weighted data to represent all students in grades 9 through 12 attending public and private schools in the United States. Source: Centers for Disease Control and Prevention (18).
[c] During the 7 days before the survey.
[d] Defined as at least 1 drink of alcohol on at least 1 day during the 30 days before the survey.
[e] Defined as use on at least 1 day during the 30 days before the survey.

Table 3. Population Attributable Fractions and 95% Confidence Intervals for Modifiable Risk Factors of Obesity Among High School Students, United States (N = 15,624), 2015 Youth Risk Behavior Survey

Modifiable Risk Factors[a]	Population Attributable Fraction, % (95% Confidence Interval)
Dietary-related risk factors	
Did not eat fruit or drink 100% fruit juices[b]	1.53 (0.73 to 2.32)
Did not eat vegetables[b]	−1.00 (−1.26 to −0.74)
Drank a can, bottle, or glass of soda or pop[b]	2.43 (1.96 to 2.89)
Did not eat breakfast[b]	2.38 (1.80 to 2.97)
Did not drink milk[b]	−3.73 (−3.83 to −3.63)
Drank a can, bottle, or glass of a sports drink[b]	−0.05 (−0.74 to 0.64)
Dietary-related risk factors combined	2.29 (0.87 to 3.71)
Physical activity–related risk factors	
Did not participate in at least 60 minutes of physical activity on at least 1 day[b]	0.63 (0.32 to 0.94)
Did not attended physical education classes on ≥1 days during the past week	1.01 (−0.25 to 2.28)
Did not play on at least 1 sports team during the past school year	16.57 (15.30 to 17.84)
Watched television ≥3 hours per day on an average school day	7.13 (6.89 to 7.36)
Played video or computer games or used a computer ≥3 hours per day on an average school day	6.27 (4.21 to 8.32)
Physical activity–related risk factors combined	27.96 (26.14 to 29.78)
Other lifestyle risk factors	
Currently drink alcohol[c]	−0.34 (−1.15 to 0.47)
Currently use cigarettes, cigars, or smokeless tobacco[d]	5.73 (5.07 to 6.39)
Had ≤8 hours of sleep on an average school night	1.95 (1.19 to 2.70)
Other lifestyle risk factors combined	7.28 (6.51 to 8.05)
All modifiable risk factors combined	34.80 (32.09 to 37.51)

[a] Values are expressed as percentages. Percentages are based on weighted data to represent of all students in grades 9 through 12 attending public and private schools in the United States. Source: Centers for Disease Control and Prevention (18).
[b] During the 7 days before the survey.
[c] Defined as at least 1 drink of alcohol on at least 1 day during the 30 days before the survey.
[d] Defined as use on at least 1 day during the 30 days before the survey.

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ORIGINAL RESEARCH

A Novel Decision Aid to Encourage Smoking Cessation Among Patients at an Urban Safety Net Clinic

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PEER REVIEWED

Abstract

Introduction

Decision aids are not readily available to individualize the benefits of smoking cessation but could help health care providers engage in meaningful conversations with their patients to explore and encourage an attempt to quit smoking. We conducted a pilot study of a novel decision aid among an underserved population to assess its effectiveness in increasing readiness to quit and quit attempts.

Methods

We designed a decision aid that used images of birthday cakes to highlight the number of years of life that could be gained from smoking cessation and tested it in an urban safety net clinic. Active adult smokers were randomized to receive smoking cessation counseling, either with motivational interviewing techniques alone (control) or with motivational interviewing and the decision aid (intervention). The primary outcome assessed was readiness to quit, measured by using a previously validated contemplation ladder. The secondary outcome assessed was making a quit attempt.

Results

Immediately following the interview, 21.1% of patients rose on the readiness-to-quit ladder; at 1 month, 40.6%; and at 3 months, 46.6%. We saw no significant difference between the control and intervention groups immediately after the interview (*P* = .79), at 1 month (*P* = .92), or at 3 months (*P* = .79). Over the 3-month follow-up period, 25% of patients in the control group made a quit attempt, and 15.4% of patients in the intervention group made a quit attempt (*P* = .30). Patients found the decision aid useful and easy to understand.

Conclusion

Patients from an underserved population were highly receptive to a visual and personalized decision aid that highlighted the positive impact of smoking cessation. However, we found no difference in readiness to quit between patients who received motivational interviewing with the decision aid or without it.

Introduction

From 1964 through 2012, the prevalence of cigarette smoking fell dramatically in the United States, from 42% to 18%, but progress has recently slowed (1). Forty-two million Americans continue to smoke, and large disparities in tobacco use exist by race/ethnicity, educational level, and socioeconomic status (2,3). The clinical encounter between a health care provider and patient can play an important role in promoting smoking cessation. Nonpharmacologic interventions, such as brief personalized advice, motivational interviewing, and use of office supports show varying levels of success in improving cessation rates (4–6).

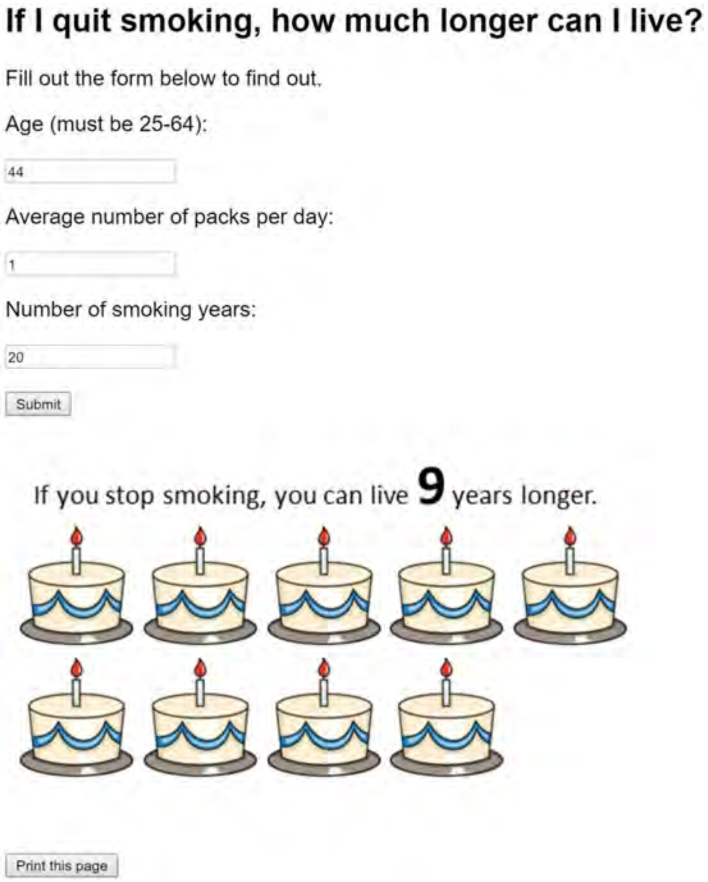
Although not commonly used for smoking cessation, decision aids could help enhance the efficacy of nonpharmacologic interventions in the clinical encounter, particularly among patients who are less motivated (ie, precontemplative or contemplative) about changing their behavior. Decision aids have been shown to increase patient engagement, improve patient knowledge and perception of risk, reduce decisional conflict, and improve adherence to medication (7–10). Aids are an effective method of communicating health information to patients and can complement the principles of motivational interviewing. If decision aids are designed appropriately, they can also be effective tools among people with low health literacy or disadvantaged populations (11–13).

To our knowledge, no available decision aids individualize the benefits of smoking cessation and focus on those benefits rather than focusing on the harms of continuing to smoke. Although considerable research describes the harms of smoking, including increased risk of disease and death related to cardiovascular disease, chronic obstructive lung disease, and lung cancer, emerging evidence has also begun to identify and quantify the benefits of cessation (14). Those who quit before the age of 35 or 40, for example, can avoid most of the excess mortality that comes from continuing to smoke (15–19).

We developed a novel decision aid and studied its use among smokers at an urban safety net clinic. The decision aid focused on the benefits of cessation rather than the harms of smoking and was designed to be both provocative and easy to understand. We hypothesized that a decision aid, when used in conjunction with motivational interviewing, could help health care providers engage in a meaningful conversation with their patients, advance patients' readiness to quit, and ultimately encourage a quit attempt.

Methods

We conducted a pilot study at an urban safety net clinic in Virginia. The clinic was located in an academic medical center with a predominantly underserved patient population. Patients were enrolled and completed follow-up over a course of 6 months, from October 1, 2016, through March 31, 2017. In this 2-arm controlled trial, patients in the control arm received motivational interviewing. Patients in the intervention arm received motivational interviewing and a decision aid that showed patients the benefits of smoking cessation (Figure). Interviews were conducted by 2 medical students who underwent formal training in motivational interviewing before patient enrollment.


If I quit smoking, how much longer can I live?

Fill out the form below to find out.

Age (must be 25-64): 44

Average number of packs per day: 1

Number of smoking years: 20

If you stop smoking, you can live 9 years longer.

Figure. Screenshot of a web-based decision aid that highlights the benefits of smoking cessation. Medical students used the decision aid to engage with patients in a conversation about smoking cessation using motivational interviewing techniques.

Because it was meant to target a population with low health literacy, the decision aid was designed to be easy-to-understand, evocative, and memorable. It personalized and heightened the perceived benefits of quitting by using the poignant image of birthday cakes to display the potential years of life gained by quitting at the patient's current age. To calculate the years of life gained by quitting, we used evidence from a study by Jha and colleagues, which showed that adults who quit smoking between the ages of 25 and 34 could gain 10 years of life, compared with those who continue smoking; similarly, adults who quit smoking between the ages of 35 and 44, 45 and 54, and 55 and 64 could gain 9 years, 6 years, and 4 years of life, respectively (19). The decision aid was readily accessible as a web application (http://smoking.skap.work/) and printable so that patients could take their personalized results home with them.

We targeted an enrollment of 100 active smokers with a 1:1 allocation ratio. One author (S.D.A.) used a random-number generator to place slips of paper labeled "intervention" or "control" into sequentially numbered, sealed envelopes for allocation concealment. Two medical students (M.K., J.M.) opened each envelope in sequential order as patients were enrolled, and patients were accordingly assigned to either the intervention or control arm on the basis of the slip of paper in the corresponding envelope. The study was not blinded.

Patient population

We enrolled English-speaking men and women aged 25 to 64. Potential participants were identified by reviewing the clinic schedule for the day and subsequently approaching those who were listed in the electronic medical record as active or former tobacco users. Current smoking status was confirmed with the patient. Those who were active smokers were considered eligible for the study. Consent was obtained by using a verbal consent script.

Measures

After randomization, all patients were given a 1-page questionnaire to obtain baseline characteristics, including smoking history ("At what age did you start smoking?" and "How many cigarettes do you smoke per day?"), and as assessment of their baseline readiness to quit. The questionnaire asked patients to place themselves on a readiness-to-quit ladder. The ladder scored from 1 to 10, where 1 indicated that the patient had no interest in quitting, 4 indicated that the patient sometimes thought about quitting but has no current plans to quit, and 8 indicated that the patient had begun to change, for example, by cutting back and setting a quit date. The contemplation ladder, which is based on stages of change (precontemplation, contemplation, preparation, action, and maintenance), is well validated (20–24). It captures meaningful changes in thinking that predict future quit attempts. After motivational interviewing, with or without use of the decision aid, patients were asked to place themselves again on the same readiness-to-quit ladder.

We gave an additional survey to patients in the intervention group to assess their receptiveness to the decision aid. On a 5-point Likert scale (strongly disagree, disagree, undecided, agree, and strongly agree) patients indicated how much they agreed with the following statements: "Before seeing the birthday cakes, I did not know that I could live longer if I quit smoking," "That information was helpful and useful to learn," and "The birthday cakes as a representation of how much longer I could live were easy to understand."

One and 3 months later, we asked patients to again place themselves on a readiness-to-quit ladder. Patients were also asked whether they had made a successful quit attempt, even for a short time. For those patients in the intervention group who received the decision aid, we also asked, "Do you remember talking about how many extra years you can live if you quit smoking, displayed using birthday cakes?" The answer was recorded as yes or no.

Statistical analysis

The primary outcome of our study was readiness to quit, assessed on a 10-point scale. The secondary outcome was making a quit attempt. We used χ^2 analyses to compare proportions of patients in the intervention and control groups who rose on the readiness-to-quit ladder and the proportion of patients who made a quit attempt.

Analyses were conducted by using SAS, version 9.4 (SAS Institute, Inc.). All statistical tests were 2-tailed with a level of significance set at $P < .05$. The study was approved by the University of Virginia Institutional Review Board.

Results

Trial population and characteristics. We randomized 100 patients to control and intervention groups. Five patients became unavailable for motivational interviewing between the time of randomization and their scheduled physician appointments. Final counts were 45 patients in the motivational interviewing-only group (control arm) and 50 patients in the motivational interviewing plus decision aid group (intervention arm). Baseline characteristics were similar between the 2 groups (Table 1). The average patient age was 49.7 years in the control group and 49.2 in the intervention group, and approximately 75% of patients in each group had either Medicaid or qualified for indigent care. The baseline score on the quit scale was 5.7 in the control group and 5.9 in the intervention group. A total of 34 patients in the control group (75.6%) and 35 patients in the intervention group (70.0%) completed follow-up at 1 month (Table 2). At 3 months, a total of 29 patients in the control group (64.4%) and 29 patients in the intervention group (58.0%) had completed follow-up.

Change in readiness to quit and quit attempts. Immediately after the interview, 20 patients (21.1%) rose on the readiness-to-quit ladder; we found no significant difference between the control and intervention groups ($P = .79$) (Table 2). Among all patients with at least 1 month of follow-up, 40.6% rose on the readiness-to-quit ladder, 41.2% in the control group and 40.0% in the intervention group ($P = .92$). By 3 months, 46.6% of all patients rose on the ladder, 44.8% in the control group and 48.3% in the intervention group ($P = .79$). Over the 3-month follow-up period, 25% of patients in the control group and 15.4% of patients in the intervention group made a quit attempt ($P = .30$).

Survey results. Of patients who received the decision aid, 56% reported not knowing they could live longer if they quit smoking, 84% found the decision aid to be useful, and 100% found it easy to understand. Nearly all patients remembered the birthday cakes at follow-up.

Discussion

In our study, we found that at 3 months, both motivational interviewing without the decision aid (control group) and with the decision aid (intervention group) improved patients' readiness-to-quit and motivated quit attempts. However, we saw no significant difference in readiness to quit or quit attempts between the 2 groups. Decision aids have been shown to confer several benefits, such as improving patient knowledge and engagement. The lack of benefit seen in our study may be because both motivational interviewing and decision aids (used in a shared decision-making process) capitalize on the same mechanism: they both spur a meaningful conversation between health care providers and patients. Because our decision aid was designed to complement and build on the principles of motivational interviewing, it could, theoretically, be used independently to trigger a discussion between providers and their patients similar to that of motivational interviewing. For example, the practice of motivational interviewing involves developing a dissonance between a patient's goals or values and his or her current behavior, adjusting to resistance rather than opposing it directly, and supporting self-efficacy and optimism (25). The decision aid attempts to encourage these 3 efforts by going beyond the harms of smoking and highlighting instead the benefits of quitting.

Because 75% of our study's patients had either Medicaid or received free care because of indigent status, we targeted a truly vulnerable and underserved population. We demonstrated that such patients are highly receptive to a decision aid that is visual, personalized, and highlights the positive effect of smoking cessation. Months later, nearly all patients in the intervention group remembered talking about the potential years of life gained with smoking cessation, displayed as birthday cakes. We conducted motivational interviewing in a single session, but, because nearly all patients remembered the decision aid 3 months later, we might have seen greater gains by conducting additional motivational interviewing sessions and by using the decision aid as a launching point. The decision aid provided memorable teaching that health care providers could use to have a sustained dialogue with their patients about quitting.

Our study also showed that motivational interviewing can be effective even when done around the scheduled office visit and when conducted by someone other than a physician (eg, a medical student). Although providers frequently screen for smoking among their patients, they offer practical support for cessation less often (26,27). Involving other members of the clinical team to assist with motivational interviewing could increase the frequency of high-quality motivational interviewing in the setting of a busy clinical practice.

Our study had several limitations. First, as a pilot study, our sample size may have limited the power with which we could detect a significant difference between the 2 study groups. Second, the lack of blinding and the use of self-reporting of the outcomes could have biased our results. Some patients may have wanted to appear more willing and ready to quit. Third, we conducted only a single session of motivational interviewing and followed patients for only 3 months. Additional sessions and longer follow-up could have resulted in more dramatic changes and additional quit attempts. Fourth, as a single site study at an urban safety net clinic, our results may have limited generalizability. Finally, combining the decision aid with an already effective method (ie, motivational interviewing) may have diluted the effect of the decision aid. Future directions for this research include studying the effect of the decision aid alone or supplementing the effort with pharmaceutical interventions.

In conclusion, although we saw no difference in readiness to quit between patients who received motivational interviewing with a decision aid versus those who received motivational interviewing without a decision aid, patients from an underserved population were highly receptive to a visual and personalized decision aid that highlighted the positive impact of smoking cessation.

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Tables

Table 1. Characteristics of Patients (N = 95), Study of a Decision Aid to Encourage Smoking Cessation Among Patients at an Urban Safety Net Clinic, October 1, 2016–March 31, 2017[a]

Characteristic	Motivational Interviewing With Decision Aid (Intervention Group), n = 50	Motivational Interviewing Without Decision Aid (Control Group), n = 45
Age, mean (SD), y	49.2 (9.6)	49.7 (8.6)
Sex		
Male	20 (40.0)	27 (60.0)
Female	30 (60.0)	18 (40.0)
Race		
White	28 (56.0)	30 (66.7)
Nonwhite	22 (44.0)	15 (33.3)
Insurance		
Virginia indigent	26 (52.0)	22 (48.9)
Medicaid	12 (24.0)	11 (24.4)
Other	12 (24.0)	12 (26.7)
Marital status		
Married	9 (18.0)	1 (2.2)
Single or separated	22 (44.0)	25 (55.6)
Divorced or widowed	19 (38.0)	19 (42.2)
Age when started smoking, mean (SD), y	17.9 (6.6)	16.5 (4.8)
Number of cigarettes smoked per day, mean (SD)	13.4 (9.2)	16.4 (10.1)
Baseline score on quit scale, mean (SD)	5.9 (1.7)	5.7 (1.6)

Abbreviation: SD, standard deviation.
[a] Values are n (%) unless otherwise indicated.

Table 2. Readiness-to-Quit Status of Patients in Control (n = 45) and Intervention (n = 50) Groups, Study of a Decision Aid to Encourage Smoking Cessation Among Patients at an Urban Safety Net Clinic, October 1, 2016–March 31, 2017

Timing of Intervention	Increase in Readiness-to-Quit, %	No Change (or Decrease) in Readiness-to-Quit, %	*P* Value
Immediately after interview			
Motivational interviewing alone (control group) (n = 45)	22.2	77.8	.79
Motivational interviewing plus decision aid (intervention group) (n = 50)	20.0	80.0	
1 month after interview			
Motivational interviewing alone (control group) (n = 34)	41.2	58.8	.92
Motivational interviewing plus decision aid (intervention group) (n = 35)	40.0	60.0	
3 months after interview			
Motivational interviewing alone (control group) (n = 29)	44.8	55.2	.79
Motivational interviewing plus decision aid (intervention group) (n = 29)	48.3	51.7	

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ORIGINAL RESEARCH

Effect of Media Use on Adolescent Body Weight

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PEER REVIEWED

Abstract

Introduction
Adolescents spend a substantial amount of time consuming media, including watching television, playing video games, and using electronic devices to access the internet. We examined the relationship between prolonged media use on screen devices and its potential association with obesity through several mechanisms.

Methods
We used data from 659,288 eighth and eleventh grade students who participated in the 2015–2016 School Physical Activity and Nutrition (SPAN) survey in Texas to examine the associations between hours of media use per day and 3 behaviors related to obesity: timing of last food intake, unhealthy eating behavior, and sleep hours. Also, mediation analyses were conducted to examine the pathways between hours of media use and body mass index (BMI).

Results
Compared with adolescents who used media 2 hours or less per day, those who used media 6 hours or more had higher odds of nighttime eating (odds ratio [OR], 3.16; 95% confidence interval [CI], 1.76–5.66) and inadequate sleep (OR, 1.57; 95% CI, 1.05–2.36) and a higher coefficient for Unhealthy Eating Index score (3.87; 95% CI, 1.3–6.37). Mediation analysis demonstrated that for males sleep hours and timing of last food intake mediated the pathway between hours of media use and BMI. For females, unhealthy eating behavior mediated this pathway.

Conclusion
Adolescents who used electronic media 6 or more hours at night had higher odds of unhealthy eating behavior and inadequate sleep hours than those with 2 hours' use or less. Attention to behaviors associated with adolescents' prolonged media use is needed to reduce risk of obesity.

Introduction

Adolescents are inundated with media and spend more than 6 hours each day watching television, YouTube, and movies; playing video games; listening to music; and surfing the internet (1). Use of television and other screen devices (eg, smartphone, tablets, computers) is associated with risk of obesity through a variety of mechanisms, including insufficient physical activity and increased calorie intake while using screen devices (2,3).

Several studies have shown that increased media use is associated with shorter and poorer quality sleep (3,4), which is also a significant risk factor for obesity (5,6). After-school screen time is associated with increased size of evening snack portions and overall poor diet quality in adolescents (7). Moreover, epidemiologic studies have reported that consuming most daily calories in the evening is associated with higher body mass index (BMI) and an increased risk of obesity and metabolic syndrome. Taken together, media use is associated with negative effects on a variety of adolescent health behaviors, including unhealthy eating at night and inadequate sleep hours, which can ultimately lead to increased risk of overweight and obesity (2–9). However, few studies have examined the association between media use and timing of last food intake, unhealthy eating, and inadequate sleep hours in a representative sample of adolescents. Because Texas has the second largest population of US states and is racially diverse (10), patterns observed there may be used as an indicator of national prevalence of media use and related behaviors among adolescents.

The two objectives of our study were 1) to examine the association between categories of increased hours of media use as the targeted exposure variable and 3 behavioral outcomes (timing of last food intake, unhealthy eating behaviors, and hours of sleep, stratified by sex); and 2) to test the mediation effects of timing of last food intake, unhealthy eating behavior, and sleep hours between hours of media use and BMI, stratified by sex. We hypothesized that media use would be positively associated with the 3 behavioral outcomes and that these outcomes would also act as mediators between hours of media use and BMI in an adolescent population. This article was written in accordance with the STrengthening the Reporting of OBservational Studies in Epidemiology (STROBE) statement (11).

Methods

Study design and sampling. Data were obtained from the School Physical Activity and Nutrition Survey (SPAN), a surveillance system designed to identify factors among school-age children that may underlie obesity, including dietary behaviors, nutrition knowledge and attitudes, and physical activity (12). Since 2000, SPAN has collected these serial cross-sectional data over 4 time periods (2000–2002, 2004–2005, 2009–2011, and 2015–2016). SPAN's stratified, multistage probability sampling scheme yielded samples that represent 8th and 11th grade students in Texas. Further details on SPAN sampling are presented elsewhere (13). In our study, all 8th and 11th grade student respondents from the most re- cent 2015–2016 SPAN data were included (weighted count, 659,288; unweighted count, 9,056; 52.7% 8th graders and 47.3% 11th graders). Students with missing data (4.7%, n = 423) were excluded from the analyses.

Data collection

Trained field staff members administered the SPAN questionnaire and obtained anthropometric data at randomly selected schools. The questionnaire included items about demographic information, diet, and physical activity. The validity of food frequency questionnaire items was evaluated with 24-hour food recall, and reliability of the questionnaire was established with test–retest methods (14). The SPAN protocol was approved by The University of Texas Health Science Center's Committee for Protection of Human Subjects (HSC-SPH-17–0965).

Measures

Hours of media use. Hours of media use were measured by asking how many hours per day the student usually watched or used 1) television, 2) a computer for schoolwork, 3) a computer for outside schoolwork, and 4) video games. For each of the 4, the 8 ordinal responses for per-day use were 0 (I don't use or watch [specific media]), 0.5 (I watch less than 1 hour), 1 (1 hour), 2 (2 hours), 3 (3 hours), 4 (4 hours), 5 (5 hours), and 6 (6 hours or more per day). Hours of use of the 4 media were summed as a continuous variable ranging from 0 to 24 and stratified into 2 hours or less, 3 to 5 hours, and 6 hours or more per day. The questions about television viewing and video gaming were tested previously for their reliability with test–retest κ value 0.71 and 84% agreement (14); computer questions were adapted from the television and gaming questions.

Timing of last food intake. The timing of last food intake was measured with the question, "What is the latest time that you usually eat or drink anything (except water)?" on school days and on weekends. The response categories were before 7 PM, 7 PM to 7:59 PM, 8 PM to 8:59 PM, 9 PM to 9:59 PM, 10 PM to 10:59 PM, 11 PM to 11:59 PM, and 12 AM or later. These were collapsed into 3 categories: before 7 PM, between 7 PM and 10 PM, and 10 PM or later. We used 7 PM and 10 PM as the earliest and latest cutoffs on the basis of the average dinner time for adults (15) and the definition of nighttime eating (16). The responses were combined by taking an average of the recorded responses for weekdays and weekend days.

SPAN unhealthy eating index. We created a SPAN unhealthy eating index, which was based on methods used in previous work (17), as a summary measure of unhealthy food items, identified as fried meats, sugary drinks, salty fried snacks, and various desserts. Frequency measures of the consumption of each food item were added and scaled to a range of 0 to 100 — the higher the value, the unhealthier the diet. Healthy foods were not included in the analyses, but foods such as baked meat, vegetables, fruits, milk, yogurt, and whole-grain pasta and bread were assessed by additional SPAN survey questions.

Sleep. SPAN measured hours of sleep with a single question: "On an average school night, how many hours of sleep do you get?" with 7 response options: 4 or less, 5, 6, 7, 8, 9, or 10 or more. This construct, adopted from the Youth Risk Behavior Surveillance System (YRBSS) questionnaire (18), was treated both as a continuous variable and a categorical variable (<8 h, 8–9 h, and ≥10 h).

Bodyweight. The SPAN field staff measured students' height to the nearest 0.1 cm and weight to the nearest 0.1 kg on site. Measurements were taken with shoes and socks off with a digital scale (Tanita BWB-800S) and a stadiometer (Perspective Enterprise Portable Adult/Infant Measuring Unit PE-AIM-101). Interrater reliability was assessed for a 5% sample of the population and showed a strong agreement. BMI percentile and weight status were determined by using the Centers for Disease Control and Prevention (CDC) standard growth charts for children and adolescents: healthy weight (<85th percentile), overweight (85th percentile to <95th percentile), and obese (≥95th percentile) (19).

Covariates. Demographic variables were age, grade (8th or 11th), sex (male or female), and race/ethnicity (white/other, Hispanic, black), which were used in the multistage probability sampling scheme. School-level poverty status was estimated by the proportion of students who were eligible for free or reduced-price lunch at each school (20) and were categorized into tertiles where the highest poverty status was represented by the upper tertile. Physical activity was measured by asking, "During the past 7 days, on how many days were you physically active for a total of at least 60 minutes per day?" Answers were stratified into those who were active for 7 days or less than 7 days during the past week.

Statistical analysis

All analyses were performed by using SAS 9.4 (SAS Institute, Inc) where complex multistage survey design and sampling weights were accounted by using PROC SURVEY procedures. Descriptive statistics examined the distribution of hours of media use, timing of last food intake, sleep hours, and unhealthy eating behavior, stratified by sex. A Rao-Scott χ^2 test was conducted to evaluate the difference between the sexes. Three separate weighted regression analyses were performed to examine separ- ately the associations between categories reflecting hours of me- dia use and the 3 outcomes (unhealthy eating behaviors, timing of last food intake, and hours of sleep). A linear regression model was conducted for unhealthy eating behaviors, and multinomial lo- gistic regression models were conducted for timing of last food in- take and sleep hours. Models Analyses for each of the 3 outcomes were stratified by sex and adjusted for age, race/ethnicity, physic- al activity, and economic disadvantage tertile (model 1). Further- more, additional dependent variables (timing of last food intake, unhealthy eating behavior, and hours of sleep) were added to pro- duce the full model (model 2).

We conducted mediation analyses to separate the dynamic relationship between hours of media use and BMI percentile via timing of last food intake, unhealthy eating behaviors, and hours of sleep (21). All mediation analyses were stratified by sex and were implemented in Mplus Version 7 (Muthén & Muthén).

Results

Most of our sample of 659,288 adolescents were Hispanic/Latino (50.9%), and 59.8% had a healthy BMI (<85th percentile) (Table 1). Overall, 37.2% of adolescents reported nighttime eating (at 10 PM or later), with higher proportions of girls (39.4%) than boys (35.1%; *P* = .30). The percentage of nighttime eating was 20% greater on weekends than on weekdays. With regard to sleep, 58.8% of our sample reported sleeping less than 8 hours per day (62.5% of girls and 55.3% of boys) (*P* = .001) (Table 1).

Among all adolescents in our sample, the SPAN unhealthy eating index increased by 3.87 units (95% CI, 1.38–6.37) for those who used media 6 hours or more per day compared with those who used media 2 hours or less per day (Table 2). This overall association also remained significant in model 2. However, when stratified by sex, only the association for girls in model 1 remained significant (coefficient 3.03; 95% CI, 1.55–4.51).

For timing of last food intake, the odds of nighttime eating (eating last food at 10 PM or later relative to 7 PM or earlier) were 3.16 (95% CI, 1.76–5.66) times higher for adolescents who used media 6 hours or more per day than those who reported 2 hours or less of media use (Table 3). These positive associations for nighttime eating were significant in both sexes.

The odds of sleeping less than 8 hours per day relative to 8 to 9 hours were 1.57 (95% CI, 1.05–2.36) times higher for adolescents who used media more than 6 hours per day compared with those who used media 2 hours or less (Table 4). This association remained significant for boys only. Among boys, the only significant mediation effect (β = 0.017, *P* = .008) between hours of media use and BMI percentile (Table 5) was that of sleep hours. This relationship was also reflected in direct paths from hours of media use to sleep hours (β = −0.03, *P* = .008) and from sleep hours to BMI percentile (β = −3.42, *P* < .001) (Figure 1). The indirect effect of hours of media use via timing of last food intake was also positively associated with unhealthy food intake (β = 0.015, *P* = .05) (Table 5) among boys, with a strong direct pathway from timing of last food intake to unhealthy eating behavior (β = 0.52, *P* = .03) (Figure 1). Among teenage girls, negative mediation effects of timing of last food intake (β = −0.019, *P* = .02) and unhealthy eating behavior (β = −0.016, *P* = .009) were observed between hours of media use and BMI percentile (Table 5). The timing of last food intake and unhealthy eating behavior together acted as a mediator (β = −0.002, *P* = .03) between media use and BMI percentile. Hours of media use were negatively associated with BMI percentile via timing of last food intake and unhealthy eating behavior among girls (Table 5). This relationship was also reflected in direct pathways from timing of last food intake to BMI percentile (β = −2.04, *P* = .002) and from unhealthy eating behaviors to BMI percentile (β = −0.36, *P* = .004) (Figure 2). However, hours of media use were positively associated with unhealthy eating behavior via timing of last food intake (β = 0.024, *P* = .002), which means that as hours of media use increased, timing of last food intake played a significant role in increasing unhealthy food intake (Table 5).

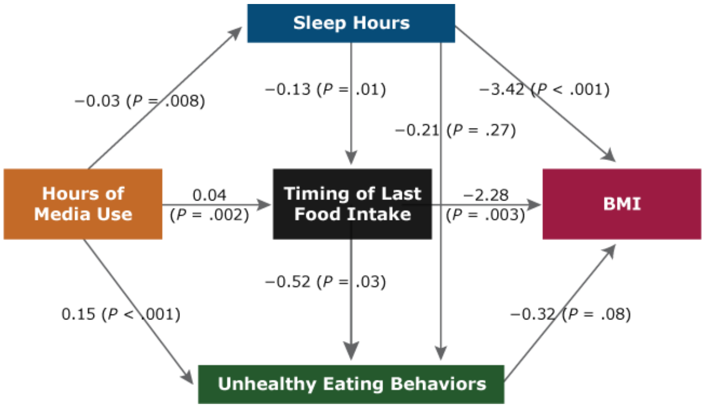

Figure 1. Mediation model examining the association between hours of media use and body mass index (BMI) percentile among adolescent males (8th and 11th grade students) in Texas, 2015–2016. Data are from the 2015–2016 School Physical Activity and Nutrition Survey (32).

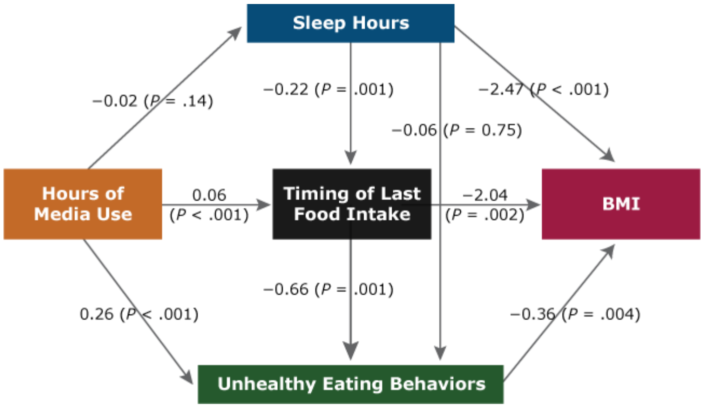

Figure 2. Mediation model examining the association between hours of media use with body mass index (BMI) percentile among adolescent girls (8th and 11th grade students) in Texas, 2015–2016. Data are from the 2015–2016 School Physical Activity and Nutrition Survey (32).

Discussion

We evaluated the distribution of hours of media use and its association with timing of last food intake, sleep hours, and unhealthy eating behavior in a representative sample of 8th and 11th grade Texas adolescents. According to the Kaiser Family Foundation, children and adolescents aged 8 to 18 years spend an average of 7.5 hours per day using media, which totals 114 full days of media use in a year (22). In our study population, 88.7% of adolescents reported media use for 3 or more hours per day, which was higher than the percentage in the 2017 YRBSS report for 3 hours or more per day of television viewing (20.7%) and video games or computer use (43.0%) (3).

Overall, hours of media use were positively associated with unhealthy eating behaviors, nighttime eating, and inadequate sleep. The association between hours of media use and increased consumption of fast foods, snacks, and sugary drinks in adolescents was well established in previous studies (23,24). Moreover, media use is known to be a distracting activity that suppresses sensations of satiety and fullness when eating (25). Eating is often accompanied by media use, especially at night. Media use can also mimic the gratifying aspects of food as a way to mitigate negative emotions (26).

Hours of sleep are another concern. A growing body of literature indicates that the prevalence of inadequate sleep (<8 hours per night) was high among adolescents who used media devices (3,27). These results were also confirmed in our sample; the odds of having inadequate sleep were higher for those who used media more than 6 hours per day than those who used it 2 hours or less. In a systematic review, Gradisar suggested several mechanisms by which media use may affect sleep duration and quality: 1) media use may shorten sleep hours; 2) media use before sleep may trigger emotional, mental, or physiological alertness; and 3) light emission from the screen may interfere with sleep (28).

In our study, sleep hours were inversely associated with BMI percentile for both sexes. Accumulating evidence from laboratory and epidemiologic studies supports the premise that inadequate sleep duration and poor sleep quality are risk factors for develoPMent of obesity (5,6). Spiegel and colleagues showed alterations of hormone levels in healthy young men (ie, decrease in leptin levels and increase in ghrelin levels) and increased reports of hunger and appetite after sleep restriction (5). Moreover, mediation analyses revealed that sleep hours functioned as a significant mediator between hours of media use and BMI percentile in boys. In girls, hours of media use were negatively associated with BMI percentile via timing of last food intake and unhealthy eating behavior. This result was contrary to previous studies where a significant longitudinal correspondence between time spent on media use and increased body fat was observed from childhood to adolescence (29). However, in cross-sectional studies, the results were somewhat mixed: some reported no evidence of a significant association between use of media and BMI (24,29), and others reported that media use appeared to be positively associated with BMI for girls only (29,30). Taken together, these inconsistent results further suggest the need for more prospective longitudinal studies to evaluate the effect of media use, timing of last food intake, sleep hours, and unhealthy eating behavior on BMI.

Our study has strengths and limitations. SPAN was a cross-sectional survey with multistage probability sampling, which enabled us to generalize the results to Texas adolescents. Because of the sampling procedure, its results cannot be extended to other adolescent populations. However, because the SPAN sample is racially/ethnically diverse, the patterns observed in Texas may be used to forecast future national trends in adolescents. Nonetheless, temporality of exposure and outcome cannot be determined because of the cross-sectional study design. Hours of media use include computer use for schoolwork and represent overall media use rather than media use for leisure alone. Although we took the anthropometric measurements in our study, all other variables were self-reported and therefore subject to recall and social desirability bias. Previous studies have shown that people who are overweight or obese tend to overreport socially accepted behavior (ie, eating healthier or less food) than those with normal bodyweight (31). To measure eating behavior precisely, portion size and frequency of eating would need to be assessed.

Our study extended earlier work by investigating pathways between media use and BMI in an adolescent population. Results indicated that long hours of media use were associated with unhealthy eating behavior at nighttime; thus, the incidence of overweight and obesity may escalate in the near future in adolescents who engage in excessive media use. Therefore, it is crucial to evaluate interventions that focus on decreasing adolescents' media use to prevent overweight and obesity and other related chronic health conditions. Strategies to decrease media use can include parental limits and school-wide guidelines for appropriate media use.

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Tables

Table 1. Demographic Characteristics of Respondents, Study of Effect of Media Use on Body Weight Among Adolescents, Texas 2015–2016[a,b]

Variable	All	Boys	Girls	*P* Value[c]
Unweighted sample size, no.	9,056	4,555	4,501	NA
Weighted sample size, no.	659,288	336,613	322,675	
Sex, % (CI)	NA	51.1 (46.9–55.2)	48.9 (44.8–53.1)	.60
School grade				
8th	52.7 (39.9–65.6)	53.1 (39.3–67.0)	52.3 (39.1–65.5)	.90
11th	47.3 (34.4–60.1)	46.9 (33.0–60.7)	47.7 (34.5–60.9)	
Age, mean (SD)	15.0 (0.2)	15.0 (0.2)	14.9 (0.2)	.80
Race/ethnicity				
Black	12.5 (8.0–17.1)	12.5 (7.8–17.2)	12.5 (7.4–17.7)	>.99
Hispanic	50.9 (43.1–58.8)	50.9 (42.0–59.7)	51.0 (42.8–59.2)	
White/other	36.6 (28.1–45.0)	36.6 (26.8–46.4)	36.5 (28.2–44.8)	
Economic disadvantage tertiles[d]				
Lowest	46.5 (34.0–59.0)	47.9 (34.3–61.4)	45.1 (32.5–57.7)	.60
Middle	29.6 (20.2–39.1)	29.7 (19.1–40.3)	29.5 (20.0–39.1)	
Upper	23.9 (12.1–35.6)	22.4 (11.3–33.6)	25.4 (12.5–38.2)	
Body mass index[e]				
Healthy weight	59.8 (56.8–62.8)	57.7 (52.6–62.9)	62.0 (58.5–65.4)	.01
Overweight	17.9 (15.8–20.0)	16.7 (13.1–20.2)	19.2 (16.7–21.7)	
Obese	22.3 (19.3–25.2)	25.6 (21.3–29.9)	18.8 (16.4–21.2)	
Timing of last food intake, mean of weekdays and weekends				
Before 7 PM	12.3 (8.7–15.8)	13.4 (7.7–19.1)	11.2 (8.3–14.0)	.30
Between 7 PM and 10 PM	50.5 (47.1–53.9)	51.5 (46.5–56.5)	49.4 (45.3–53.5)	
10 PM or later	37.2 (34.2–40.3)	35.1 (31.1–39.1)	39.4 (36.0–42.9)	
Timing of last food intake, weekdays only				
Before 7 PM	17.3 (13.7–20.9)	18.3 (12.4–24.2)	16.2 (13.3–19.2)	.04
Between 7 PM and 10 PM	50.1 (46.3–53.9)	53.0 (48.0–58.0)	47.2 (42.6–51.7)	
10 PM or later	32.6 (29.9–35.3)	28.7 (25.3–32.1)	36.6 (32.9–40.3)	
Timing of last food intake, weekends only				
Before 7 PM	11.1 (7.9–14.3)	13.3 (7.6–19.1)	8.8 (6.8–10.9)	.03
7 PM–10 PM	35.9 (32.6–39.1)	37.5 (32.5–42.5)	34.2 (30.8–37.5)	
10 PM or later	53.0 (49.7–56.3)	49.2 (44.7–53.7)	57.0 (53.3–60.7)	

Abbreviations: CI, confidence interval; NA, not applicable; SD, standard deviation.

[a] Data are from the School Physical Activity and Nutrition Survey, 2015–2016 (32).

[b] Values are weighted percentage (95% CI) unless otherwise indicated.

[c] Rao-Scott χ^2 test was used to calculated *P* values.

[d] Economic status data were obtained from the Texas Education Agency (20).

[e] CDC standard growth charts for children and adolescents. (https://www.cdc.gov/healthyweight/bmi/calculator.html) were used to classify BMI categories (healthy weight, <85th percentile; overweight, 85th–95th percentile; obese, ≥95th percentile).

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Table 1. Demographic Characteristics of Respondents, Study of Effect of Media Use on Body Weight Among Adolescents, Texas 2015–2016[a,b]

Variable	All	Boys	Girls	*P* Value[c]
Hours of sleep, mean (SD)	7.0 (0.2)	7.1 (0.2)	6.9 (0.2)	.91
<8	58.8 (54.7–63.0)	55.3 (49.9–60.7)	62.5 (58.7–66.4)	.001
8–9	37.8 (34.0–41.5)	41.9 (36.8–47.0)	33.5 (30.1–36.8)	
≥10	3.4 (2.2–4.5)	2.8 (1.5–4.1)	4.0 (2.4–5.6)	
Hours of media use				
≤2	11.3 (9.6–13.0)	9.7 (7.6–11.8)	13.0 (10.9–15.0)	.10
3–5	26.2 (22.5–29.9)	28.3 (22.6–34.0)	24.0 (20.0–28.1)	
≥6	62.5 (58.4–66.6)	62.0 (55.9–68.2)	63.0 (58.7–67.3)	
Unhealthy eating behavior, tertile, mean (SD)	50.9 (0.2)	50.4 (0.3)	51.4 (0.2)	.90
Lowest	33.0 (29.7–36.4)	35.3 (31.5–39.1)	30.6 (26.6–34.7)	.006
Middle	41.1 (36.5–45.7)	42.1 (37.1–47.1)	40.1 (35.0–45.2)	
Upper	25.9 (23.1–28.6)	22.6 (18.8–26.3)	29.3 (25.9–32.6)	
Reported days of physical activity				
≥7	22.5 (20.5–24.4)	31.3 (27.5–35.0)	13.4 (10.9–15.9)	<.001
<7	77.5 (75.6–79.5)	68.7 (65.0–72.5)	86.6 (84.1–89.1)	

Abbreviations: CI, confidence interval; NA, not applicable; SD, standard deviation.

[a] Data are from the School Physical Activity and Nutrition Survey, 2015–2016 (32).

[b] Values are weighted percentage (95% CI) unless otherwise indicated.

[c] Rao-Scott χ^2 test was used to calculated *P* values.

[d] Economic status data were obtained from the Texas Education Agency (20).

[e] CDC standard growth charts for children and adolescents. (https://www.cdc.gov/healthyweight/bmi/calculator.html) were used to classify BMI categories (healthy weight, <85th percentile; overweight, 85th–95th percentile; obese, ≥95th percentile).

Table 2. Weighted Regression Models, Unhealthy Eating Behavior, Study of Effect of Media Use on Body Weight Among Adolescents[a], Texas 2015–2016[b]

Hours of Media Use	Coefficient (95% Confidence Interval)		
	All	Boys	Girls
Model 1[c]			
≤2	0	0	0
3–5	0.28 (−2.19 to 2.74)	−0.63 (−2.43 to 1.17)	0.21 (−1.04 to 1.45)
≥6	3.87 (1.38 to 6.37)	1.22 (−0.15 to 2.58)	3.03 (1.55 to 4.51)
Model 2[d]			
≤2	0	0	0
3–5	−0.41 (−3.00 to 2.17)	−0.79 (−2.51 to 0.93)	−0.20 (−1.32 to 0.93)
≥6	2.73 (0.45 to 5.01)	0.93 (−0.40 to 2.26)	2.35 (0.95 to 3.75)

[a] Weighted number, 659,288; unweighted number, 9,056.
[b] Data are from the School Physical Activity and Nutrition (SPAN) Survey, 2015–2016 (32).
[c] Model 1: Adjusted for age, race/ethnicity, physical activity, and economic disadvantage tertiles.
[d] Model 2: Adjusted for variables in model 1 plus timing of last food intake and sleep hours.

Table 3. Weighted Regression Models, Timing of Last Food Intake[a], Study of Effect of Media Use on Body Weight Among Adolescents[b], Texas 2015–2016[c]

	Odds Ratio (95% CI)								
	All			Boys			Girls		
Hours of Media Use	Before 7 PM	7 PM–10 PM	10 PM or later	Before 7 PM	7 PM–10 PM	10 PM or later	Before 7 PM	7 PM–10 PM	10 PM or later
Model 1[d]									
≤2	1 [Reference]								
3–5	1 [Reference]	1.84 (1.14–2.96)	2.16 (1.25–3.70)	1 [Reference]	1.96 (1.07–3.60)	2.73 (1.25–5.96)	1 [Reference]	1.77 (0.76–4.12)	1.92 (0.70–5.28)
≥ 6	1 [Reference]	1.32 (0.74–2.37)	3.16 (1.76–5.66)	1.00[e]	1.34 (0.68–2.61)	3.50 (1.61–7.61)	1 [Reference]	1.44 (0.66–3.13)	3.33 (1.66–6.66)
Model 2[e]									
≤2	1 [Reference]								
3–5	1 [Reference]	1.92 (1.11–3.31)	2.20 (1.27–4.15)	1 [Reference]	2.01 (1.05–3.81)	2.76 (1.26–6.02)	1 [Reference]	1.79 (0.82–3.89)	1.89 (0.73–4.93)
≥ 6	1 [Reference]	1.29 (0.70–2.39)	2.66 (1.51–4.69)	1 [Reference]	1.44 (0.64–3.22)	3.03 (1.40–7.78)	1 [Reference]	1.38 (0.68–2.84)	2.78 (1.52–5.10)

[a] Weighted number, 659,288; unweighted number, 9,056.
[b] Mean of weekdays and weekends.
[c] Data are from the School Physical Activity and Nutrition (SPAN) survey, 2015–2016 (32).
[d] Model 1: Adjusted for age, race/ethnicity, physical activity, and economic disadvantage tertiles.
[e] Model 2: Adjusted for variables in model 1 plus unhealthy eating behavior and sleep hours.

Table 4. Weighted Regression Models, Hours of Sleep, Study of Effect of Media Use on the Timing of Last Food Intake and Body Weight Among Adolescents[a], Texas 2015–2016[b]

Hours of Media Use	Hours, Odds Ratio (95% Confidence Interval)								
	All			Boys			Girls		
	<8	8–9	≥10	<8	8–9	≥10	<8	8–9	≥10
Model 1[c]									
≤2	1 [Reference]								
3–5	1.32 (0.86–2.02)	1 [Reference]	0.42 (0.20–0.90)	1.49 (0.85–2.61)	1 [Reference]	0.55 (0.12–2.60)	1.17 (0.74–1.86)	1 [Reference]	0.33 (0.09–1.24)
≥6	1.57 (1.05–2.36)	1 [Reference]	0.51 (0.22–1.14)	1.90 (1.27–2.84)	1 [Reference]	0.57 (0.23–1.46)	1.30 (0.77–2.21)	1 [Reference]	0.48 (0.14–1.61)
Model 2[d]									
≤2	1 [Reference]								
3–5	1.29 (0.82–2.03)	1 [Reference]	0.41 (0.21–0.81)	1.42 (0.77–2.62)	1 [Reference]	0.44 (0.13–1.54)	1.16 (0.73–1.84)	1 [Reference]	0.37 (0.11–1.18)
≥ 6	1.44 (0.93–2.24)	1 [Reference]	0.55 (0.28–1.09)	1.73 (1.11–2.67)	1 [Reference]	0.56 (0.22–1.42)	1.18 (0.67–2.10)	1 [Reference]	0.53 (0.20–1.43)

[a] Weighted number, 659,288; unweighted number, 9,056.
[b] Data are from the School Physical Activity and Nutrition Survey, 2015–2016 (32).
[c] Model 1: Adjusted for age, race/ethnicity, physical activity, and economic disadvantage tertiles.
[d] Model 2: Adjusted for variables in model 1 plus unhealthy eating behavior and timing of last food intake.

Table 5. Indirect Paths in Mediation Model, by Sex[a], Study of Effect of Media Use on Body Weight Among Adolescents[b], Texas 2015–2016[c]

Hours of Media Use	Body Mass Index Percentile, β (*P*)				Unhealthy Eating Behavior, β (*P*)
	(via) Timing of Last Food Intake	(via) Unhealthy Eating Behavior	(via) Sleep Hours	(via) Timing of Last Food Intake and Unhealthy Eating Behavior	(via) Timing of Last Food Intake
Boys	—[d]	—[d]	0.017 (.008)	—[d]	0.015 (.05)
Girls	−0.019 (.02)	−0.016 (.009)	—[d]	−0.002 (.03)	0.024 (.002)

[a] Weighted number, 659,288; unweighted number, 9,056.
[b] All results are weighted and adjusted for age, race/ethnicity, physical activity, and economic disadvantage tertiles.
[c] Data are from the School Physical Activity and Nutrition Survey, 2015–2016 (32).
[d] Not significant.

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ORIGINAL RESEARCH

Association Between Individual and Intimate Partner Factors and Cervical Cancer Screening in Kenya

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PEER REVIEWED

Abstract

Introduction
Cervical cancer is the most prevalent cancer among women in Kenya. Although cervical cancer screening could reduce illness and death, screening rates remain low. Kenyan women's individual characteristics and intimate partner factors may be associated with cervical cancer screening; however, a lack of nationally representative data has precluded study until recently. The objective of our study was to examine individual and intimate partner factors associated with cervical cancer screening in Kenya.

Methods
We conducted secondary data analysis of responses by women who completed the cervical cancer screening and domestic violence questions in the Kenya Demographic and Health Survey, 2014 (N = 3,222). By using multivariable regression analyses, we calculated the association of cervical cancer screening with age, religion, education, wealth, recent exposure to family planning on television, head of household's sex, and experience of intimate partner violence.

Results
Rates of cervical cancer screening among women in Kenya increased with age. The wealthiest women and women with post-secondary education had greater odds of reporting being screened for cervical cancer than the poorest women and uneducated women. Christians and women exposed to prevention messaging on television had higher odds of screening than Muslims and women with no exposure. Victims of intimate partner violence had lower odds of being screened than women who had not experienced intimate partner violence.

Conclusion
Identified barriers to screening in this sample mirror previous findings, though with additional nuances. Model fit data and theoretical review suggest that additional, unmeasured variables may contribute to variability in cervical cancer screening rates. Inclusion of additional variables specific to cervical cancer in future national surveys could strengthen the ability to identify factors associated with screening.

Introduction

Cervical cancer is the most prevalent cancer among women in Kenya (1). The World Health Organization (WHO) calls for early detection and treatment of precancerous lesions to prevent cervical cancer and reduce disease-related illness and death (2). However, the effectiveness of cervical cancer screening in reducing population-level cervical cancer rates depends on access and uptake, quality of screening, adequacy of follow-up, and diagnosis and treatment (3). WHO notes that low- and middle-income countries struggle to implement early detection programs (2), often because of obstacles such as poverty, lack of information and knowledge, and health care infrastructure (4).

Available options for cervical cancer screening in Kenya are Papanicolaou testing and visual inspection of the cervix with acetic acid followed by visual inspection with Lugol's iodine. The Loop Electrosurgical Excision Procedure for removal of abnormal or cancerous cervical cells is available at some national and district hospitals (5). Kenyan national guidelines recommend screening women aged 25 to 49 and women younger than 25 who are at high risk for cervical cancer (6). However, despite the availability of screening options and national efforts to increase screening, use of cervical cancer screening services remains low in Kenya, with the lowest rates among rural women and those belonging to nomadic livestock-herding tribes (7–9). Concurrently, Kenya has experienced an increase in cervical cancer cases, from 2,454 in 2012 to 4,802 (crude incidence rate = 22.4) in 2016. An estimated 4,100 Kenyan women are expected to develop cervical cancer, and an estimated 3,300 will die from the disease by 2025 if prevention efforts are not increased (1).

Studies undertaken in sub-Saharan Africa showed that cervical cancer screening uptake is a complex issue associated with multiple individual and interpersonal factors (10). Individual factors include age, education level, access and affordability (including transportation to cervical cancer screening facilities), attitude toward personal health, and fear of a cervical cancer diagnosis (11,12). Previous studies also suggested a positive association between women's autonomy and cervical cancer screening, but the relationship is indirect. Women's autonomy is associated with individual factors such as education, income, control over household finances, knowledge of the signs and symptoms of cervical cancer, and intimate partner agency, such as communication between partners and freedom from threat of intimate partner violence (2,13). Some studies in sub-Saharan Africa also examined religious affiliation as it relates to women's autonomy and health care decision making and access (14). In these countries, a complex interplay of individual and intimate partner factors, along with organizational factors such as infrastructure and technical, human, and health care resources, are necessary to sustain effective cervical cancer screening programs (15).

Concomitant with studies in sub-Saharan Africa, studies exploring factors associated with the uptake of cervical cancer screening in Kenya showed that women's perceived susceptibility to cervical cancer increased their tendency to be screened for the disease (10,12). However, these studies were mostly conducted in selected health care facilities or in counties and did not use a national data set. To supplement this knowledge base, this study used a nationally representative Kenyan data set to examine the association between cervical cancer screening and selected individual and intimate partner factors identified by previous research that have both theoretical and research-driven linkages to women's autonomy and to cervical cancer screening uptake.

Methods

Sampling

Data were from the Kenya Demographic Health Survey (KDHS), 2014, which was administered from May 2014 through October 2014 by the Kenya National Bureau of Statistics (KNBS) in partnership with numerous national and international agencies and foundations. This was the sixth and most recent demographic health survey conducted in Kenya since 1989. It was the first to provide representative data for all 47 Kenyan counties and national and regional findings and was also the first to include specific questions about cervical cancer screening (16). The sample for the 2014 KDHS consisted of 5,360 clusters split into 4 equal subsamples and was drawn by using stratified probability proportional to size sampling from a master sampling frame developed by KNBS. Data for our study were drawn from the full women's survey, which was administered to women aged 15 to 49 (N = 14,741). Of those women, 70.1% (n = 10,333) had ever heard of cervical cancer and responded to the question about whether they had been screened for cervical cancer. Separately, 38.5% (n = 5,672) of the full women's sample were selected to take the domestic violence module; 15 women were excluded a priori because they either could not be interviewed for privacy or other unspecified reasons. Because the study's purpose was to examine the association between cervical cancer screening and individual and intimate partner variables, our sample included women who had been in a union (ie, reported being married or living with a partner or widowed, divorced, or separated), responded to the cervical cancer screening questions (ie, were part of the 10,333-woman subsample), and completed the domestic violence module (ie, were part of the 5,672-woman subsample) for a final sample of 3,222 women. Additional details about the survey are available (16) (Figure).

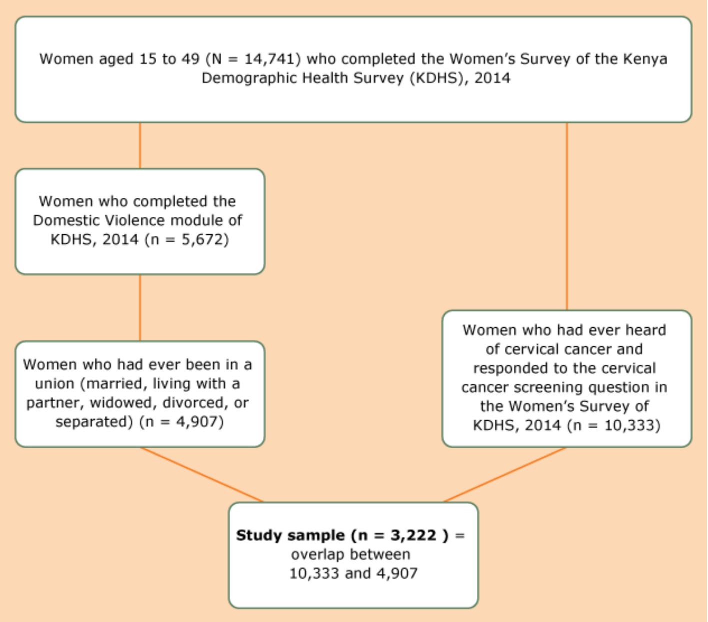

Figure. Study sample of women selected from the Kenya Demographic Health Survey, 2014, to analyze the association between cervical cancer screening and women's individual characteristics and intimate partner factors.

Some women selected to complete the domestic violence module who were currently or had previously been in a union were ineligible for the study sample because they either 1) had not heard of cervical cancer or 2) were not sure whether they had heard of it and thus, because of the survey structure, could not indicate whether they had received screening. To investigate how women having no knowledge of cervical cancer might affect sample selection, researchers ran a preliminary logistic regression with having heard of cervical cancer as the outcome variable (1 = no/unsure, 2 = yes). The Hosmer–Lemeshow test was used to test for goodness of fit for the logistic regression models. All preparatory analyses indicated appropriate model fit and nonviolation of statistical assumptions.

Measures

The outcome variable, screening for cervical cancer, was binary (1 = reported ever having been screened, 0 = reported never having been screened). Some independent variables were selected on the basis of our literature review, including age, religion, education, wealth quintile, and sex of the head of household. Others were chosen because of similarity with theoretical covariates that were not captured in KDHS (for example, exposure to family planning on television is within the same conceptual domain as general knowledge about cervical cancer, though less precise; intimate partner violence is a component of interpartner agency). However, some variables identified in previous research were not measured in the recent KDHS (7), including attitude toward personal health and fear of cervical cancer, though potentially related to cervical cancer screening.

Age was measured as a continuous variable within the allowable range for participants (15–49). Religion was measured as a categorical variable with 4 possible choices (0 = Roman Catholic, 1 = Protestant/other Christian, 2 = Muslim, 3 = no religion), and education was measured as a categorical variable with 6 possible choices (0 = no education, 1 = incomplete primary, 2 = complete primary, 3 = incomplete secondary, 4 = complete secondary, 5 = higher). In Kenya, primary education encompasses the first 8 years, and secondary is the next 4 years (equivalent to US high school). Wealth index was captured as a categorical variable with 5 quintiles calculated by KDHS (0 = poorest, 1 = poor, 2 = middle, 3 = richer, 4 = richest). Sex of the head of household was a binary variable (1 = male, 2 = female), as was having heard of family planning on television in the last few months (0 = no, 1 = yes).

Being subjected to intimate partner violence was constructed as a dummy variable (0 = no intimate partner violence, 1 = any intimate partner violence) on the basis of responses to questions modified from the Conflict Tactics Scale (CTS): "Did your husband/partner ever do any of the following things to you," with 10 item choices, such as "slap you and punch you with his fist or something that could hurt you." Information about question wording and location within the survey instrument is available in the KDHS survey monograph (16).

Statistical analysis

All statistical analyses were completed with SPSS version 24 (IBM Corp). All categorical independent variables (religion, education, wealth, exposure to family planning on television, sex of head of household, and intimate partner violence) were analyzed by using Wald χ^2 tests of independence to determine associations with cervical cancer screening for inclusion in the regression model. A model was used to assess the association, expressed as adjusted odds ratios (AORs), between the dependent variable — cervical cancer screening — and the 6 independent variables (age, religion, education, wealth, exposure to family planning on television, and intimate partner violence). All but one bivariate test was significant (critical $\alpha = 0.05$, Bonferroni's adjusted $\alpha = 0.008$). Thus, all the selected variables except sex of head of household ($P = .98$) were included in the multivariable logistic regression model to compute AORs. Age, the only continuous independent variable, was tested in a single-variable logistic regression model to calculate an unadjusted odds ratio. Age was significant, so it was also included in the final model.

The independent variables were tested for multicollinearity before analysis, and no problematic patterns emerged (all tolerance values were >0.20). The single noncategorical variable, age, was normally distributed, with no univariate outliers and no skewness or kurtosis values exceeding an absolute value of 1.

Results

Our first analysis, designed to identify characteristics of women included in the sample, was not the primary purpose of the study. In brief, we found that the odds of having heard of cervical cancer (and thus being eligible for study inclusion) increased substantially with each new level of educational attainment relative to no education, whereas all other variables and levels, excepting Roman Catholic religion and intimate partner violence, had modest but significant association with knowledge of cervical cancer. In the sample of 3,222 women who were eligible for our study, 18.2% reported having received cervical cancer screening (Table 1). The mean age of women who reported being screened was 33.8, compared with 31.8 for those who reported not being screened. Among those screened, nearly all women (97.3%) self-identified as some variant of Christianity, whereas those who reported not having been screened were more religiously heterogeneous (89.9% Christian). Among those screened, most women (52.8%) had at least some primary school education, about a third belonged to the richest wealth quintile (30.5%), and more than half (54.3%) were exposed to family planning messaging on television. In addition, 31.9% of women who reported being screened for cervical cancer reported intimate partner violence, whereas 38.6% of women who reported never having been screened reported intimate partner violence.

The model used in our study to assess the association, expressed as AORs, between the dependent variable – cervical cancer screening – and the 6 independent variables (age, religion, education, wealth, exposure to family planning on television, and intimate partner violence) was a significant, modest improvement over the constant-only model ($\chi^2 = 193.34$, $P < .001$; −2LL improved from 3,058.91 to 2,864.77). The Hosmer and Lemeshow Test was nonsignificant, indicating a likelihood of good model fit.

Each additional year of age increased the odds of being screened for cervical cancer by 1.04 relative to the previous year of age ($P <$ .001) (Table 2). Muslim women had 5 times lower odds than Protestants or other Christians of having been screened ($P < .001$). Women who reported an education level higher than secondary had 1.93 times greater odds than women who reported no education of having been screened for cervical cancer ($P = .04$). In addition, women who were in the top 2 wealth quintiles (richer and richest) had significantly greater odds of having been screened for cervical cancer than women in the lowest wealth quintile (poorest), 1.95 times ($P = .001$) for richer, and 2.53 times ($P <$ .001) for richest. Women who reported having heard family planning messaging on television within the past few months had 1.34 times greater odds of having been screened than those who had not ($P = .01$). Finally, women who experienced at least one type of intimate partner violence had 1.28 times lower odds (the reciprocal of AOR .78) of having been screened for cervical cancer than women who had not experienced intimate partner violence ($P <$.001).

Discussion

Ours is one of the few studies in Africa and the first in Kenya to use national data to examine the association between women's individual characteristics and those of their intimate partner relationships and cervical cancer screening. Although our study showed that a low percentage of Kenyan women, 18%, were being screened for cervical cancer, screening rates appear to be increasing. A 2003 study found that only 3.5% of Kenyan women had been screened for cervical cancer (8). Nevertheless, the increase in screening rates remained much lower than the national target of 75% by the year 2009 (4).

Our findings mirror other studies in developing countries reporting that older age is associated with increased odds of being screened for cervical cancer (2,17). This could be a function of increased sensitization through prevention messaging over a period of time. However, lower uptake of cervical screening among young women is a matter of concern because screening has the greatest impact when initiated early (3).

Our study found a strong relationship between religious affiliation and cervical cancer screening, mirroring work from Nigeria that reported that use of antenatal services was more likely among Christian women than among their Muslim counterparts (18). However, the relationship between an individual's religion, religiosity, and sexual and contraception behaviors is nuanced and merits further investigation (14,15). Studies of cervical cancer screening among Muslim women demonstrated that screening practices were perceived as incompatible with cultural and religious values (19), such as cancer being a function of God's will (20). These studies suggest that religious coping may function as an extension of prevailing gender constructs in these countries, which are patriarchal, and where talking about female genitalia and sexuality is taboo (21).

The association between formal education and cervical cancer screening was not significant among women with no education until reaching a threshold of an education level higher than secondary education, at which point education was associated with higher odds of reported screening. This finding is conceptually similar to results from a study conducted in India (22). The directionality in this area has not been universal, however. One study in India suggested that women's autonomy and prevention decision making were not related to education level (23). The association between wealth quintile and cervical cancer screening is likewise unsurprising; prior research in Mexico showed wealth quintile to be one of the most consistent determinants of cervical cancer screening (24). In our study, the association was strong, but only significant for the top 2 wealth quintiles relative to the lowest. Given acute poverty in the arid and semi-arid parts of Kenya and prevailing patriarchal norms, women have inequitable access to economic assets (16). Thus, even when screening is provided free of cost by the Kenyan Government, out-of-pocket expenses to reach the facility for screening and associated loss of wages may present barriers to access even for those of moderate means (25). Research in Ethiopia examined a similar relationship in the context of patriarchal norms and found that women were reluctant to ask for payment for cervical cancer screening expenses from their husbands or partners (26).

Although our study suggested a positive association between exposure to family planning messaging on television and cervical cancer screening, the mechanism of this relationship cannot be determined given the available data; viewing family planning messages on television has multiple possible moderating and mediating effects, such as access to television (independent of the type of messaging) (27) and the quality of the family planning content. To provide more data, a question specific to receipt of cervical cancer information could be included in future iterations of KDHS.

Finally, in our study, experiencing intimate partner violence was associated, to a moderate degree, with decreased odds of having been screened for cervical cancer. However, because ours was a cross-sectional study, directionality could not be assumed. This, too, is consistent with previous research that demonstrated that control imposed by an abusive partner and the associated limited access to financial support can restrict women's ability to seek cervical cancer services (28). The same study also found that seeking cervical cancer screening is often perceived by the husband or partner as a consequence of adultery, resulting in intimate partner violence. In our study, however, the association between intimate partner violence and screening was moderate relative to the magnitude of other associations, especially religious affiliation. Given the sensitive nature of this topic, the degree to which survey participants accurately reported their experiences of intimate partner violence is uncertain. Intimate partner violence is socially stigmatized, and women may be concerned that reporting intimate partner violence might increase the risk of additional violence from an intimate partner. The relationship between these variables is also unlikely to be unidimensional and may include other psychosocial factors such as stress, social support, self-esteem (29), and diverse variations in concepts of family and of women's autonomy.

Our study had limitations. First, as a cross sectional study, it was not possible to assess causality. In addition, the overall multivariable logistic regression model met tests of model goodness-of-fit and improved on the constant-only model by a modest amount. Although these variables were important to understanding cervical cancer screening among the study population, they did not represent the totality of variance within that behavior. The model did not control for multiple residual confounding variables, because data were not available from KDHS. A survey more directly targeting cervical cancer may facilitate more robust model fit. Also, as noted in Methods, the ability to respond to the question about cervical cancer screening was not randomly distributed among women. Finally, using only intimate partner violence indicators for intimate partner relations might not have captured the complex gender relations that influenced cervical cancer screening behaviors and might have provided biased estimates of the affect that autonomy has on preventive health care (30).

The low rate of cervical cancer screening in Kenya represents a significant preventable health burden for women. The results of our study suggest that, despite low cervical cancer screening rates, Kenyan women's barriers to screening mirror those found in other national and local studies, with some additional nuances (eg, the lack of association between moderate income increases and screening). These findings reinforce specific issues that might be addressed to advance cervical cancer screening (eg, the impact of post-secondary education on screening) as well as some broader conceptual issues that might facilitate health care improvement, such as facilitating responses to sensitive intimate partner–related questions. We recommend including additional cervical cancer–specific questions in future national surveys.

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Tables

Table 1. Screening for Cervical Cancer Among Kenyan Women Aged 15 to 49 Currently or Previously in a Marriage or Domestic Partnership (N = 3,222), Kenya Demographic Health Survey, 2014

Characteristic	Screened for Cervical Cancer, n (%)	Not Screened for Cervical Cancer, n (%)	χ^{2a}	*P* Value
Total sample[b]	587 (18.2)	2,635 (81.8)	—	—
Individual Factors				
Age, y, mean (standard deviation)	33.81 (7.9)	31.76 (7.8)	—	—
Religion				
Protestant or other Christian	423 (72.1)	1,834 (69.6)	38.15	<.001
Roman Catholic	148 (25.2)	535 (20.3)		
Muslim	9 (1.5)	221 (8.4)		
No religion	7 (1.2)	44 (1.7)		
Education				
No education	16 (2.7)	195 (7.4)	66.86	<.001
Incomplete primary	134 (22.8)	767 (29.1)		
Complete primary	176 (30.0)	795 (30.2)		
Incomplete secondary	76 (12.9)	314 (11.9)		
Complete secondary	90 (15.3)	373 (14.2)		
Higher	95 (16.2)	191 (7.2)		
Sex of household head				
Male	386 (65.8)	1,734 (65.8)	0.00	.98
Female	201 (34.2)	901 (34.2)		
Wealth index[c]				
Poorest	49 (8.3)	478 (18.1)	94.40	<.001
Poor	101 (17.2)	618 (23.5)		
Middle	102 (17.4)	545 (20.7)		
Richer	156 (26.6)	558 (21.2)		
Richest	179 (30.5)	436 (16.5)		
Heard of family planning on television in the last few months				
Yes	319 (54.3)	998 (37.9)	53.8	<.001
No	268 (45.7)	1,636 (62.1)		
Intimate Partner				
Experienced intimate partner violence by husband/partner				
Yes	187 (31.9)	1,017 (38.6)	9.32	.002
No	400 (68.1)	1,618 (61.4)		

Abbreviation: —, not applicable.

[a] Results of χ^2 test.

[b] Values are number (percentage) unless otherwise indicated.

[c] The wealth index in the Kenya Demographic Health Survey is constructed by using household asset data collected in the survey's Household Questionnaire.

Table 2. Multivariable Logistic Regression Analysis of Women's Individual and Intimate Partner Measures and Cervical Cancer Screening Among Kenyan Women Aged 15 to 49 (N = 3,222), Kenya Demographic Health Survey, 2014

Variable	Adjusted Odds Ratio (95% Confidence Interval)	β	*P* Value
Individual			
Age, y[a]	1.04 (1.03–1.05)	0.04	<.001
Religion[a]			
Protestant or other Christian	Reference		
Roman Catholic	1.22 (0.98–1.51)	0.20	.08
Muslim[a]	0.20 (0.10–0.40)	−1.62	<.001
No religion	0.98 (0.43–2.24)	−0.25	.95
Education			
No education	Reference		
Incomplete primary	1.42 (0.80–2.51)	0.35	.23
Complete primary	1.40 (0.79–2.48)	0.33	.26
Incomplete secondary	1.40 (0.76–2.58)	0.33	.29
Complete secondary	1.17 (0.64–2.16)	0.16	.61
Higher education[a]	1.93 (1.03–3.64)	0.66	.04
Wealth index			
Poorest	Reference		
Poor	1.32 (0.90–1.92)	0.27	.15
Middle	1.42 (0.97–2.08)	0.35	.07
Richer[a]	1.95 (1.34–2.86)	0.67	.001
Richest[a]	2.53 (1.67–3.84)	0.93	<.001
Heard of family planning on television, last few months[a,b]	1.34 (1.07–1.68)	0.29	.01
Intimate Partner			
Intimate partner violence[a]	0.78 (0.64–0.95)	−0.25	<.001

[a] Indicates significance at $P < .05$.
[b] Reference answer was no.

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ORIGINAL RESEARCH

Prevalence of Chronic Hepatitis B and C Infection in Mongolian Immigrants in the Washington, District of Columbia, Metropolitan Area, 2016–2017

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Summary

What is already known on this topic?

Mongolia has the highest liver cancer incidence in the world. The most common risk factor for hepatocellular carcinoma is chronic viral hepatitis infection.

What is added by this report?

Using data from community-based screenings, we are the first to report the prevalence of chronic hepatitis B and hepatitis C infection in Mongolian American immigrants, an understudied minority population.

What are the implications for public health practice?

Foreign-born immigrants have a high prevalence of chronic viral hepatitis infection. Targeted screening, vaccination, and treatment programs can help decrease immigrant risk for developing hepatocellular carcinoma.

Abstract

Introduction

Mongolia has the highest liver cancer incidence in the world. Hepatocellular carcinoma is the most prevalent primary liver cancer, and the most common risk factors are hepatitis B virus (HBV) or hepatitis C virus (HCV) infection. Although viral hepatitis occurs mostly in the developing world, migration of people from high prevalence countries contributes to the health outcomes of the United States. Data on Mongolian Americans is limited. The objective of this study was to estimate HBV and HCV infection prevalence among Mongolia-born immigrants living in the Washington, District of Columbia, metropolitan area.

Methods

We tested Mongolia-born immigrants for chronic hepatitis at community-based screening events from 2016 to 2017. Descriptive statistics were generated to describe the screening results. Bivariate analysis was conducted to examine the relationship between hepatitis prevalence and sociodemographic characteristics.

Results

Of 634 participants, most did not speak English primarily, were uninsured, and did not have a regular primary care provider. Eighty-two participants (12.9%) had chronic HBV or HCV infection after accounting for HBV and HCV co-infection. Thirty-nine (6.2%) were chronically infected with HBV, and 233 (36.8%) were susceptible to HBV. Sixty-three (9.9%) participants were positive for HCV exposure, and 45 (7.1%) had confirmed chronic HCV infection. While no sociodemographic characteristics were associated with HBV infection, age and primary spoken language (Mongolian) were significantly associated with HCV exposure.

Conclusion

Foreign-born immigrants such as Mongolian Americans have a high prevalence of chronic viral hepatitis infection. Targeted screening, vaccination, and treatment programs can help decrease immigrant risk for developing hepatocellular carcinoma.

Introduction

Liver cancer is the second most common cause of death from cancer worldwide (1). Hepatocellular carcinoma (HCC) is the most prevalent primary liver cancer, and its incidence is increasing (2). Infection from hepatitis B virus (HBV) or hepatitis C virus (HCV) is the greatest risk factor for developing HCC (3,4). Mongolia has the highest liver cancer incidence in the world at a rate of 78.1 cases per 100,000 people (5). In comparison, the liver cancer incidence for the United States is 6.1 per 100,000 (5). Furthermore, in Mongolia, 99.3% of all cancer cases including liver cancer are attributed to infection (6).

In 2017, a nationwide survey in Mongolia found that 19.4% of the adult population was infected with either HBV or HCV (7). Prevalence of HBV infection in Mongolia is approximately 9% to 11.8% (7–9) and HCV prevalence is approximately 8.5% to 11.0% (7,9). In contrast, HBV infection prevalence in the United States is estimated at 0.3% to 0.7% and HCV prevalence at 1% to 1.6% (1,10). These differences are due to higher rates of perinatal and iatrogenic transmission in developing countries like Mongolia (9–11).

While most viral hepatitis cases occur in the developing world, migration of people from high prevalence countries contributes to the public health system of their host countries (10). For instance, three-quarters of HBV infections in the United States are among foreign-born persons (12). Studies have also found that Asian Americans and Pacific Islanders have a higher incidence of HCC compared with other groups in the United States (13,14).

Chronic viral hepatitis infection is preventable and treatable. The objective of this study was to estimate HBV and HCV infection prevalence among Mongolia-born immigrants in the Washington, District of Columbia (DC), metropolitan area and to identify sociodemographic factors associated with infection. Findings from this study may support initiatives to prevent and treat viral hepatitis in migrant populations and ultimately decrease HCC incidence.

Methods

Data collection

We analyzed retrospective data obtained from community health screenings held from 2016 through 2017 for Mongolian immigrants living in the Washington metropolitan area (Maryland, Virginia, and Washington, DC). These events were partnered with local Mongolian community leaders to help gather participation. They were held at a community health center and were promoted as free health screenings that included hepatitis B and C status, lipid profile levels, and point-of-care blood glucose checks. Advertisements that were culturally tailored and linguistically sensitive were distributed among religious organizations, businesses, media outlets, and community centers.

On the day of the events, screening staff included community partner representatives, bilingual volunteers, and trained phlebotomists. Health educators were also present to provide further information about chronic hepatitis infection and the importance of screening. Event participants aged 18 years or older gave consent and were given a brief survey about their demographic information, which included questions about country of birth, age, sex, year of arrival to the United States, health insurance status, and established access to a regular primary care provider. These surveys were offered in both English and Mongolian. Free on-site HBV and HCV testing was then administered by the phlebotomists. Participants were contacted within 2 to 3 weeks with their results. Study participants who tested positive for chronic hepatitis were contacted by a care coordinator to provide medical follow-up. In addition, participants who did not have immunity against HBV were referred to programs that provided the complete vaccination series free of charge. This study was approved by The George Washington University Institutional Review Board.

Measures

Serology results included status of hepatitis B surface antigen (HBsAg), hepatitis B surface antibody (anti-HBs), and hepatitis C antibody (anti-HCV). Participants who were positive for anti-HCV also had results for reflex HCV RNA quantitative testing through reverse transcription polymerase chain reaction assay. The sensitivity threshold for HCV RNA was at 15 IU/mL.

For HBV screening, participant results were grouped as follows: 1) HBV infected (positive HBsAg), 2) susceptible to HBV infection (negative HBsAg and negative anti-HBs), and 3) immune to HBV infection (negative HBsAg and positive anti-HBs). For HCV screening, participant results were grouped by 1) HCV infected (positive anti-HCV with reflex quantitative HCV RNA ≥15 IU/mL), 2) resolved HCV infection (positive anti-HCV with reflex quantitative HCV RNA <15 IU/mL), and 3) negative (negative anti-HCV).

Analysis

Descriptive statistics were generated to describe the screening results. Bivariate analysis was then conducted to examine the relationship of prevalence and categorical demographic characteristics using χ^2 tests and Fisher exact tests. All statistical analyses were performed with Stata, version 14 (StataCorp LLC). Significance was set at $P < .05$.

Results

A total of 637 immigrants were screened. Three were excluded from further analysis because birth country was outside of Mongolia. The final study sample size was 634. Of the study participants, 39 (6.2%) were chronically infected with HBV, 233 (36.8%) were susceptible to infection, and 362 (57.1%) were immune to infection (Table 1). Sixty-three (9.9%) participants tested positive for anti-HCV, indicating previous exposure to HCV. Among these 63 seropositive for anti-HCV, 45 (71.4%) had detectable HCV-RNA and 18 (28.6%) did not. The total number of participants with chronic HCV infection was thus 45 (7.1%). Five hundred and seventy-one (90.0%) were negative for previous HCV exposure. Two participants (0.3%) were positive for both HBV and HCV infection.

The mean (standard deviation) age of participants was 41 (11.4) years. Most participants were women (n = 366, 57.7%) (Table 2). About half of the participants (n = 318, 50.2%) were living in the United States for 5 years or less, and the largest group was those in the United States for 1 to 5 years (n = 253, 39.9%). Most of the sample group spoke Mongolian primarily (n = 434, 68.4%), while 200 (31.6%) reported English as their primary language. Most were uninsured (n = 564, 89.0%) and did not have an established regular primary care provider (n = 569, 89.8%).

When stratifying for sociodemographic factors, no characteristics were significantly associated with HBV infection (Table 2). However, age and primary spoken language were significantly associated with HCV exposure ($P < .05$). The highest prevalence of HCV exposure was among those aged 51 to 60 years (14 positive of 93; 15.1%) and those aged 61 years or older (10 positive of 35; 28.6%). Prevalence was lower among those aged 18 to 30 years (4 positive of 125; 3.2%) and those aged 31 to 40 years (8 positive of 183; 4.4%). Of the 434 participants who reported Mongolian as their primary spoken language, 53 (12.2%) tested positive for HCV exposure. For the 200 who reported English as their primary spoken language, 10 (5.0%) tested positive.

Discussion

This study is the first to report viral hepatitis prevalence for both HBV and HCV in Mongolia-born individuals living in the United States. Of the 634 immigrants screened, 12.9% were found to have chronic HBV and/or HCV infection after accounting for HBV/HCV co-infection (n = 2). This is lower than the endemic prevalence of 19% in Mongolia but higher than that of the general United States population (7). These findings support other studies that have shown foreign-born populations uniquely contribute to chronic hepatitis infection prevalence in the United States (14,15).

The prevalence of HBV in Asian Americans has been extensively studied through surveys, community-based participatory initiatives, and outreach screenings (16–18). Approximately 7% of Asian Americans have chronic HBV (15,17). However, limited data exist for those of Mongolian ethnicity. Of those screened in this study, 6.2% were positive for chronic HBV infection. Only one other study reports HBV prevalence in Mongolian Americans, where 13 (6.8%) of 190 participants in Alameda County, California, were HBsAg positive (16). These rates for Mongolian immigrants are lower than those reported by a 2012 systematic review of chronic HBV infection in foreign-born populations of the United States (15). That study estimated distinct prevalence rates for immigrant communities from 102 different countries, and Mongolians were grouped as other nonspecified Eastern Asian at a prevalence of 8.97% (15). The discrepancies in HBV infection prevalence reveal the nuances of current data on viral hepatitis epidemiology. The true burden of chronic HBV in the United States is limited by inadequate representation of foreign-born populations that face barriers to care including health literacy and access (10,15). The Centers for Disease Control and Prevention (CDC) and US Preventive Services Task Force (USPTF) recommend HBV testing for persons born in countries where HBV infection is endemic at prevalence of 2% or higher (12,15).

Over one-third (36.8%) of participants had no immunity to HBV. Universal HBV immunization for newborns was not implemented in Mongolia until 1991 (19). This may have contributed to the lack of immunity for this study's immigrant group of predominantly middle-aged adults (mean age >40 y). Since HBV is a strong risk factor for the development of HCC, vaccination can prevent liver cancer (11,14). While vaccination initiatives substantially decreased the incidence of HBV in children worldwide, unvaccinated adults still represent an ongoing risk for HBV infection and HCC (14,19).

More than half (57.1%) of the study participants were immune to HBV infection, identified by positive anti-HBs in serology. Because hepatitis B core antibody (anti-HBc) was not measured, it remains unclear if these individuals were immune secondary to vaccination history or recovery from previous infection. This finding was varied compared with other studies of Asian American immigrants, whose prevalence of HBV immunity was between 46% and 64% (16,18,20). The most recent published data in Mongolia estimates 37% prevalence of positive anti-HBs for adults aged 20 years or older (7).

This study is the first to report HCV prevalence in Mongolia-born individuals in the United States. Of the Mongolian immigrants screened in this study, 7.1% were positive for chronic HCV infection. HCV in Asian Americans has been understudied secondary to overshadowing disparities in HBV prevalence (21,22). An estimated 3% to 6% of the Asian American population is seropositive for anti-HCV (20,23). CDC and USPTF recommend HCV screening for those in the 1945 through 1965 birth cohort and those with high-risk factors including history of past or current injection drug use, blood transfusion before 1992, long-term hemodialysis, HIV infection, maternal HCV infection, or occupational exposure (22,23). However, multiple studies have found that these traditional risk factors for HCV are not evident in seropositive Asian Americans and thus they are often underdiagnosed for HCV (22,23). HCV prevalence in Mongolia has been associated with iatrogenic factors including medical equipment sterilization and disinfection (7,9). Single-use syringes were not nationally mandated in health care facilities until 1995 (9). Mongolia did not screen for HCV in transfusions until 1997 (24). This study's high prevalence of HCV in Mongolia-born immigrants suggests that factors unique to county-of-birth contribute to risk for viral hepatitis infection. Screening guidelines for HCV should be expanded to include foreign-born persons whose native country's HCV prevalence is 2% or higher (21,22).

Demographic characteristics of the study participants indicated disparities common for immigrant populations in the United States. Most participants had a primary spoken language other than English, were uninsured, and did not have an established regular primary care provider. This study used data from community-based screening initiatives that were able to target a hard-to-reach population such as Mongolia-born immigrants. Community-based efforts thus provide opportunities for engaging high-risk, foreign-born individuals who are limited by cultural, economic, and environmental barriers (15).

While no sociodemographic characteristics were associated with HBV infection, age and primary spoken language were significantly associated with HCV exposure. Older age was associated with HCV, reflecting similar age distributions for studies in Mongolia (7–9). This is consistent with the issues of iatrogenic transmission in Mongolia. Those who are older are more likely than younger people are to have been exposed to unsterile medical equipment or blood products before the implementation of regulations. Participants who reported Mongolian as their primary spoken language were also more often associated with HCV exposure than those who reported English as their primary spoken language. This suggests the role of acculturation in infection risk, where those who speak English may be better able to navigate health services and have increased health literacy.

There are several limitations in this study. First, chronic hepatitis prevalence was only assessed in Mongolian immigrants who were living in the Washington metropolitan area. In 2015, the population of Mongolian Americans was approximately 21,000, with Chicago and Washington, DC, as the top metropolitan areas with approximately 3,000 Mongolian Americans each (25). Viral hepatitis infection prevalence in Mongolia-born immigrants may vary depending on settled area. In addition, the study sample may have selection bias secondary to data obtained from community-based screenings, which recruited voluntary participants by targeted local advertising. This nonprobability sampling method may not represent the entire Mongolia-born immigrant population of the Washington metropolitan area. Furthermore, HBV-positive or HCV-positive individuals who were aware of their viral hepatitis status may have been less likely to participate in screening events, and this could have resulted in underestimation of prevalence. The use of screening data from Mongolian community-based initiatives also did not allow for screening the general population of the area. This resulted in the lack of a comparison group for the study. Moreover, chronic hepatitis infection surveillance is not mandated, and reporting varies nationwide (12). No published data from the Washington metropolitan area were available to provide adequate comparison of prevalence. Lastly, the prevalence rates determined do not consider severity of hepatitis infection as this was out of scope for the study. Thus, liver sequelae including HCC in the participants found to be HBV or HCV seropositive was not addressed.

The strength of this study was determining the prevalence of both HBV and HCV in an understudied population of immigrants, whose native country has endemic viral hepatitis and the highest incidence of HCC worldwide. Through community-based initiatives, over 600 immigrants were screened for chronic hepatitis B and C in this study. Most participants of this study did not speak English primarily and had health barriers including lacking insurance or a primary health care provider. These findings support the need for targeted screening, vaccination, and treatment programs for foreign-born individuals such as Mongolian immigrants, among whom prevalence is high compared with that of the general US population. Furthermore, the high HCV infection prevalence in immigrants reflects the infection risks of their county of birth, and this should be addressed in the screening guidelines. Overall, the high prevalence of viral hepatitis in immigrant populations ultimately contributes to the hepatitis disease burden in the United States.

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Tables

Table 1. Hepatitis Results for Mongolia-born Screening Participants (N = 634) in the Washington, District of Columbia, Metropolitan Area, 2016–2017

Screening Result	n	% (95% Confidence Interval)
Hepatitis B		
Chronic infection (HBsAg positive)	39	6.2 (4.5–8.4)
Susceptible to infection (HBsAg negative and anti-HBs negative)	233	36.8 (32.7–40.9)
Immune (HBsAg negative, anti-HBs positive)	362	57.1 (52.7–61.4)
Hepatitis C		
Exposed (anti-HCV positive and HCV RNA <15 IU/mL)	63	9.9 (7.7–12.8)
Chronic infection (anti-HCV positive and HCV RNA ≥15 IU/mL)	45	7.1 (5.6–8.9)
Negative (anti-HCV negative)	571	90.0 (87.9–91.8)

Abbreviations: anti-HBs, hepatitis B surface antibody; anti-HCV, hepatitis C antibody; HBsAg, hepatitis B surface antigen; HCV, hepatitis C virus.

Table 2. Demographic Characteristics of Mongolia-born Screening Participants (N = 634) in the Washington, District of Columbia, Metropolitan Area, 2016–2017

Characteristic	Total Participants, N (%)	Hepatitis B Infected[a]		Hepatitis C Exposed[b]	
		n (%)	*P* Value	n (%)	*P* Value
Age, y					
18–30	125 (19.7)	8 (6.4)	.44[c]	4 (3.2)	<.001[c]
31–40	183 (28.9)	10 (5.5)		8 (4.4)	
41–50	198 (31.2)	9 (4.6)		27 (13.6)	
51–60	93 (14.7)	9 (9.7)		14 (15.1)	
≥61	35 (5.5)	3 (8.6)		10 (28.6)	
Sex					
Female	366 (57.7)	25 (6.8)	.41[c]	40 (10.9)	.33[c]
Male	268 (42.3)	14 (5.2)		23 (8.6)	
Years in the United States[d]					
<1	65 (10.3)	6 (9.2)	.64[c]	9 (13.9)	.26[c]
1–5	253 (39.9)	18 (7.1)		24 (9.5)	
6–10	104 (16.4)	6 (5.8)		5 (4.8)	
11–14	136 (21.5)	6 (4.4)		17 (12.5)	
≥15	68 (10.7)	3 (4.4)		7 (10.3)	
Primary spoken language					
English	200 (31.6)	8 (4.0)	.13[c]	10 (5.0)	.011[c]
Mongolian	434 (68.4)	31 (7.1)		53 (12.2)	
Health insured					
Yes	70 (11.0)	1 (1.4)	.11[e]	7 (10.0)	.98[c]
No	564 (89.0)	38 (6.7)		56 (9.9)	
Regular primary care provider					
Yes	65 (10.2)	2 (3.1)	.41[e]	8 (12.3)	.50[c]
No	569 (89.8)	37 (6.5)		55 (9.7)	

[a] Hepatitis B surface antigen positive.

[b] Hepatitis C antibody positive.

[c] χ^2 analysis.

[d] Eight participants had missing data for years living in the United States, including 1 participant who was positive for hepatitis C exposure.

[e] Fisher exact test analysis.

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Transitions From Heart Disease to Cancer as the Leading Cause of Death in US States, 1999–2016

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PEER REVIEWED

Abstract

Introduction

Heart disease has been the leading cause of death in the United States since 1910 and cancer the second leading cause of death since 1933. However, cancer emerged recently as the leading cause of death in many US states. The objective of this study was to provide an in-depth analysis of age-standardized annual state-specific mortality rates for heart disease and cancer.

Methods

We used population-based mortality data from 1999 through 2016 to compare 2 underlying cause-of-death categories: diseases of heart (*International Classification of Diseases, 10th Revision* [ICD-10] codes I00–I09, I11, I13, and I20–I51) and malignant neoplasms (ICD-10 codes C00–C97). We calculated age-standardized annual state-specific mortality rate ratios (MRRs) as heart disease mortality rate divided by cancer mortality rate.

Results

In 1999, age-standardized heart disease mortality exceeded that for cancer in all 50 states. Median state-specific MRR in 1999 was 1.26 (interquartile range [IQR], 1.17–1.34; range, 1.03–1.56), indicating predominance of heart disease mortality nationwide. Median state-specific MRR decreased annually through 2010, reaching a low of 1.00 (IQR, 0.95–1.07; range, 0.71–1.25), indicating that predominance of heart disease mortality prevailed in approximately half of states. Median state-specific MRR increased to 1.03 (IQR, 0.97–1.12; range, 0.77–1.31) in 2016. In 2016, age-standardized cancer mortality exceeded that for heart disease in 19 states. State-level transitions were most apparent for people aged 65 to 84 and affected men, women, and all racial/ethnic groups.

Conclusion

State-level data indicated heterogeneity across US states in the predominance of heart disease mortality relative to cancer mortality. Timing and magnitude of transitions toward cancer mortality predominance varied by state.

Introduction

In the early 1900s, the United States went through an epidemiologic transition in which chronic diseases displaced acute infections as the leading causes of death. Heart disease was the leading cause of death nationally from 1910 through 2016, except from 1918 through 1920 (1,2). Cancer was the second leading cause of death nationally from 1933 through 2016, except in 1936 and 1937 (1,2). In the mid-1900s, heart disease mortality far exceeded cancer mortality (1–3). For example, in 1963 heart disease deaths were 375.5 per 100,000 population, accounting for 39% of all deaths, and cancer deaths were 151.4 per 100,000 population, accounting for 16% of all deaths (1).

Now the United States is going through another epidemiologic transition, in which cancer may eventually become the leading cause of death nationally (2–4). Since 1964, heart disease mortality rates have steadily declined (1–6). Cancer mortality rates increased through 1991 and then started to decline, though at a much slower pace than the decline in heart disease mortality. For example, from 1991 through 2014 the cancer mortality rate decreased 25%, whereas the heart disease mortality rate decreased

47% (2). From 2012 through 2014, 23.5% of deaths were attributed to heart disease and 22.7% of deaths were attributed to cancer (2,4).

Although heart disease was the leading cause of death nationally as of 2016 (2–4), it is not so in many US states. Cancer mortality counts exceeded heart disease mortality counts in 23 US states in 2010, 21 states in 2012, and 22 states in 2014, up from only 1 state in 1993 and 2 states in 2000 (4,7,8). The objective of our study was to provide an in-depth analysis of age-standardized annual state-specific mortality rates for heart disease and cancer. We hypothesized that the timing and magnitude of transitions toward cancer mortality predominance would vary by state, and we sought to investigate this heterogeneity.

Methods

We studied longitudinal state-specific mortality patterns in the United States by using population-based annual mortality data, which are publicly available via the National Vital Statistics System and the Centers for Disease Control and Prevention's online integrated information and communication system, WONDER (Wide-ranging Online Data for Epidemiologic Research) (2). We obtained underlying cause-of-death data for each of the 50 states for each calendar year from 1999 through 2016 (2). Underlying cause of death was based on the *International Classification of Diseases, 10th Revision* (ICD-10) (9). We defined heart disease as ICD-10 codes I00–I09, I11, I13, and I20–I51 (diseases of heart) and cancer as ICD-10 codes C00–C97 (malignant neoplasms).

We compared age-standardized annual state-specific mortality rates for heart disease and cancer by using mortality rate ratios (MRRs), calculated as heart disease mortality rate divided by cancer mortality rate. We then made categories of MRRs (<0.7, 0.7 to <0.8, 0.8 to <0.9, 0.9 to <1.0, >1.0 to <1.1, 1.1 to <1.2, 1.2 to <1.3, 1.3 to <1.4, and ≥1.4).

Data on age-standardized rates were based mostly on 10-year age categories (<1 y, 1–4 y, 5–14 y, 15–24 y . . . 75–84 y, ≥85 y) and the year 2000 standard US population (2,10). MRRs greater than 1 indicate predominance of heart disease mortality, with the age-standardized heart disease mortality rate exceeding the age-standardized cancer mortality rate. MRRs less than 1 indicate predominance of cancer mortality, with the age-standardized cancer mortality rate exceeding the age-standardized heart disease mortality rate. MRRs equal to 1 indicate equal age-standardized heart disease and cancer mortality rates. The MRR provides richer information than ranking causes of death as first or second, because the MRR shows the magnitude of the gap between age-standardized rates of deaths from different causes.

We used age-standardized annual state-specific MRRs to generate a choropleth map and summary statistics for each calendar year, including the following values: minimum, maximum, median, and 10th, 25th, 75th, and 90th percentiles of MRR, and number of states in each MRR category. We further analyzed MRRs for selected age groups (<65 y, 65–84 y, and ≥85 y), sex (male and female), and race/ethnicity (non-Hispanic white, non-Hispanic black, Hispanic, and non-Hispanic other [consisting of American Indian/Alaska Native and Asian/Pacific Islander]). In some states, data were sparse for certain racial/ethnic groups. Therefore, we combined the first 3 calendar years of data (1999–2001) and the last 3 calendar years of data (2014–2016) to calculate stable state-specific MRRs for racial/ethnic groups. In those analyses, we considered states where heart disease or cancer mortality counts in racial/ethnic groups were less than 20 deaths per 3-year period to have insufficient data, and we did not calculate MRRs for those subgroups in those states. Although we did not round MRR calculations during our analysis, tabulated results were rounded to 2 decimal places.

Data were analyzed by using SAS version 9.4 (SAS Institute), Microsoft Excel 2016 (Microsoft Corporation), ArcMap version 10.4 (Esri), and R 3.4.3 (The R Foundation).

Age-standardized mortality rates were used to calculate MRRs because the relationship between age and heart disease mortality differs from the relationship between age and cancer mortality (3,11), and age distributions differ across states, calendar years, and demographic subgroups. State-specific MRRs and comparisons of MRRs across states, calendar years, and demographic groups may thus be confounded by age. Age-standardization reduces the effect of different age distributions and rules out age differences as an explanation for heterogeneity across states in the timing of the transition toward cancer mortality predominance.

In secondary analyses, actual mortality counts were used rather than age-standardized mortality rates to calculate unadjusted mortality count ratios (MCRs). The MCR compares the absolute number of heart disease deaths with the absolute number of cancer deaths. Comparisons of MCRs across states or calendar years may be influenced by state-specific age distributions or population aging over time. When we analyzed unadjusted MCRs, all patterns observed in our age-standardized analysis were still evident, with only minor differences. Therefore, the conclusions drawn in this report would not change, so we did not report results from the unadjusted analyses.

Results

In 1999, age-standardized heart disease mortality exceeded that for cancer in all 50 states (Figure 1). New York State had the highest state-specific MRR (1.56), meaning that heart disease mortality was 56% higher than cancer mortality. New York State was followed by Oklahoma (1.53), Mississippi (1.52), West Virginia (1.45), Missouri (1.45), Alabama (1.44), and Michigan (1.43). Minnesota had the weakest predominance of heart disease mortality in 1999, with a MRR of 1.03, meaning that heart disease mortality was 3% higher than cancer mortality. Minnesota was followed by Oregon (1.04), Alaska (1.04), Vermont (1.07), Washington (1.09), and Montana (1.10). Among the 50 states, median state-specific MRR in 1999 was 1.26 (interquartile range [IQR], 1.17–1.34) (Figure 2).

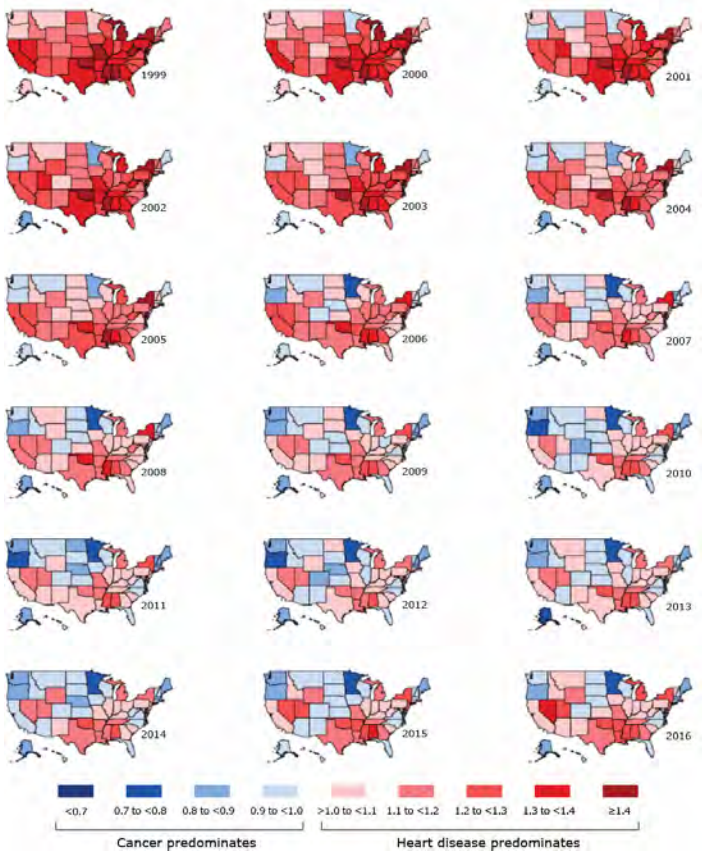
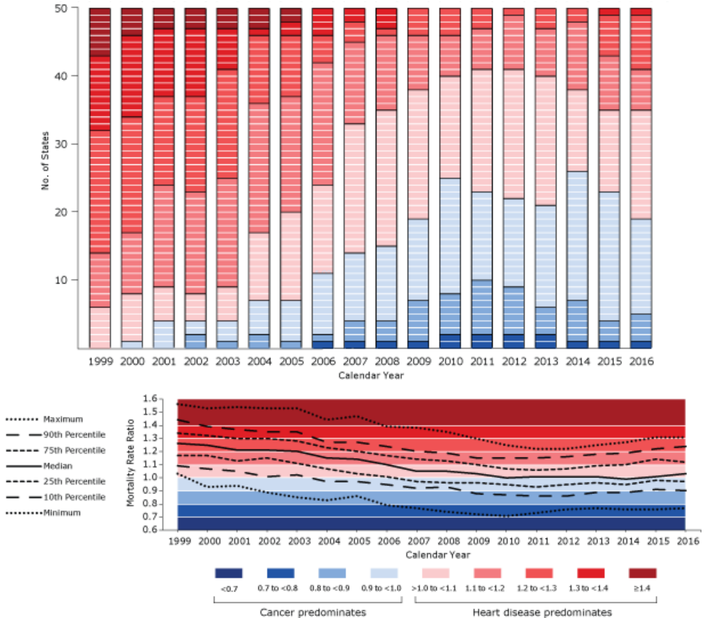


Figure 1. Distribution, by state, of age-standardized state-specific mortality rate ratios (MRRs), calculated by dividing the mortality rate of heart disease by the mortality rate of cancer, among all ages, both sexes, and all races and ethnicities, United States, 1999–2016. A ratio of <1.0 indicates that cancer predominates, and a ratio of >1.0 indicates that heart disease predominates.

Figure 2. Frequency of categories of state-specific mortality rate ratios (MRRs), calculated by dividing the mortality rate of heart disease by the mortality rate for cancer, among all ages, both sexes, and all races and ethnicities, United States, 1999–2016. Top, number of states in each category of MRR, by calendar year. Each cell represents 1 state. Bottom, summary statistics by calendar year.

From 1999 through 2016, age-standardized cancer mortality exceeded heart disease mortality (MRR <1.00) in several calendar years in 27 states (Figure 1). Higher cancer mortality than heart disease mortality occurred for at least 10 calendar years in 11 states, 5 to 9 calendar years in 13 states, and 2 to 4 calendar years in 3 states. Some states, such as Minnesota and Maine, after first transitioning from heart disease mortality predominance to cancer mortality predominance, remained consistently cancer mortality predominant every calendar year thereafter. In contrast, other states, such as Montana and Connecticut, fluctuated between cancer and heart disease mortality predominance over time. In addition to the 27 states in which cancer mortality predominated in several calendar years, 4 states were cancer mortality predominant during a single calendar year (Ohio in 2009, Wyoming in 2010, and California and West Virginia in 2014). In 19 states, age-standardized heart disease mortality exceeded cancer mortality in every calendar year studied. The transition toward state-specific cancer mortality predominance occurred steadily from 1999 through 2010, then leveled and even reversed slightly from 2011 through 2016 (Figure 2). This pattern is reflected in the median state-specific MRR over time, which was 1.26 (IQR, 1.17–1.34) in 1999, 1.00 (IQR, 0.95–1.07) in 2010, and 1.03 (IQR, 0.97–1.12) in 2016.



In 2016, age-standardized cancer mortality exceeded heart disease mortality in 19 states (Figure 1 and Figure 2). Minnesota had the strongest predominance of cancer mortality in 2016, with a MRR of 0.77, meaning that heart disease mortality was 23% lower than cancer mortality. Other states with relatively strong predominance of cancer mortality in 2016 were Oregon (0.87), Maine (0.88), Alaska (0.89), and Massachusetts (0.90). Nevada had the strongest predominance of heart disease mortality in 2016, with a MRR of 1.31, meaning that heart disease mortality was 31% higher than cancer mortality. Nevada was followed by Oklahoma (1.28), Alabama (1.28), Arkansas (1.25), Mississippi (1.24), Louisiana (1.24), Utah (1.23), New York State (1.21), and Michigan (1.21) (Figure 2).

State-level transitions from heart disease to cancer as the leading cause of death from 1999 to 2016 were most apparent in the group aged 65 to 84, for both men and women (Table 1). Among men aged 65 to 84, the number of states with cancer mortality predominance increased from 8 states in 1999 to 42 states in 2016. Similarly, among women aged 65 to 84, the number of states with cancer mortality predominance increased from 16 states in 1999 to 47 states in 2016. In contrast, men and women aged 85 or older were more likely to die of heart disease than of cancer in every state in both 1999 and 2016; MRRs in both years were 1.40 or more. For men younger than 65, the cancer mortality rate exceeded the heart disease mortality rate in 33 states in 1999 and in 27 states in 2016. For women younger than 65, the cancer mortality rate exceeded the heart disease mortality rate in every state in both 1999 and 2016; MRRs were less than <0.70 in nearly every state. For both sexes younger than 65, several states shifted toward weaker cancer mortality predominance, opposite of the trend seen for older ages.

Some patterns were consistent across all racial/ethnic groups: strong predominance of heart disease mortality among people aged 85 or older, especially women; numerous state-specific transitions from heart disease predominance to cancer predominance in the group aged 65 to 84; and the predominance of cancer mortality among people younger than 65, especially women (Table 2). Heart disease mortality predominated more strongly on average among non-Hispanic black people than among non-Hispanic white people during 1999–2001 (median MRR, 1.26 vs 1.23) and during 2014–2016 (median MRR, 1.07 vs 1.00). Heart disease mortality also predominated more strongly on average among Hispanic people than among non-Hispanic white people during 1999–2001 (median MRR, 1.25 vs 1.23), but during 2014–2016 predominance shifted among Hispanic people more toward cancer mortality (median MRR, 0.94 vs 1.00). Cancer mortality predominated more strongly among non-Hispanic other races than among non-Hispanic white people during 2014–2016 (median MRR, 0.91 vs 1.00). Compared with the range of MRRs among non-Hispanic white people, the range among other racial/ethnic groups was broader across states.

Discussion

The transition from heart disease to cancer as the leading cause of death has occurred in many US states. Our analysis, based on age-standardized annual state-specific heart disease and cancer mortality rates, showed that from 1999 through 2016, the state-specific cancer mortality rate exceeded that for heart disease in more than half of US states in several calendar years. The timing and magnitude of transition varied by state. State-specific transitions toward cancer as the leading cause of death occurred most rapidly through the mid- to late-2000s, tapering off in more recent years. In 2016, heart disease mortality was either lower than cancer mortality or was less than 10% higher than cancer mortality in most states, whereas in 1999, heart disease mortality had been more than 20% higher than cancer mortality in nearly all states.

Cancer mortality tends to exceed heart disease mortality at younger ages, whereas heart disease mortality tends to predominate at older ages (3). One study showed that by 2002 cancer became the leading cause of death nationally for people younger than 85, while heart disease remained the leading cause of death for people aged 85 or older (12). Further exploration of national data on age groups showed that this pattern persisted in more recent years. For example, in 2014, among people aged 40 to 79, the number of cancer deaths (405,885) was 45% higher than the number of heart disease deaths (280,773), whereas among people aged 80 or older, the number of heart disease deaths (325,040) was 85% higher than the number of cancer deaths (175,504) (13). However, our analysis based on age-standardized rates showed that state-level variability in the timing of the transition from heart disease to cancer as the leading cause of death cannot be explained by state-level and time-related differences in population age distributions.

The transition toward cancer as the leading cause of death applies to both sexes and to all racial/ethnic groups. One study showed that cancer mortality first surpassed heart disease mortality nationally among non-Hispanic Asians and Pacific Islanders in 2000 and among Hispanics in 2009 (4). Our analysis of state-level data stratified by sex and racial/ethnic groups showed geographic heterogeneity in the timing of the transition among these groups. The greater ratio of cancer to heart disease mortality among women younger than 65, compared with men younger than 65, may be due primarily to high mortality rates of female breast cancer among that age group. Breast cancer ranks second among cancer deaths among women, after lung cancer (13). For 1999 through 2001, heart disease mortality predominated in most states among people aged 65 to 84 of both sexes in all racial/ethnic groups, except non-Hispanic white women and non-Hispanic black men. The exception in non-Hispanic black men may have resulted from the relatively high incidence and mortality rates of lung and prostate cancers among black men in the United States (13). During 1999–2001, among men aged 65 to 84, the age-standardized mortality rate of lung cancer among non-Hispanic black men (557.1 per 100,000) was 25% higher than among non-Hispanic white men (444.3 per 100,000), and the age-standardized mortality rate of prostate cancer among non-Hispanic black men (383.9 per 100,000) was 167% higher than among non-Hispanic white men (143.6 per 100,000) (2). The strong predominance of heart disease mortality among non-Hispanic black women aged 65 to 84 in the Southeast during 1999–2001 is perhaps partly explained by relatively low levels of lung cancer among black women (13). During 1999–2001, among women aged 65 to 84, age-standardized lung cancer mortality was 14% lower among non-Hispanic black women (209.5 per 100,000) than among non-Hispanic white women (242.6 per 100,000) (2). These patterns remained evident during 2014–2016.

The driving force behind these transitions, as documented in previous reports, is a decline in heart disease mortality (4–8,14). Possible causes for the patterns we observed include state-level and time-related differences in tobacco smoking, other risk factors for heart disease and cancer, and successful treatment of heart disease and cancer. Smoking prevalence in the United States peaked in 1964 and began falling thereafter (15). A 20- to 30-year latency period between smoking and lung and other cancers is suggested by the fact that cancer death rates did not begin to decline until after 1991, whereas the reduction in heart disease mortality rates correlates more closely in time with the reduction in tobacco smoking (16). Tobacco smoking is strongly associated with lung cancer (17–19), but the decrease in age-standardized lung cancer mortality rate during the study period was 31% (from 55.4 per 100,000 in 1999 to 38.3 per 100,000 in 2016) as opposed to a decrease in age-standardized heart disease mortality rate of 38% (from 266.5 per 100,000 in 1999 to 165.5 per 100,000 in 2016) (2). The more rapid reduction in heart disease mortality than in lung cancer mortality suggests that other risk factors for heart disease were declining during the same time. Environmental tobacco smoke policies changed during the study period, and they differ across states and localities (20). Reductions in environmental tobacco smoke would be expected to reduce heart disease mortality more quickly, with a relative lag in reduction of cancer mortality. In addition, one study noted that improvements in the treatment of risk factors for heart disease have been greater than improvements in the early detection of cancer (21). The treatment of cardiovascular disease has also advanced in the past 5 decades (5,21). Geographic patterns of heart disease mortality in the United States and shifts in these patterns over time are detailed in recent comprehensive reports (22,23), but these reports do not refer to geographic or time-related patterns of cancer mortality. Thus our report adds value by directly comparing heart disease mortality with cancer mortality.

Although the relationship between heart disease and cancer mortality at the national level is well known, few state-specific in-depth explorations of heart disease versus cancer mortality are available. One such study, using mortality data from 2006 through 2009, described a transition toward cancer mortality predominance in Kentucky and Texas (24,25). This study observed a narrowing gap, driven by declining heart disease mortality, between heart disease mortality and cancer mortality in both states. A strength of our analysis was the ability to examine such patterns not only for selected states but for all 50 states, and for both sexes, selected age groups, and several racial/ethnic groups.

Our study has limitations. The validity of our study depends on the accuracy and completeness of death certificate data. We used data on underlying cause of death to be consistent with the National Center for Health Statistics' methodology for ranking causes of death (26), although we recognize that comorbidities, along with the subjectivity inherent in the process of determining cause of death, may lead to inconsistencies in the coding of underlying cause of death on death certificates. Data on racial/ethnic groups were incomplete because for race/ethnicity-specific analyses we excluded death certificates that did not indicate whether the decedent was Hispanic or non-Hispanic. In addition, certain racial/ethnic groups in certain states were represented by small populations in our analysis, but we mitigated this shortcoming by aggregating data across multiple calendar years.

The oft-repeated message that "heart disease is the leading cause of death in the United States," while true at the national level as of 2016, obscures the heterogeneity in the relative predominance of heart disease mortality or cancer mortality across states and over time. Our longitudinal analysis of state-level data enriches our understanding of this epidemiologic transition toward cancer becoming the leading cause of death in the United States. Our findings can aid public health and medical professionals in interpreting vital statistics, creating public health messaging, and setting priorities in chronic disease prevention and control programs, particularly at the state level.

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Tables

Table 1. Summary Statistics for Age-Standardized State-Specific MRRs (Heart Disease Mortality Rate to Cancer Mortality Rate) for All Races and Ethnicities Groups, by Sex, Age, and Calendar Year, United States,1999–2016[a]

Category	MRR >1.0 (Heart Disease Predominant), No. of States in Each MRR Category						MRR <1.0 (Cancer Predominant), No. of States in Each MRR Category					Distribution of MRRs Across States, Percentile		
	≥1.4	1.3 to <1.4	1.2 to <1.3	1.1 to <1.2	>1.0 to <1.1	Total	0.9 to <1.0	0.8 to <0.9	0.7 to <0.8	<0.7	Total	25th	50th	75th
Both Sexes														
All ages														
1999	7	11	18	8	6	50	0	0	0	0	0	1.17	1.26	1.34
2016	0	1	8	6	16	31	14	4	1	0	19	0.97	1.03	1.12
Aged ≥85														
1999	50	0	0	0	0	50	0	0	0	0	0	2.88	3.14	3.46
2016	50	0	0	0	0	50	0	0	0	0	0	2.15	2.37	2.56
Aged 65–84														
1999	0	2	8	11	16	37	10	3	0	0	13	1.00	1.08	1.18
2016	0	0	0	0	6	6	4	15	19	6	44	0.75	0.80	0.88
Aged <65														
1999	0	0	0	0	0	0	3	11	10	26	50	0.62	0.70	0.81
2016	0	0	0	0	3	3	5	7	13	22	47	0.66	0.72	0.86
Men														
All ages														
1999	4	15	17	10	4	50	0	0	0	0	0	1.18	1.27	1.35
2016	1	0	11	12	19	43	6	1	0	0	7	1.02	1.10	1.19
Aged ≥85														
1999	50	0	0	0	0	50	0	0	0	0	0	2.07	2.32	2.42
2016	50	0	0	0	0	50	0	0	0	0	0	1.77	1.96	2.14
Aged 65–84														
1999	0	1	6	17	18	42	8	0	0	0	8	1.05	1.09	1.17
2016	0	0	1	0	7	8	9	26	6	1	42	0.83	0.88	0.94
Aged <65														
1999	0	0	1	6	10	17	15	15	3	0	33	0.87	0.96	1.05
2016	1	0	3	13	6	23	14	8	4	1	27	0.90	0.99	1.13
Women														
All ages														
1999	8	8	11	11	9	47	9	0	0	0	3	1.10	1.23	1.37
2016	0	0	4	4	5	13	19	13	4	1	37	0.87	0.92	1.05
Aged ≥85														
1999	50	0	0	0	0	50	0	0	0	0	0	3.53	3.82	4.27
2016	50	0	0	0	0	50	0	0	0	0	0	2.49	2.64	2.97

Abbreviation: MRR, mortality rate ratio.
[a] Data source: Centers for Disease Control and Prevention (2).

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Table 1. Summary Statistics for Age-Standardized State-Specific MRRs (Heart Disease Mortality Rate to Cancer Mortality Rate) for All Races and Ethnicities Groups, by Sex, Age, and Calendar Year, United States,1999–2016[a]

Category	MRR >1.0 (Heart Disease Predominant), No. of States in Each MRR Category						MRR <1.0 (Cancer Predominant), No. of States in Each MRR Category					Distribution of MRRs Across States, Percentile		
	≥1.4	1.3 to <1.4	1.2 to <1.3	1.1 to <1.2	>1.0 to <1.1	Total	0.9 to <1.0	0.8 to <0.9	0.7 to <0.8	<0.7	Total	25th	50th	75th
Aged 65–84														
1999	1	5	5	8	15	34	7	7	2	0	16	0.95	1.05	1.18
2016	0	0	0	0	3	3	2	9	16	20	47	0.66	0.72	0.84
Aged <65														
1999	0	0	0	0	0	0	0	0	1	49	50	0.36	0.45	0.52
2016	0	0	0	0	0	0	0	0	5	45	50	0.37	0.43	0.55

Abbreviation: MRR, mortality rate ratio.
[a] Data source: Centers for Disease Control and Prevention (2).

Table 2. Summary Statistics for Age-Standardized State-Specific Mortality Rate Ratios (Heart Disease Mortality Rate to Cancer Mortality Rate), by Sex, Age, Race/Ethnicity, and Calendar Year, United States, 1999–2016[a]

Category	Both Sexes					Male					Female				
	No. of States With Data[b]	No. of States With MRR <1.0	Distribution of MRRs, Percentile			No. of States With Data[b]	No. of States With MRR <1.0	Distribution of MRRs, Percentile			No. of States With Data[b]	No. of States With MRR <1.0	Distribution of MRRs, Percentile		
			25th	50th	75th			25th	50th	75th			25th	50th	75th
All Ages															
Non-Hispanic white															
1999–2001	50	1	1.16	1.23	1.32	50	0	1.20	1.25	1.32	50	5	1.08	1.17	1.29
2014–2016	50	25	0.95	1.00	1.12	50	6	1.02	1.07	1.18	50	36	0.85	0.90	1.03
Non-Hispanic black															
1999–2001	42	2	1.16	1.26	1.36	42	8	1.04	1.12	1.19	39	1	1.23	1.35	1.50
2014–2016	44	15	0.97	1.07	1.15	44	14	0.97	1.09	1.18	42	18	0.93	1.00	1.11
Hispanic															
1999–2001	44	3	1.15	1.25	1.43	40	4	1.09	1.21	1.42	40	7	1.10	1.30	1.49
2014–2016	48	32	0.87	0.94	1.04	44	26	0.89	0.97	1.14	41	29	0.77	0.90	1.01
Non-Hispanic other[c]															
1999–2001	48	8	1.05	1.23	1.37	46	7	1.07	1.24	1.42	45	10	1.00	1.19	1.32
2014–2016	49	36	0.83	0.91	1.00	47	21	0.91	1.02	1.12	47	42	0.71	0.81	0.95
Aged ≥85															
Non-Hispanic white															
1999–2001	50	0	2.87	3.15	3.41	50	0	2.11	2.32	2.47	50	0	3.44	3.83	4.12
2014–2016	50	0	2.23	2.39	2.57	50	0	1.86	2.01	2.13	50	0	2.62	2.74	2.98
Non-Hispanic black															
1999–2001	37	0	2.25	2.52	2.78	31	0	1.48	1.59	1.86	33	0	2.97	3.20	3.69
2014–2016	38	1	1.79	1.97	2.13	34	1	1.33	1.49	1.65	35	1	2.14	2.42	2.66
Hispanic															
1999–2001	20	0	2.31	2.90	3.29	11	0	1.95	2.25	2.68	14	0	2.38	3.53	4.08
2014–2016	25	1	1.74	2.05	2.27	26	1	1.50	1.73	1.95	24	0	2.07	2.37	2.58
Non-Hispanic other[c]															
1999–2001	21	0	1.86	2.48	3.09	12	0	1.70	2.11	2.44	12	0	3.02	3.16	3.85
2014–2016	33	1	1.64	1.95	2.19	25	0	1.57	1.73	1.92	27	0	1.72	2.16	2.53
Aged 65–84															
Non-Hispanic white															
1999–2001	50	19	0.95	1.02	1.12	50	13	0.99	1.07	1.13	50	31	0.88	0.96	1.11
2014–2016	50	46	0.73	0.77	0.88	50	44	0.80	0.84	0.92	50	50	0.63	0.67	0.79
Non-Hispanic black															
1999–2001	40	8	1.02	1.12	1.23	39	24	0.86	0.97	1.04	39	2	1.19	1.30	1.49

Abbreviations: MRR, mortality rate ratio.

[a] Data source: Centers for Disease Control and Prevention (2).

[b] States where heart disease or cancer mortality counts for a race/ethnicity-sex-age subgroup were <20 deaths per 3-year period were considered to have insufficient data, and MRRs were not calculated for those subgroups in those states. Years were combined to provide stable state-specific MRRs for racial/ethnic groups.

[c] Non-Hispanic other consisted of American Indian/Alaska Native and Asian/Pacific Islander.

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Table 2. Summary Statistics for Age-Standardized State-Specific Mortality Rate Ratios (Heart Disease Mortality Rate to Cancer Mortality Rate), by Sex, Age, Race/Ethnicity, and Calendar Year, United States, 1999–2016[a]

Category	Both Sexes					Male					Female				
	No. of States With Data[b]	No. of States With MRR <1.0	Distribution of MRRs, Percentile			No. of States With Data[b]	No. of States With MRR <1.0	Distribution of MRRs, Percentile			No. of States With Data[b]	No. of States With MRR <1.0	Distribution of MRRs, Percentile		
			25th	50th	75th			25th	50th	75th			25th	50th	75th
2014–2016	42	31	0.81	0.92	1.01	39	29	0.86	0.93	1.03	39	28	0.81	0.90	1.02
Hispanic															
1999–2001	38	6	1.03	1.17	1.28	34	9	1.00	1.13	1.27	31	7	1.10	1.25	1.51
2014–2016	43	40	0.71	0.83	0.94	39	30	0.76	0.86	1.00	38	34	0.65	0.78	0.89
Non-Hispanic other[c]															
1999–2001	46	14	0.97	1.10	1.26	34	11	0.94	1.11	1.30	35	14	0.82	1.10	1.21
2014–2016	47	44	0.67	0.75	0.87	42	34	0.71	0.80	0.93	41	37	0.62	0.74	0.84
Aged <65															
Non-Hispanic white															
1999–2001	50	50	0.62	0.67	0.74	50	39	0.87	0.93	1.00	50	50	0.34	0.38	0.44
2014–2016	50	49	0.63	0.66	0.79	50	35	0.85	0.92	1.02	50	50	0.35	0.40	0.54
Non-Hispanic black															
1999–2001	40	29	0.90	0.94	1.01	39	6	1.05	1.11	1.20	38	37	0.69	0.77	0.86
2014–2016	42	20	0.87	1.01	1.06	39	4	1.11	1.25	1.32	38	36	0.61	0.72	0.81
Hispanic															
1999–2001	37	35	0.61	0.69	0.81	33	18	0.86	0.98	1.07	21	21	0.40	0.47	0.56
2014–2016	42	40	0.56	0.62	0.75	39	28	0.79	0.87	1.01	31	31	0.30	0.36	0.45
Non-Hispanic other[c]															
1999–2001	41	37	0.54	0.62	0.85	32	21	0.72	0.81	1.05	26	25	0.28	0.36	0.53
2014–2016	45	38	0.48	0.59	0.79	43	28	0.73	0.83	1.17	31	31	0.23	0.32	0.44

Abbreviations: MRR, mortality rate ratio.

[a] Data source: Centers for Disease Control and Prevention (2).

[b] States where heart disease or cancer mortality counts for a race/ethnicity-sex-age subgroup were <20 deaths per 3-year period were considered to have insufficient data, and MRRs were not calculated for those subgroups in those states. Years were combined to provide stable state-specific MRRs for racial/ethnic groups.

[c] Non-Hispanic other consisted of American Indian/Alaska Native and Asian/Pacific Islander.

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ORIGINAL RESEARCH

Adolescent Beliefs About Hookah and Hookah Tobacco Use and Implications for Preventing Use

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PEER REVIEWED

Summary

What is already known on this topic?

Hookah tobacco use is popular among youths, and there is evidence that perceived risks and normative beliefs are associated with hookah use.

What is added by this report?

Greater perceived social acceptability of hookah tobacco use among friends was associated with higher odds of having ever tried hookah tobacco.

What are the implications for public health practice?

These normative beliefs may be important targets of interventions aimed at preventing youth hookah use. These findings can inform the development of interventions targeting the beliefs associated with youth hookah use as a prevention strategy.

Abstract

Introduction

Hookah tobacco use is popular among youths and there is evidence that perceived risks and normative beliefs are associated with hookah use. The aim of this study was to further examine associations between perceived risks of hookah use, normative beliefs, and lifetime hookah use among youths.

Methods

Participants were adolescents aged 12 to 17 years (n = 257, mean [standard deviation] age, 14.9 [1.6] years, 40% nonwhite, 66% female) attending well-visit checkups at an urban pediatric clinic. Participants completed a survey of measures of cigarette smoking, risk factors for smoking, hookah use, perceived risks, and normative beliefs. Analyses examined associations among lifetime hookah use, beliefs about hookah use, and other smoking risk factors.

Results

Overall, 15% of the sample had ever tried hookah smoking and 60% had ever tried cigarette smoking or were susceptible to cigarette smoking. Of those who had tried hookah smoking, 84% had also tried cigarettes or were susceptible to trying cigarettes ($P < .001$). One-third (33%) indicated that hookah smoking was less harmful than cigarettes, 38% indicated hookah smoking is less addictive than cigarettes, and 48% perceived that hookah smoking is somewhat or very socially acceptable among friends. In multivariable analyses adjusting for demographic and cigarette smoking–related factors, perceiving hookah use to be somewhat or very socially acceptable was associated with a significantly higher odds of ever having tried hookah smoking.

Conclusion

The study findings indicate that stronger perceived social acceptability of hookah use is associated with a higher likelihood of trying hookah smoking among youths. These normative beliefs may be important targets of interventions aimed at preventing hookah use among youths.

Introduction

Hookah tobacco use exposes users to high levels of harmful chemicals and is associated with short-term and long-term health effects, including cancer and lung disease (1). Nicotine exposure through hookah tobacco use produces dependence (2), and there is evidence that young people who try hookah smoking are more likely to initiate cigarette smoking (3). This suggests that factors that affect the risk of youth cigarette smoking (4) may also influence the risk of initiating hookah smoking.

Population data indicate that from 3.3% to 7.5% of US youths have tried hookah tobacco (5,6), but evidence of interventions to prevent hookah use initiation is limited (7). In the context of comprehensive tobacco control efforts, interventions such as mass media campaigns and education messaging targeted toward youths could be expanded to address youth hookah tobacco use (8).

Research examining factors associated with youth hookah use is critical to guide intervention development. Behavioral beliefs, including perceived risks and normative beliefs, are potentially modifiable preventive intervention targets. Some studies indicate that youths view hookah smoking to be equally or more harmful and addictive than cigarettes, while others demonstrate that youths view hookah smoking as less harmful and addictive than cigarettes (9). Normative beliefs are consistently associated with youth hookah use (9), but there is limited research on the independent associations of perceived risks and normative beliefs with youth hookah use behavior when examined concurrently and while accounting for other factors that may influence the risk of using hookah tobacco (4).

This study examined associations between perceived risks of hookah use, normative beliefs, and lifetime hookah use in a sample of youths aged 12 to 17 years. We hypothesized that after accounting for factors associated with cigarette smoking, youths who perceive hookah tobacco to be less risky than cigarettes and more socially acceptable will be more likely to have ever tried hookah tobacco.

Methods

Sample and procedures

This study analyzed data that were collected as part of a larger study of cigarette smoking prevention messaging among youths (N = 319) conducted in 2013 through 2015 in Washington, DC (7). Briefly, participants were offered the option of visiting a to- bacco use prevention website after completion of the baseline sur- vey; a follow-up survey was conducted 1 month later. Data on hookah tobacco use, hookah tobacco beliefs, and other factors were added as part of a study follow-up assessment and collected for 81% of the original study sample.

Adolescents aged 12 to 17 years (n = 257) attending well-visit checkups at an urban pediatric clinic were recruited to participate. Eligible participants were within the study age range, had internet access, and had access to an email address to complete the study procedures. All participants provided signed assent and parental consent. Study procedures were reviewed and approved by the Georgetown University Institutional Review Board.

Enrolled participants completed a confidential online assessment. The baseline assessment included measures assessing demographic characteristics, cigarette smoking, and risk factors for cigarette smoking. The follow-up assessment 1 month after baseline asked about hookah use and beliefs about hookah tobacco.

Measures

Demographic characteristics assessed were participants' sex, race, ethnicity, and age. We captured data on adolescents' risk of cigarette smoking by using 2 variables: lifetime cigarette smoking and cigarette smoking susceptibility. Lifetime cigarette smoking was measured by using a valid item from adolescent tobacco surveys (10), and adolescents were categorized into never smokers and those who had tried cigarette smoking (11–13). Data on cigarette smoking susceptibility among never smokers were captured by using a valid 4-item measure assessing the likelihood that youths will try cigarette smoking under various scenarios in the future (11). This measure identifies nonsmokers who are at risk of smoking initiation and is predictive of youth cigarette smoking be- havior (11). By using these measures, we created a binary vari- able indicating if participants 1) were susceptible to cigarette smoking in the future or had ever tried cigarette smoking or 2) were not susceptible and had never tried cigarette smoking (7). Susceptible never smokers and ever smokers were combined be- cause of the low prevalence of ever smoking in the sample (11.7%).

Established risk factors for adolescent cigarette smoking were measured to account for their potential influence on hookah use behavior (4). Exposure to others' cigarette smoking was measured with items assessing cigarette smoking by parents and among male and female friends (14,15). These were used to create 2 variables indicating if any parents or friends smoked cigarettes (yes/no). Frequency of exposure to tobacco advertising in movies, the internet, print media, and point of sale was measured with 4 items adapted from a previously validated adolescent tobacco use survey (16,17). Items were summed to create a score, with higher values indicating more frequent tobacco advertising exposure (range, 4–20).

Perceived harm and addictiveness of hookah smoking compared with cigarettes were measured by using a single item each. Response options were much less, less, about the same, more, or much more harmful or addictive (18). For analyses, responses were grouped into dummy variables indicating perceptions that hookah smoking is as about the same, more harmful or addictive than cigarettes, or less harmful or addictive than cigarettes.

Perceived peer use and social acceptability of hookah use were measured with a single item each (19). Perceived peer hookah use was assessed by asking how many peers at school have ever smoked hookah with the following response options: none, very few, about half, more than half, most, or all. Data on social acceptability were captured by asking how acceptable participants thought it was to smoke hookah tobacco among their friends, with response options not acceptable, somewhat acceptable, or very acceptable. For analyses, the items for perceived peer hookah use were grouped into dummy variables none or very few, about half, more than half, most, or all. Social acceptability was analyzed based on the response categories for not acceptable, somewhat acceptable, or very acceptable.

Lifetime hookah use was assessed by using a valid item (10) asking whether participants had ever tried hookah smoking, even 1 or 2 puffs (yes/no). We measured lifetime use as an indicator of hookah tobacco initiation among youths to identify potential targets for primary prevention.

Statistical analysis

Sample characteristics were examined by using descriptive statistics. Bivariate analyses were used to assess associations between variables measured and the dependent variable of lifetime hookah use. A multivariable logistic regression model was then created where characteristics associated with lifetime hookah use in the bivariate analyses at *P* less than .05 were included as independent variables to examine multivariable associations with ever hookah use (yes/no) as the dependent variable. The Hosmer-Lemeshow test was used to assess goodness-of-fit for the model. All analyses used SAS version 9.4 (SAS Institute, Inc).

Results

Overall, 15% had ever tried hookah tobacco and 60% had either tried cigarette smoking or were susceptible to cigarette smoking (Table 1). One-third of participants viewed hookah smoking to be less harmful than cigarettes, and 38% viewed it to be less addictive than cigarettes. Nearly 40% of participants reported that half or more of their peers use a hookah, and 48% perceived hookah smoking to be somewhat or very socially acceptable (Table 1).

Those who had tried hookah smoking were on average older, most had tried cigarette smoking or were susceptible to trying cigarette smoking, and most had friends who smoked cigarettes (Table 2). Those who had ever tried hookah smoking perceived it to be less addictive than cigarettes, perceived greater peer hookah use, and perceived hookah use to be more socially acceptable than those who had never tried hookah smoking (Table 2).

The multivariable logistic regression model including factors associated with ever trying hookah smoking at *P* less than .05 in bivariate analyses fit the data well (Hosmer-Lemeshow [8 *df*] = 6.37, *P* = .61) (Table 3). Controlling for other variables in the model, the odds of having ever tried hookah tobacco increased with age (adjusted odds ratio [aOR], 1.60; 95% confidence interval [CI], 1.09–2.35), were greater among those who had ever tried cigarette smoking or were susceptible to trying cigarette smoking (aOR, 2.97; 95% CI, 1.03–8.56), and were greater among those who reported having parents who smoke cigarettes (aOR, 5.41; 95% CI, 1.54–19.02). Controlling for other variables in the model, we found an increase in the odds of having ever tried hookah tobacco among those who viewed hookah tobacco use as somewhat (aOR, 5.70; 95% CI, 1.37–23.77) or very socially acceptable (aOR, 12.36; 95% CI, 2.61–58.50), compared with those who perceived hookah tobacco use as not socially acceptable.

Discussion

This study examined associations among perceived risks of hookah tobacco use, normative beliefs, and lifetime hookah tobacco use in a convenience sample of youths aged 12 to 17 years. The findings indicate that, in multivariable models accounting for other demographic characteristics and cigarette smoking–related factors, greater perceived social acceptability of hookah tobacco use among friends was associated with higher odds of having ever tried hookah tobacco. Lower perceived addictiveness of hookah tobacco compared with cigarettes was associated with having ever tried hookah smoking in bivariate analyses but not in the multivariable analysis. Perceived harms of hookah smoking compared with smoking cigarettes were not associated with having ever tried hookah smoking in bivariate or multivariable analyses. The findings of this study can help to inform the development of interventions aimed at preventing youth hookah tobacco use.

This study adds to the evidence on factors associated with youth hookah tobacco use in several ways. Prior research on beliefs among youths about the harms and addictiveness of hookah tobacco use is somewhat mixed (9). Although some studies demonstrate that youths perceive hookah tobacco to be comparable to cigarette smoking in terms of health harms, others report divergent results (9). Many studies demonstrate that youths tend to hold beliefs that hookah tobacco use is not addictive and they can quit at any time (9). In our sample, although most youths viewed hookah tobacco as equally or more harmful and addictive than cigarettes, one-third or more endorsed views that hookah tobacco is less harmful and less addictive than cigarettes. However, these beliefs about risks were not significantly associated with lifetime hookah use in multivariable analyses. Studies with young adults demonstrate that public health messages communicating the harms and addictiveness of hookah tobacco may be effective to prevent use initiation among young adult nonusers (20). Our findings indicate that messages targeting youths that are limited to communicating potential harms and addictiveness of hookah tobacco alone may have limited effectiveness for prevention. Considering other factors such as perceived social acceptability may help to improve the effectiveness of messages for prevention among youths.

Messaging campaigns to prevent tobacco use among youths that have improved behavioral outcomes integrate messages targeting multiple themes that affect tobacco use behavior among youths (21). The key finding of our study is that as participants' perceived social acceptability of hookah tobacco use among their friends increased, the odds of having ever tried hookah tobacco increased by more than 5-fold. Hookah tobacco is often used in social settings with peers (22), and research conducted in diverse geographical settings demonstrates the influence of peers on youth hookah use (20). This finding is also consistent with studies among young adults, highlighting the role of normative beliefs and peer influence on hookah initiation and use (9). In addition to other known risk factors (23), social acceptability was found in our study to be a content area to examine in future studies seeking to develop interventions aimed at preventing youth hookah use. The outcome we examined was whether youths had ever tried hookah tobacco, suggesting such messages may be optimally targeted toward nonuser populations as a strategy for primary prevention. This targeting is an important avenue for future research given the limited available evidence on interventions to prevent youth hookah use (18).

The tobacco regulatory context in the United States creates opportunities to address youth hookah use through such interventions. In 2016, the Food and Drug Administration (FDA) finalized the regulations expanding FDA's tobacco regulatory authority to include hookah and other tobacco products (24). The 2016 regulations subject hookah tobacco to many of the regulations of the Family Smoking Prevention and Tobacco Control Act (eg, minimum age of sale, prohibitions on youth-oriented marketing and promotions), and position FDA to engage in public education messaging alongside other public health agencies to communicate the risks of hookah use to youths. The Centers for Disease Control and Prevention also seeks to educate the public about the risks of hookah tobacco through online communications (25,26). These materials could be optimized or delivered in various contexts with these results in mind as well.

Research is needed to identify the optimal channels for delivering and engaging youths with hookah tobacco prevention messaging. Tobacco prevention media campaigns targeting youths have leveraged multiple media, including social media (21,27). Messages delivered online that communicate the health risks associated with cigarette smoking can motivate youths to engage with online smoking prevention content (7); however, our findings indicate that messages that target youth hookah use would be best positioned by integrating content targeting their beliefs about social acceptability and potentially other constructs. Evidence suggests social media where youths spend time and engage with content is a prominent source of messages promoting hookah tobacco (28,29). Messages promoting hookah tobacco through social media often include themes normalizing social aspects of hookah tobacco use and promote features that appeal to youths, such as flavoring, yet social media channels infrequently include messaging on hookah use prevention (28,29). In addition to investigating message content, examining message delivery channels that appeal to and engage youths, such as social media for the delivery of hookah tobacco use prevention messaging, is an important avenue for future research.

Our findings should be interpreted in light of limitations of this study. The study included a convenience sample of youths recruited from a single geographic location, limiting generalizability of the findings to other populations. In the parent study from which our data were drawn, participants lost to follow-up were mostly black, had parents who smoked, and had greater exposure to tobacco advertising at baseline than others in the study (7), which may affect our findings. Study participants also had an opportunity to visit a tobacco use prevention website, which may have affected their responses. The cross-sectional data do not allow for inferences about causal associations among hookah tobacco beliefs and the behavior examined. All measures were based on participant self-report. Although valid measures were used, they are subject to potential reporting biases.

Despite these limitations, our findings indicate that perceived social acceptability of hookah tobacco use is associated with lifetime use of hookah among youths when taking into account demographic, cigarette smoking, and other hookah-related covariates. These findings can inform the development of interventions targeting the beliefs associated with youth hookah use as a prevention strategy.

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Tables

Table 1. Characteristics of Adolescents (n = 257) Aged 12 to 17 Years Asked About Hookah and Hookah Tobacco Use, Washington, DC, 2013–2015[a]

Characteristic	Value[b]
Sex	
Male	88 (34.2)
Female	169 (65.8)
Race	
White	154 (59.9)
Black	55 (21.4)
Other race	48 (18.7)
Ethnicity	
Hispanic	33 (12.8)
Non-Hispanic	224 (87.2)
Age, mean (SD), y	14.9 (1.6)
Adolescent cigarette smoking risk	
Tried smoking or susceptible never smoker	153 (60.0)
Not susceptible, never smoker	102 (40.0)
Parents smoke cigarettes	
Yes	26 (10.1)
No	231 (89.9)
Friends smoke cigarettes	
Yes	71 (27.6)
No	186 (72.4)
Tobacco advertising exposure, mean (SD)[c]	11.6 (3.0)
Perceived harms of hookah	
Less harmful than cigarettes	84 (33.1)
About the same as cigarettes	110 (43.3)
More harmful than cigarettes	60 (23.6)
Perceived addictiveness of hookah smoking	
Less addictive than cigarettes	97 (38.0)
About the same as cigarettes	123 (48.2)
More addictive than cigarettes	35 (13.7)
Perceived peer hookah use	
More than half, most, or all	45 (17.7)
About half	53 (20.8)
None or very few	157 (61.6)

Abbreviation: SD, standard deviation.

[a] Data displayed are n (%) unless otherwise indicated.

[b] Some totals do not sum to total sample n because of sporadic missing data (<5% for any given variable).

[c] Range, 4–20.

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Table 1. Characteristics of Adolescents (n = 257) Aged 12 to 17 Years Asked About Hookah and Hookah Tobacco Use, Washington, DC, 2013–2015[a]

Characteristic	Value[b]
Social acceptability of hookah use	
Very acceptable	38 (15.0)
Somewhat acceptable	83 (32.7)
Not acceptable	133 (52.4)
Ever tried hookah	
Yes	38 (14.8)
No	219 (85.2)

Abbreviation: SD, standard deviation.

[a] Data displayed are n (%) unless otherwise indicated.

[b] Some totals do not sum to total sample n because of sporadic missing data (<5% for any given variable).

[c] Range, 4–20.

Table 2. Bivariate Associations With Ever Trying Hookah Tobacco Among Adolescents (n = 257) Aged 12 to 17 Years Asked About Hookah and Hookah Tobacco Use, Washington, DC, 2013–2015

Characteristic	Ever Tried Hookah Smoking[a]		*P* Value
	Yes	No	
Sex			
Male	13 (34.2)	75 (34.2)	>.99
Female	25 (65.8)	144 (65.8)	
Race			
White	26 (68.4)	128 (58.5)	.18
Black	9 (23.7)	46 (21.0)	
Other race	3 (7.9)	45 (20.5)	
Ethnicity			
Hispanic	5 (13.2)	28 (12.8)	.95
Non-Hispanic	33 (86.8)	191 (87.2)	
Age, mean (SD), y	16.2 (0.87)	14.7 (1.6)	< .001
Adolescent cigarette smoking risk			
Tried smoking or susceptible never smoker	32 (84.2)	121 (55.8)	.001
Not susceptible, never smoker	6 (15.8)	96 (44.2)	
Parents smoke cigarettes			
Yes	8 (21.0)	18 (8.2)	.02
No	30 (79.0)	201 (91.8)	
Friends smoke cigarettes			
Yes	24 (63.2)	47 (21.5)	< .001
No	14 (36.8)	172 (78.5)	
Tobacco Advertising Exposure, mean (SD)[b]	12.4 (2.6)	11.5 (3.1)	.10
Perceived harms of hookah			
Less harmful than cigarettes	11 (29.7)	73 (33.6)	.08
About the same as	12 (32.4)	98 (45.2)	
More harmful than cigarettes	14 (37.8)	46 (21.2)	
Perceived addictiveness of hookah smoking			
Less addictive than cigarettes	23 (60.5)	74 (34.1)	.008
About the same as	12 (31.6)	111 (51.2)	
More addictive than cigarettes	3 (7.9)	32 (14.8)	
Perceived peer hookah use			
More than half, most, or all	16 (42.1)	29 (13.4)	<.001
About half	9 (23.7)	44 (20.3)	
None or very few	13 (34.2)	144 (66.4)	
Social acceptability of hookah use			

Abbreviation: SD, standard deviation.

[a] Data displayed are n (%) unless otherwise indicated. Some totals do not sum to total sample n because of sporadic missing data (<5% for any given variable).

[b] Range, 4–20.

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(continued)

Table 2. Bivariate Associations With Ever Trying Hookah Tobacco Among Adolescents (n = 257) Aged 12 to 17 Years Asked About Hookah and Hookah Tobacco Use, Washington, DC, 2013–2015

Characteristic	Ever Tried Hookah Smoking[a]		*P* Value
	Yes	No	
Very acceptable	18 (47.4)	20 (9.3)	<.001
Somewhat acceptable	17 (44.7)	66 (30.6)	
Not acceptable	3 (7.9)	130 (60.2)	

Abbreviation: SD, standard deviation.

[a] Data displayed are n (%) unless otherwise indicated. Some totals do not sum to total sample n because of sporadic missing data (<5% for any given variable).

[b] Range, 4–20.

Table 3. Logistic Regression Analysis of Correlates of Ever Trying Hookah Tobacco Among Adolescents (n = 257) Aged 12 to 17 Years Asked About Hookah and Hookah Tobacco Use, Washington, DC, 2013–2015

Characteristic	Adjusted Odds Ratio (95% Confidence Interval)	*P* Value
Age	1.60 (1.09–2.35)	.02
Adolescent cigarette smoking risk		
Tried smoking or susceptible never smoker	2.97 (1.03–8.56)	.04
Not susceptible, never smoker	1 [Reference]	
Parents smoke cigarettes		
Yes	5.41 (1.54–19.02)	.009
No	1 [Reference]	
Friends smoke cigarettes		
Yes	1.68 (0.68–4.17)	.27
No	1 [Reference]	
Perceived addictiveness of hookah smoking		
Less addictive than cigarettes	2.90 (0.55–15.40)	.21
About the same as	1.32 (0.25–7.05)	.74
More addictive than cigarettes	1 [Reference]	
Perceived peer hookah use		
More than half, most, or all	1.68 (0.57–5.00)	.35
About half	0.84 (0.29–2.44)	.75
None or very few	1 [Reference]	
Social acceptability of hookah use		
Very acceptable	12.36 (2.61–58.50)	.002
Somewhat acceptable	5.70 (1.37–23.77)	.02
Not acceptable	1 [Reference]	

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ORIGINAL RESEARCH

Patterns of Polysubstance Use Among Non-Hispanic White and American Indian/Alaska Native Adolescents: An Exploratory Analysis

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PEER REVIEWED

Summary

What is already known on this topic?

Polysubstance use among adolescents in the United States is rising, and rates of substance use differ by race/ethnicity. Typically, substance use among non-Hispanic white adolescents is less prevalent than among American Indian/Alaska Native adolescents.

What is added by this report?

American Indian/Alaska Native adolescents tended to use steroids and injected drugs together, whereas non-Hispanic white adolescents used cocaine and ecstasy together. Both groups used tobacco, marijuana, and alcohol together and a cluster of other illicit substances together.

What are the implications for public health practice?

These findings can be used in the clinical setting to screen for and prevent substance and polysubstance use among adolescents.

Abstract

Introduction

The prevalence of polysubstance use is well described, but less is known about correlates and patterns of polysubstance use. Previous research characterized latent subgroups of substance users by the type substance used. Racial disparities in the prevalence of polysubstance use exist, particularly for American Indian/Alaska Native (AI/AN) populations. The objective of our study was to describe differences in patterns of polysubstance use between non-Hispanic white and AI/AN adolescents.

Methods

We obtained data from the 2013 Youth Risk Behavior Survey (YRBS). We analyzed substance use patterns (cigarettes, alcohol, marijuana, cocaine, inhalants, heroin, methamphetamines, ecstasy, steroids, and injected drugs) separately among 375 AI/AN and 15,633 non-Hispanic white adolescents. We calculated pairwise correlations. Exploratory factor analysis identified latent factors of polysubstance use patterns.

Results

The use of all substances by AI/AN adolescents was the same or higher than use by non-Hispanic white adolescents, particularly for cocaine, heroin, and steroids. We found strong correlations between use of heroin and injected drugs and between use of cocaine and ecstasy among both populations. We found a latent factor for cigarettes, alcohol, and marijuana and another factor for broad polysubstance use among both populations. We found a factor for steroids and injected drugs among AI/AN adolescents, a factor for cocaine and ecstasy among non-Hispanic white adolescents, and a unique factor for methamphetamines.

Conclusion

Differences in substance use patterns exist between AI/AN and non-Hispanic white adolescents, particularly for illegal drug use. If validated in future research, information on these differences could be used to inform tailored intervention programs aimed at preventing substance use.

Introduction

Substance use is well understood to have negative, life-long consequences. Particularly concerning is the use of substances among adolescents, because initiation often occurs during these formative years, thus increasing the likelihood of addiction and continued use (1). In 2013, 7.8% of adolescents used tobacco, 22.7% drank alcohol, and 8.8% used illegal drugs (2,3).

Prevalence of substance use is well known for individual substances at the general population level; however, substance use differs widely across subgroups of the population. For example, with the exception of alcohol, substance use is more prevalent among American Indian/Alaska Native (AI/AN) populations than among white populations (3). In addition to racial disparities in the prevalence of substance use, racial differences in risk factors and correlates of risky behaviors exist (4–6).

Even after accounting for demographic characteristics, adolescent populations have distinct heterogeneous subgroups (ie, latent classes) that differ in their patterns of polysubstance use (7–9). Common subgroups include nonusers or infrequent users, broad polysubstance users, and users of 1 or more substances (7), such as alcohol (7,8,10) or dual use of marijuana and cigarettes (8). These subgroups differ in their environmental-level and/or individual-level risk factors for substance use (7).

Considering that racial differences exist among these social and environmental risk factors for substance use, it is plausible that common patterns of substance use could fundamentally differ by racial or ethnic group. Little is known about whether such differences in patterns of substance use exist between AI/AN and non-Hispanic white adolescents. If differences do exist, then that information could be used to identify adolescents at higher risk for polysubstance use. Effective treatment plans and education could then be designed and implemented to prevent additional substance use. Our study used data from the 2013 Youth Risk Behavior Survey (YRBS) to examine potential differences in correlations and patterns of substance use between AI/AN and non-Hispanic white adolescents.

Methods

We used publicly available data from the 2013 YRBS (the most recent data available at the beginning of this research, in March 2015). The YRBS is an observational, cross-sectional survey designed in 1990 by the Centers for Disease Control and Prevention to monitor the leading risk behaviors of US adolescents and young adults that contribute to death, disability, and social problems (11).

We limited our analysis to 2 self-reported race/ethnicities: AI/AN (n = 1,096) and non-Hispanic white (n = 45,187). We found a substantial amount of missing data on substance use variables, which was handled with listwise deletion, resulting in a final sample size of 375 AI/AN adolescents and 15,633 non-Hispanic white adolescents. We used listwise deletion because research shows that it is preferable to other methods (eg, imputation) in pattern-based analyses such as ours (12).

The University of North Dakota Institutional Review Board approved this study. All analyses were conducted at the University of North Dakota, Grand Forks, North Dakota, from March 2015 through February 2018.

Measures

We analyzed survey data on the following substances: tobacco (cigarettes), alcohol, marijuana, cocaine, inhalants, heroin, methamphetamines, ecstasy, steroids, and injected drugs.

Cigarette and alcohol use were each assessed by the self-reported number of days of the past 30 days that each substance was used. Original responses were given as 0 days, 1 or 2 days, 3 to 5 days, 6 to 9 days, 10 to 19 days, 20 to 29 days, or all 30 days. We used the midpoint value of each category for the analyses of the responses.

Marijuana was assessed by the self-reported number of lifetime uses of marijuana. Original responses were given as 0 times, 1 or 2 times, 3 to 9 times, 10 to 19 times, 20 to 39 times, 40 to 99 times, or 100 or more times. We used the midpoint value of each category for the analyses of the responses, and values were top coded at 100.

Cocaine (including “powder, crack, or freebase”), inhalants (including “glue, aerosol spray cans, paints, or sprays to get high”), heroin (including “smack, junk, or China white”), methamphetamines (including “speed, crystal, crank, or ice”), ecstasy (including “MDMA”), and steroids (“steroid pills or shots without a doctor’s prescription”) were assessed by the self-reported number of days in the participant’s lifetime that each substance was used. Original responses were given as 0 times, 1 or 2 times, 3 to 9 times, 10 to 19 times, 20 to 39 times, or 40 or more times. We used the midpoint value of each category for the analyses of the responses, and values were top coded at 40.

The use of injected drugs (“used a needle to inject any illegal drug”) was assessed by the self-reported number of days in the participant’s lifetime that the substance was used. Original responses were given as 0 times, 1 time, or 2 or more times. These values were analyzed numerically and were top coded at 2.

Analysis

The YRBS has a complex, multistage sampling process, and survey weights are available to account for this sampling design in standard analyses (eg, regressions). However, we intentionally did not account for survey weights because 1) our study was exploratory and 2) standard and automatic procedures for incorporating survey weights are lacking for the type of analysis we conducted.

In other words, our focus was to examine broad, qualitative differences in *patterns* of polysubstance use across AI/AN and non-Hispanic white samples rather than to produce population-level parameter estimates.

To quantify the pairwise association between each possible pair of substances, we calculated Spearman ρ, a nonparametric correlation statistic; we used a nonparametric test because the data were not normally distributed. We adjusted for multiple comparisons of the Spearman ρ test by using the Bonferroni correction. We then visualized all pairwise correlations simultaneously by creating a heatmap.

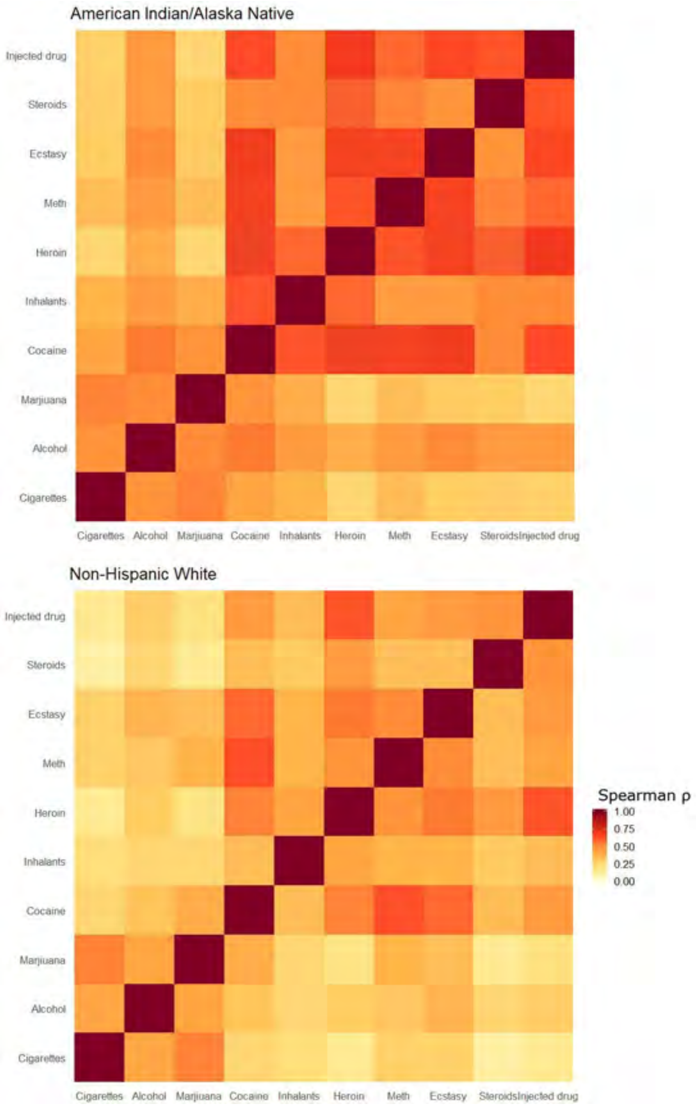
Next, we performed an exploratory factor analysis on each group to identify latent factors based on substance use patterns among each group. Exploratory factor analysis tests the hypothesis that each group (non-Hispanic white and AI/AN) contains subgroups with fundamentally different substance use patterns. Preliminary analyses based on scree plots (not shown) suggested that the optimal number of factors was 2 to 5 factors for the AI/AN group and 4 or 5 factors for the non-Hispanic white group. We selected the final number of factors on the basis of interpretability, model fit, and simplicity of structure (ie, single-loading of variables onto factors with a threshold of 0.3). We used oblique rotation to allow correlation between the latent factors and ordinary least squares factoring to find the minimum residual solution while accounting for nonnormality among variables. We used the Tucker-Lewis Index and the root-mean-square error of approximation to evaluate the goodness-of-fit for the exploratory factor analysis. A Tucker-Lewis Index of 0.9 or greater is considered a good fit (13) as is a root-mean-square error of approximation of 0.05 or less (14).

We conducted all analyses and plots by using R version 3.1.3 (R Foundation for Statistical Computing) run separately for AI/AN and non-Hispanic white samples.

Results

AI/AN adolescents had a higher rate than non-Hispanic white adolescents of past 30-day use of tobacco and alcohol and lifetime use of marijuana, cocaine, inhalants, heroin, methamphetamines, ecstasy, steroids, and injected drugs (Table 1). Among users of each substance, the median frequency of use was the same or higher among AI/AN adolescents, with large differences found in use of cocaine (14.5 vs 6.0 lifetime uses), heroin (22.0 vs 1.5 lifetime uses), and steroids (29.5 vs 6.0 lifetime uses).

Pairwise correlations showed strong similarities across groups in which pairs of substances were correlated with each other and, in general, the correlations were slightly stronger among AI/AN adolescents than among non-Hispanic white adolescents (Figure). The top 3 pairwise correlations for AI/AN adolescents were heroin with injected drugs ($\rho = 0.669$, $P < .001$), cocaine with methamphetamines ($\rho = 0.661$, $P < .001$), and steroids with injected drugs ($\rho = 0.599$, $P < .001$). The top 3 pairwise correlations for non-Hispanic white adolescents were cocaine with methamphetamines ($\rho = 0.614$, $P < .001$), heroin with injected drugs ($\rho = 0.608$, $P < .001$), and cigarettes with marijuana ($\rho = 0.585$, $P < .001$). Cocaine with methamphetamine and heroin with injected drugs were in the top 3 most strongly correlated pairs among both AI/AN and non-Hispanic white adolescents.


American Indian/Alaska Native

Non-Hispanic White

Figure. Pairwise correlations (Spearman ρ) among American Indian/Alaska Native and non-Hispanic white adolescents, Youth Risk Behavior Survey, 2013. Each pair of drugs is represented as a square. Abbreviation: Meth, methamphetamine.

In the exploratory factor analyses, a 3-factor solution was chosen for the AI/AN group, and a 4-factor solution was chosen for the non-Hispanic white group (Table 2). Both models showed good fit (Tucker-Lewis Index = 0.91, root-mean-square error of approximation = 0.008 for AI/AN adolescents; Tucker-Lewis Index = 0.99, root-mean-square error of approximation = 0.001 for non-Hispanic white adolescents). Among AI/AN adolescents, one of the latent factors was associated with use of cocaine, ecstasy, heroin, methamphetamines, and inhalants; the second latent factor was associated with use of injected drugs and steroids; and the third latent factor was associated with use of cigarettes, marijuana, and alcohol. Among non-Hispanic white adolescents, one of the latent factors was associated with use of heroin, injected drugs, steroids, and inhalants; the second latent factor was associated with use of cigarettes, marijuana, and alcohol; the third latent factor was associated with use of methamphetamines; and the fourth latent factor was associated with use of ecstasy and cocaine.

These results identified both similarities and differences among AI/AN and non-Hispanic white adolescents. Both groups had a distinct latent factor for cigarettes, alcohol, and marijuana. Other commonalities included a link between 1) heroin and inhalants, 2) steroids and injected drugs, and 3) cocaine and ecstasy. One prominent difference was that methamphetamine was its own independent variable among non-Hispanic white adolescents, but it was linked with other substances among AI/AN adolescents. Additionally, steroids and injected drugs comprised their own latent factor among AI/AN adolescents, whereas cocaine and ecstasy comprised their own latent factor among non-Hispanic white adolescents.

Discussion

We conducted an exploratory analysis of differences in substance use patterns among AI/AN and non-Hispanic white adolescents in the United States. Pairwise correlations overall showed similar patterns of substance use, particularly for heroin with injected drugs and cocaine with methamphetamines, although the strength of correlations was generally higher among AI/AN adolescents. Exploratory factor analysis identified a common factor for cigarettes, alcohol, and marijuana across both groups, but distinct factors also emerged in each group. Among AI/AN adolescents, injected drugs and steroids comprised a latent factor, whereas among non-Hispanic white adolescents, cocaine and ecstasy comprised a separate latent factor, and methamphetamine alone loaded onto its own factor.

Our study parallels well-known findings about substance use disparities across racial/ethnic groups in adults (15–22). It adds to this body of knowledge by describing differences among adolescents, in particular showing a higher prevalence of substance use among AI/AN adolescents than among non-Hispanic white adolescents. The primary focus of our study, however, extends beyond the prevalence of substance use by examining differences in correlations and patterns of polysubstance use between AI/AN and non-Hispanic white adolescents, about which little is known. Our findings that AI/AN and non-Hispanic white adolescents have different patterns of substance use is consistent in a broader sense with previous findings that risk factors for risky behavior differ between these 2 populations (4–6).

One pattern of substance use common among both AI/AN and non-Hispanic white adolescents was the combination of cocaine and ecstasy; these were strongly associated according to both the correlation analysis and the exploratory factor analysis. Other remarkable correlations in both populations were cigarettes with marijuana and alcohol. Both the heatmap and the factor analysis indicated that if an adolescent used cocaine, he or she would be more likely than not to have also used ecstasy, heroin, methamphetamines, or inhalants. Likewise, if an adolescent used cigarettes, he or she would be more likely than not to have used marijuana and alcohol. Our findings are broadly consistent with previous research on latent classes of substance use (7) in that a pattern emerged for “lighter” substance use (cigarettes, alcohol, and marijuana) and other patterns emerged for “heavier” substance use (substances that are illegal at any age).

We found notable differences between AI/AN and non-Hispanic white adolescents in illegal substance use. In particular, nonmedical steroid use and injected drugs were associated with both AI/AN and non-Hispanic white adolescents, but this pairing comprised its own unique factor among AI/AN adolescents. This pairing indicates that AI/AN adolescents who illicitly use steroids and injected drugs are a distinct subpopulation of AI/AN adolescents. A link between steroid use and injected drugs was reported previously (23), but to our knowledge, this link has not been reported among AI/AN adolescents. Distinct subpopulations of non-Hispanic white adolescents were uniquely characterized by methamphetamine use, indicating that non-Hispanic white methamphetamine users are a distinct subpopulation of non-Hispanic white adolescents. We found this unique characterization despite the overall lower prevalence of methamphetamine use among non-Hispanic white adolescents than among AI/AN adolescents. Similarly, cocaine and ecstasy use characterized another subpopulation of non-His- panic white adolescents.

Future research should focus on replicating these patterns in other independent samples, examining temporality and possible causality and further refining the exact nature (eg, which drugs are injected and what type of steroids are being used) and timing (eg, whether cocaine and ecstasy are being taken together in a single episode) of these patterns. Validation of racial/ethnic differences in polysubstance use patterns would motivate the development of tailored interventions for subgroups to prevent or reduce the prevalence of polysubstance use.

Strengths of our study include the novel use of exploratory methods to assess polysubstance abuse among AI/AN and non-Hispanic white adolescents. Additionally, our study extends previous research on racial/ethnic disparities in the prevalence of use to examine patterns of polysubstance use. Finally, our study used a large, national data set, which increases the generalizability of the findings to the larger population of high school–aged students in the United States.

Our study had several limitations. First, it used cross-sectional data, which cannot be used to assess causality or rule out residual confounding. Second, because YRBS data are self-reported, they are subject to social desirability and recall biases. Third, the use of cigarettes and alcohol were measured in “use within the past 30 days,” while all other substances were measured in “lifetime use.” This difference results in imperfect direct comparisons between substances. Fourth, the YRBSS has a large degree of missing data on substance use, and these data may not be missing at random. For example, because the sample is limited to students who were at school on the day of the survey, truancy could have affected the findings, especially since truancy is known to be associated with substance use. The patterns of missing data may have affected our findings in unknown ways, and thus the findings should be considered exploratory only. Fifth, it was not possible to examine national YRBS public use data by state or region, and because AI/AN subpopulations can differ by state or region in important ways, further research is needed to explore these differences. Sixth, factor analysis should be considered an exploratory method, and the results may be sensitive to the particular sample or to the specific method of measuring the latent factors (eg, the wording of the questions). Additionally, factor analysis is somewhat subjective, particularly in the way factors are interpreted and the role of interpretability in selecting the number of factors. Finally, several of the substance use items, such as steroids, inhalants, and injected drugs, were broadly defined, and detailed information on the exact substance was not available.

The practicality of our study is noteworthy. The data show strong pairwise correlations between common substances of abuse and classify AI/AN and non-Hispanic white adolescents into well-structured latent factors, indicating that distinct patterns of polysubstance use exist in each subpopulation. A health care professional could use this information to inquire about substance use if a substance is known to be used and subsequently educate susceptible adolescents about substance use habits with the goal of preventing polysubstance abuse. Public health interventions and policy makers can also use these data to formulate strategies for reaching certain racial/ethnic groups to decrease the prevalence of substance abuse with more efficiency and effectiveness.

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Tables

Table 1. Descriptive Statistics of Age, Sex, and Frequency of Substance Use Among American Indian/Alaska Native and Non-Hispanic White Adolescents, 2013 Youth Risk Behavior Survey[a]

Characteristic	American Indian/Alaska Native (n = 1,096)	Non-Hispanic White (n = 45,187)
Age, y	16.0 (15.0–17.0)	16.0 (15.0–17.0)
Male sex	617 (56.6)	23,517 (52.1)
Use of substance		
Cigarettes		
Past 30-day use	388 (38.2)	14,782 (33.7)
Frequency among users	14.5 (4.0–30.0)	14.5 (4.0–30.0)
Alcohol		
Past 30-day use	534 (54.2)	22,632 (51.8)
Frequency among users	4.0 (1.5–7.5)	4.0 (1.5–7.5)
Marijuana		
Lifetime use	575 (54.8)	17,952 (40.1)
Frequency among users	29.5 (6.0–100.0)	14.5 (6.0–69.5)
Cocaine		
Lifetime use	161 (15.2)	3,620 (8.1)
Frequency among users	14.5 (1.5–40)	6.0 (1.5–14.5)
Inhalants		
Lifetime use	169 (21.1)	5,438 (16.5)
Frequency among users	6.0 (1.5–29.5)	6.0 (1.5–6.0)
Heroin		
Lifetime use	32 (5.5)	625 (2.7)
Frequency among users	22.0 (6.0–40.0)	1.5 (1.5–29.5)
Methamphetamine		
Lifetime use	90 (15.3)	2,102 (9.1)
Frequency among users	6.0 (1.5–29.5)	6.0 (1.5–14.5)
Ecstasy		
Lifetime use	63 (13.6)	1,713 (10.1)
Frequency among users	1.5 (1.5–14.5)	1.5 (1.5–6.0)
Steroids		
Lifetime use	96 (8.9)	1,809 (4.0)
Frequency among users	29.5 (4.9–40.0)	6.0 (1.5–14.5)
Injected drugs		
Lifetime use	43 (5.3)	721 (2.2)
Frequency among users	2.0 (1.0–2.0)	2.0 (1.0–2.0)

[a] Data source: Centers for Disease Control and Prevention (11). Frequency for cigarette and alcohol use was defined as the number of days used in the past 30 days. For all other substances, frequency refers to the number of days used in lifetime. Continuous variables are summarized as median (interquartile range). Categorical variables are summarized as number (percentage).

Table 2. Exploratory Factor Analysis of Patterns of Polysubstance Use Among American Indian/Alaska Native and Non-Hispanic White Adolescents, 2013 Youth Risk Behavior Survey[a]

Substance	American Indian/Alaska Native			Non-Hispanic White			
	Factor 1	Factor 2	Factor 3	Factor 1	Factor 2	Factor 3	Factor 4
Cigarettes	—	—	0.807	—	—	0.748	—
Alcohol	—	—	0.410	—	—	0.512	—
Marijuana	—	—	0.566	—	—	0.730	—
Cocaine	—	0.816	—	—	—	—	0.629
Inhalants	—	0.561	—	—	0.334	—	—
Heroin	—	0.697	—	—	0.743	—	—
Methamphetamine	—	0.641	—	0.980	—	—	—
Ecstasy	—	0.740	—	—	—	—	0.681
Steroids	0.405	—	—	—	0.592	—	—
Injected drugs	0.981	—	—	—	0.729	—	—

[a] Data source: Centers for Disease Control and Prevention (11). The loading of each variable of substance use onto each factor is shown; blank cells indicate that the loading was below the threshold of 0.3.

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ORIGINAL RESEARCH

Living Alone and Homelessness as Predictors of 30-Day Potentially Preventable Hospital Readmission

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PEER REVIEWED

Summary

What is already known about this topic?

Health systems are encouraged to add social and behavioral measures to electronic health records (EHRs), but there is limited research that demonstrates how to leverage this information.

What is added by this report?

We assessed 2 social factors collected from EHRs — social isolation and homelessness — in predicting 30-day potentially preventable readmissions to hospital.

What are the implications for public health practice?

Because social and behavioral factors affect patient health, health care systems must rethink the way these measures are defined and captured in EHRs. Our study illustrates how social factors (ie, homelessness and social isolation) can be leveraged for predictive modeling of acute care outcomes.

Abstract

Introduction

The effect of social factors on health care outcomes is widely recognized. Health care systems are encouraged to add social and behavioral measures to electronic health records (EHRs), but limited research demonstrates how to leverage this information. We assessed 2 social factors collected from EHRs — social isolation and homelessness — in predicting 30-day potentially preventable readmissions (PPRs) to hospital.

Methods

EHR data were collected from May 2015 through April 2017 from inpatients at 2 urban hospitals on Oʻahu, Hawaiʻi (N = 21,274). We performed multivariable logistic regression models predicting 30-day PPR by living alone versus living with others and by documented homelessness versus no documented homelessness, controlling for relevant factors, including age group, race/ethnicity, sex, and comorbid conditions.

Results

Among the 21,274 index hospitalizations, 16.5% (3,504) were people living alone and 11.2% (2,385) were homeless; 4.2% (899) hospitalizations had a 30-day PPR. In bivariate analysis, living alone did not significantly affect likelihood of a 30-day PPR (16.6% [3,376 hospitalizations] without PPR vs 14.4% [128 hospitalizations] with PPR; *P* = .09*)*. However, documented homelessness did show a significant effect on the likelihood of 30-day PPR in the bivariate analysis (11.1% [2,259 hospitalizations] without PPR vs 14.1% [126 hospitalizations] with PPR; *P* = .006). In multivariable models, neither living alone nor homelessness was significantly associated with PPR. Factors that were significantly associated with PPR were comorbid conditions, discharge disposition, and use of an assistive device.

Conclusion

Homelessness predicted PPR in descriptive analyses. Neither living alone nor homelessness predicted PPR once other factors were controlled. Instead, indicators of physical frailty (ie, use of an assistive device) and medical complexity (eg, hospitalizations that required assistive care post-discharge, people with a high number of comorbid conditions) were significant. Future research should focus on refining, collecting, and applying social factor data obtained through acute care EHRs.

Introduction

Because of widespread recognition of the relationship between social factors and health care outcomes, the Institute of Medicine (IOM) provided recommendations for social and behavioral domain measures to be documented in the electronic health record (EHR) (1). Many health systems now collect some data on social factors, but practical and logistical questions remain, including how to feasibly and systematically collect such data during routine clinical care and how to use these data for more effective population health management (1–3).

“Social connection and isolation” was one domain recommended by IOM (4). A lack of social relationships has been associated with numerous health outcomes, including illness, functional decline, and death (5–7). Two substantial gaps exist in the literature. First, limited research has been done on whether social isolation plays a role in overall health care use (8,9). Second, the measure of social isolation is typically collected outside the EHR, via self-reported survey or interview (5,10–12). Thus, these measures are rarely found in analyses of administrative inpatient data.

Another critical social factor potentially contributing to inpatient health care use and readmission is homelessness. Homeless status also is not routinely collected by health care systems in the EHR, and it has been associated in several recent studies with readmissions and with overall illness and early death (13,14).

Our objective was to examine whether variables for social isolation and homelessness as captured in a health system’s EHRs over 2 years predicted 30-day potentially preventable readmission (PPR), a key measure of health care quality (15). We hypothesized that people who were documented as living alone or homeless would have a higher likelihood of PPR than those without these designations.

Methods

Data and inclusion criteria

We collected EHR data for 25,717 people aged 18 or older who had at least 1 inpatient hospitalization from May 1, 2015, through April 30, 2017, at 2 midsized urban hospitals on O‘ahu, Hawai‘i . Any hospitalizations that resulted in death were excluded from the analysis (n = 1,101). These data uniquely identified individuals longitudinally. By using this unique identifier, each person’s first inpatient hospitalization during the study period was identified. These initial hospitalizations were flagged to indicate whether they resulted in a 30-day PPR (yes/no) by using the 3M PPR methodology (16). The 3M PPR methodology has been extensively used and validated (17). People with subsequent readmission encounters were excluded from the sample (n = 949) to prevent high-use patients from biasing our understanding of demographic and clinical factors predicting PPR in general. The institutional review board of Hawai‘i Pacific Health approved our study.

Hospitalizations that were not considered eligible under the 3M PPR methodology were also excluded (n = 2,393). These were, for example, people re-admitted for conditions that were not clinically related (eg, a hospital admission for pneumonia followed by a hospitalization for an appendectomy), people admitted with multiple traumas (where multiple hospitalization may be medically necessary), and people currently in chemotherapy treatment and likely to return to the hospital (18). For the final analysis, a total of 21,274 inpatient hospitalizations were used (Figure 1). SAS Version 9.4 (SAS Institute) was used to complete both descriptive statistics and multivariable modeling. Our outcome was a binary variable that indicated whether a person’s initial hospitalization during the study period resulted in a 30-day PPR (yes/no) according to 3M PPR methods (18,19).

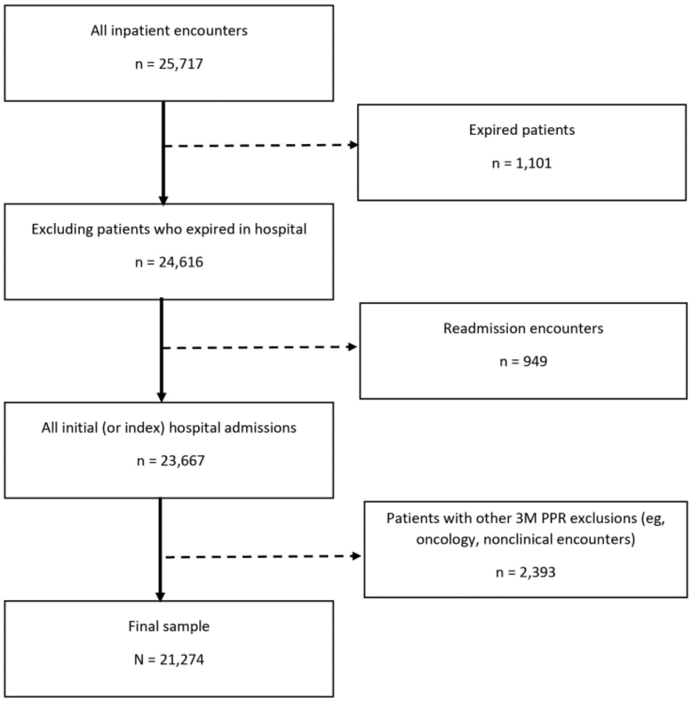

Figure 1. Selection criteria for the predictive model for all inpatient encounters (N = 25,717) collected from 2 urban hospitals in Hawai’i. Abbreviation: PPR, potentially preventable readmission.

Independent variables. At both hospitals included in our study, the “lives alone” identifier has been collected consistently since October 2015. Nurses ask patients to identify who they live with as a part of the admission process. Case managers are required to populate this field if it is missed during the admission process. Nurses and case managers are allowed to select 1 or more of the following options: alone, caregiver, family, parent, partner, roommate, spouse, or other. We used the information from this field to categorize patients into 2 groups, either as people who live alone or people who live with others.

For the independent variable of homelessness, the reporting team created a wild card search for “*homeless*” in numerous free-text fields for “residence” and collated them as a 0/1 flag. The information from this field was used to categorize patients into 2 groups, either as people with documented homelessness or people without documented homelessness.

Control variables. Several demographic factors were considered for control variables, including race/ethnicity (white, Chinese, Japanese, Filipino, Native Hawaiian, other Pacific Islander, and other), age group (<65 y and ≥65 y), sex (male/female), and insurance (public [Medicare or Medicaid], private, or other). Several clinical factors were also collected, including admission source (eg, whether a person came to the hospital through the emergency department, from another health care facility, or via physician referral), length of hospitalization, length of stay in intensive care unit, case mix index (a severity of illness weight assigned by Centers for Medicare & Medicaid Services on the basis of a patient’s principal diagnosis) whether patients had a surgical encounter (yes/no), whether patients have a device to assist with mobility (yes/no), the Elixhauser comorbidity score (a method of categorizing co-occurring diseases or disorders in addition to the primary diagnosis) (20), presence of mental health diagnoses (yes/no), and discharge disposition (eg, discharged to home, hospice, or skilled nursing facility). Data for all independent and control variables were taken from the index admission.

Statistical analysis

For the first stage of analysis, we summarized data on patients with and without 30-day PPR with descriptive statistics by using χ^2 tests or Fisher exact tests (for categorical variables) and 2-sample *t* tests (for continuous variables). Two-tailed tests using an α of .05 were used to assess the significance for these analyses in predicting 30-day PPR; significant factors were included as control variables in the logistic regression equations.

For the second stage of analysis, a logistic regression model was developed to estimate the likelihood of PPR after the index hospital admission by using control variables identified through the descriptive statistics as being significant ($P < .05$); we also used the 2 independent variables of interest, lives alone (yes/no) and homeless (yes/no). We also tested for an interaction between our 2 focal independent variables: lives alone and homeless. The interaction was not significant ($P = .99$) and was not included in the final multivariable model.

Results

Among the 21,274 index hospitalizations, 16.5% (3,504) were people living alone and 11.2% (2,385) were homeless. Of the index hospitalizations, 4.2% (899) of hospitalizations had a 30-day PPR. Of the index hospitalizations, 21,251 had documentation around whether patients lived alone (documentation for living alone was not populated for 23 cases; these encounters were excluded from bivariate analysis). Of the 21,251 that had documentation around living alone, 20,357 encounters did not have a PPR, and 894 encounters did. In bivariate analysis, living alone did not show significance for PPR. People who lived alone represented 16.6% of non-PPR encounters (3,376 of 20,357) and 14.4% of PPR encounters (128 of 894, $P = .09$).

Documentation about whether the patient was homeless was available for 21,267 of the 21,274 index hospitalizations (documentation for homelessness was not populated for 7 cases, and these encounters were excluded from bivariate analysis). Of the 21,267 that had documentation around homelessness, 20,370 encounters did not have a PPR, and 897 encounters did. In the descriptive analyses, people who were documented as homeless were significantly more likely to have a PPR encounter. People who were documented as homeless represented 11.1% of non-PPR encounters (2,259 of 20,370) and 14.1% of PPR encounters (126 of 897, $P = .006$). We found no significant differences for PPR in age, sex, length of stay, length of stay in intensive care unit, case mix index, or the presence of a mental health diagnosis (Table 1).

Thirty-day PPR differed across racial/ethnic groups ($P = .02$); people of documented Native Hawaiian race had proportionally higher rates of 30-day PPR compared with other racial/ethnic groups. A significant difference was also seen in 30-day PPR by insurance type ($P < .001$). Those with public insurance were more likely to have a 30-day PPR than those with private insurance. Other significant variables in descriptive statistics were having a surgical encounter at index hospitalization ($P = .002$), having a device to assist with mobility at index admission ($P < .001$), admission through the emergency department versus physician referral or transfer ($P < .001$), discharge to a skilled nursing facility or long-term care facility at index admission versus discharged home to self-care ($P < .001$), and Elixhauser comorbidity score ($P < .001$).

Multivariable model. In the multivariable model predicting 30-day PPR (Table 2), neither the variable for lives alone (OR = 1.17; 95% CI, 0.96–1.42) nor homelessness (OR = 0.87; 95% CI, 0.71–1.07) was a significant predictor of 30-day PPR. Factors significantly associated with 30-day PPR were index admission source (those with physician referral were less likely to have a 30-day PPR than those admitted through the emergency department [OR = 0.73; 95% CI, 0.58–0.92]), use of a device for mobility-assistance at index admission (those with a device were less likely to have a 30-day PPR than those who did not have a device [OR = 0.72; 95% CI, 0.62–0.84]), Elixhauser comorbidity score at index admission (those with ≥10 comorbidities were more likely to have a 30-day PPR than those who did not have comorbidities [OR = 9.30; 95% CI, 4.30–20.00]), and discharge disposition at index admission (those admitted to a skilled nursing facility were less likely than those who were discharged to home or self-care to have a 30-day PPR [OR = 0.65; 95% CI, 0.51–0.82]).

In our study, the percentage of homeless people with comorbidities was significantly higher than it was in those who were not homeless ($P < .001$) (Figure 2). Patients who were homeless had a higher percentage of 4 or more comorbidities (76%) than their counterparts who were not homeless (62%). None of the homeless patients studied had zero comorbidities.

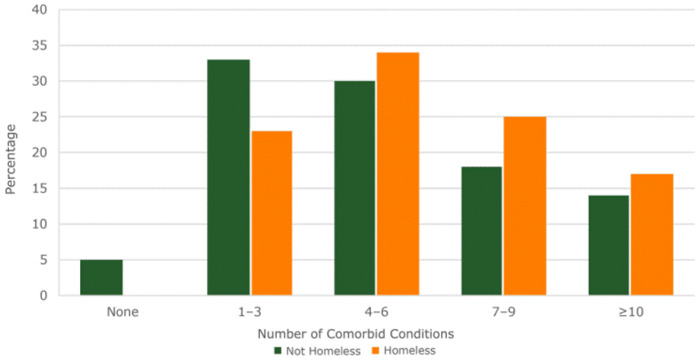

Figure 2. Number and distribution by percentage of Elixhauser comorbidity counts (20) for nonhomeless and homeless patients for 2 urban hospitals in Hawai‘i . Comorbidities are the existence of multiple chronic conditions in addition to the principal diagnosis or reason for hospitalization.

Discussion

Despite overwhelming evidence that social factors are critical determinants of health, these factors are rarely captured routinely in health system EHRs (21). Several major entities, including the Institute of Medicine and the Centers for Medicare & Medicaid Services, are calling for clinical and public health practitioners to examine ways to effectively collect data in these social and behavioral domains, including in acute care settings (4). Both the methods of collecting these data and the findings from this research add useful new evidence to the growing literature about how to effectively capture these social factors as a part of routine clinical care.

Living alone and homelessness were relatively common in our inpatient sample. Almost 20% of the sample lived alone, and over 10% were documented as homeless. Homelessness predicted PPR in descriptive analyses, although neither of these social factors predicted PPR once other factors were controlled. Instead, indicators of physical frailty (having a device to assist with mobility at index admission) and greater illness were significant; this finding is congruent with a vast body of evidence that identified the importance of comorbidity in predicting PPR, even to the exclusion of other social factors that commonly predict health disparities, particularly race/ethnicity (19,20).

Both the social domains of living alone (isolation) and homelessness may challenge the practicality of data collection. Social isolation is complex and difficult to define (22). Comprehensively measuring social relationships requires “consideration of both structural (eg, marital status, living arrangements) and functional (eg, emotional, perceived) aspects” (22) of isolation or the quantity and quality of relationships (7).

In previous literature, social isolation was identified as a contributor to all-cause mortality and higher health care use, particularly in adults aged over 65 (5,23). However, many of these studies were based on patient interview or self-reported surveys (9). Our study contributes new information by examining social isolation from administrative data documented by clinicians. Of course, a trade-off of using an administrative data point is that it may not capture the same level of complexity and nuance that can be garnered from patient interview or self-reported survey; this may explain our study findings. Further research is needed to understand how to best implement the complex measure of social isolation and other social determinants of health in a manner that is practical and useful for clinical care but nuanced enough to capture data in relevant domains.

In the Hawai‘i health care system used in our study, front-line clinicians consistently documented and referenced the measure of whether patients lived alone to determine whether additional post-discharge care would be required (eg, identified caregivers, made frequent post-discharge telephone calls). Our study helped to determine whether this simple proxy measure predicted 30-day PPR. For the 2 hospital facilities in our study, living alone did not predict 30-day PPR, which could indicate that people living alone may have some protective factors. For example, living alone may be an indicator of a person’s level of independence.

Another factor to consider when interpreting these data is how the front-line staff uses the information to inform a patient's treatment plan. At the 2 hospitals in our study, case managers assessed each patient within 24 hours of admission. Then, depending on reason for admission — comorbidities, functional changes, medical prognosis, support system — and insurance coverage, patients were referred to a medical social worker for access to community resources or long-term care planning. According to email messages from Judy Suzuki of Straub Medical Center and Rochelle Day of Pali Momi Medical Center (July 2018), shelter options were offered to homeless patients, and if they refused, refusal was documented. An interesting area of future study would be how referral resources contribute to 30-day PPR and to 30-day PPR trends for people who were offered these services but refused the referral.

Several regionally relevant factors may also explain why social isolation was not a significant predictor of 30-day PPR. First, the state of Hawai‘i has the highest national percentage of multigenerational households, 11.1% of all family households (26). This high percentage could be due to cultural or economic reasons (eg, high cost of living) (26). Accordingly, our data set may have a smaller percentage of people living alone than other areas of the United States. Living alone in the state of Hawai‘i may thus indicate certain protective factors, such as higher income.

A second factor unique to our data set is a discharge-planning bill (27) that the Hawai‘i state legislature passed in March 2016 (during our data collection). This bill requires hospitals to adopt and maintain discharge policies consistent with federal regulations and asks providers to identify and document a designated caregiver for each patient before discharge. Identification of a designated caregiver possibly improved readmission outcomes, particularly among people who live alone. Although data are not yet available on how this legislation has affected Hawai‘i 's hospital readmission rates, similar legislation was introduced in other states and yielded a 25% decrease in 90-day readmission rates compared with usual care (28).

Although homelessness was a significant predictor of readmissions in crude analyses, it was not significant once other control variables were added. This outcome ran counter to our initial hypothesis. In a previous study (29), homeless people were found to be 3 times more likely to be readmitted than their peers who were matched for age, sex, and clinical acuity (29). Homelessness was found to increase both emergency department and inpatient visits (30). People experiencing homelessness are expected to have higher readmissions for various reasons, including higher comorbidity rates associated with inadequate living conditions and limited access to primary care (13). In our study, the percentage of homeless people with 4 or more comorbidities was significantly higher than the percentage of people who were not homeless. The strength of the relationship between comorbidity and readmissions possibly masked the effect of homelessness in the multivariate models. Future research could use mediation analyses to better disentangle the causal relationship between homelessness, comorbidities, and readmissions.

For the variable of homelessness, a wild card search for the word *homeless* was created in free-text fields related to residence. This method of documenting homelessness probably significantly underestimates homelessness, and it introduces classical measurement error leading to attenuation bias, making it harder to detect an effect. For example, the method does not capture data on people who provide a homeless shelter for their residential address. Similarly, it does not address those with unstable housing situations (such as sleeping on a friend's couch), who may also be vulnerable to readmission.

Our study had limitations. Our data were limited to the frequency of 30-day PPR in 1 hospital system in Hawai‘i , which may limit generalizability. It may also underreport the true frequency of 30-day PPR per patient, particularly for people with subsequent hospital encounters at other health care systems. Future research using other measures of readmission may reveal distinct patterns by readmission type. Other potential confounding variables for which we lacked data were preferred language, compliance to post-discharge medication, and income. People with a low income could lack resources to pay for housing, leading to homelessness; low income could be indirectly associated with having the necessary resources to pay for preventive services, which in turn leads to hospital readmissions. Thus, the effect of homelessness on readmissions in this analyses may be larger in magnitude than in reality, given that we did not control for income.

Preventable readmissions are an important policy focus for the Centers for Medicare & Medicaid Services, and readmissions can be measured in various ways. In our study, we selected the 3M PPR methodology as the outcome variable of interest because it offers the logic to examine potentially preventable readmissions (ie, those clinically related to a prior admission) rather than 2 clinically unrelated, but merited, encounters (eg, appendicitis, hip fracture). Preventability is particularly useful from the perspective of a health care facility because it identifies targets to improve quality of care and reduce readmissions. Future studies should consider additional readmission metrics.

Given that our independent variable of "lives alone" did not appear to have predictive value for all-cause 30-day PPR, modifying the granularity of social isolation measures could be a fruitful area of future study. Although identification of people living alone can predict both illness and death, it does not provide the same granularity of whether the patient perceives loneliness in addition to living alone (9,22,23). Further research is needed to understand how to best operationalize more robust social measures, including social isolation, in the acute care setting.

Our study has similar limitations with respect to capturing data on homelessness in the EHR. Free-text capture of homelessness underreports those who are unstably housed or those who are currently living in shelters. The literature notes limitations and mixed approaches currently used to capture data on homelessness in the EHR, ranging from using a listing of a shelter address to the number of home address changes as a proxy for being unstably housed (14,29,30). One study by Doran and colleagues suggests that homelessness screening should be completed by multiple practitioners to ensure redundancy and increase rate of data capture (14). Identifying and implementing standard approaches to capturing data on homelessness in the EHR is critical for health policy and programming.

Because social and behavioral factors affect patient health, health care systems must rethink the way these measures are defined and captured in EHRs (21). Our study illustrates how social factors (ie, homelessness and social isolation) can be leveraged for predictive modeling of acute care outcomes. Further research is needed to refine and operationalize social and behavioral domains in a way that can be practically collected in care, specifically for acute care populations.

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Tables

Table 1. Characteristics of Patients With and Without a 30-day Potentially Preventable Hospital Readmission (PPR) (N = 21,274) Following an Index Hospitalization, Two Urban Hospitals, Hawai‘i , May 2015–April 2017[a]

Variable	All Patients (n = 21,274)		
	No PPR	Have PPR	*P* Value
Lives alone			
Yes	3,376 (16.6)	128 (14.4)	.09
No	16,981 (83.4)	766 (85.6)	
Homeless			
Yes	2,259 (11.1)	126 (14.1)	.006
No	18,111 (88.9)	771 (86.0)	
Age, y			
<65	9,312 (45.7)	394 (43.8)	.27
≥65	11,063 (54.3)	505 (56.1)	
Sex			
Male	10,611 (52.1)	480 (53.4)	.44
Female	9,762 (47.9)	419 (46.6)	
Race/ethnicity			
White	5,133 (21.2)	200 (22.3)	.02
Chinese	917 (4.5)	43 (4.8)	
Filipino	3,316 (16.3)	143 (15.9)	
Hawaiian	2,737 (13.4)	160 (17.8)	
Japanese	5,204 (25.5)	214 (23.8)	
Other Pacific Islander	1,353 (6.6)	65 (7.2)	
Other	1,715 (8.4)	74 (8.23)	
Insurance			
Private	6,902 (33.9)	266 (29.6)	<.001
Public	13,241 (65.0)	618 (68.9)	
Other	232 (1.14)	14 (1.6)	
Admission source			
Emergency	15,097 (74.1)	721 (80.2)	<.001
Referral	3,743 (19.4)	110 (12.2)	
Transfer	1,521 (7.5)	67 (7.4)	
Length of stay	5.5–6.6	7.0 ± 6.7	.99
ICU days[b]	0.4–1.7	0.5 ± 1.8	.99
Case mix index[c]	1.9–1.4	1.9 ± 1.4	.99

[a] Values are number (percentage) unless otherwise indicated. Where null values existed, index hospitalizations were removed from binary analysis. Null values for each are lives alone (n = 23), homelessness (n = 7), sex (n = 2), insurance (n = 1), admission (n = 15), and assistive device (n = 49).

[b] ICU days indicates number of days spent in an intensive care unit.

[c] The severity of illness weight assigned by Centers for Medicare & Medicaid Services on the basis of a patient’s principle diagnoses.

[d] Requires a device to aid with mobility (eg, wheelchair, cane, walker).

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Table 1. Characteristics of Patients With and Without a 30-day Potentially Preventable Hospital Readmission (PPR) (N = 21,274) Following an Index Hospitalization, Two Urban Hospitals, Hawaiʻi , May 2015–April 2017[a]

Variable	All Patients (n = 21,274)		
	No PPR	Have PPR	*P* Value
Surgery			
Yes	7,255 (35.6)	275 (30.6)	.002
No	13,120 (64.4)	624 (69.4)	
Uses assistive device[d]			
Yes	11,453 (56.3)	372 (41.5)	<.001
No	8,876 (43.7)	524 (58.5)	
Elixhauser comorbidity score (number of co-occurring disorders in addition to primary diagnosis)			
0	848 (4.2)	7 (0.8)	<.001
1–3	6,668 (32.7)	156 (17.4)	
4–6	6,206 (30.5)	234 (26.1)	
7–9	3,850 (18.9)	225 (25.1)	
≥10	2,805 (13.8)	275 (30.7)	
Mental health			
Yes	14,797 (72.6)	641 (71.3)	.38
No	5,578 (27.4)	258 (29.70)	
Discharged to			
Home/self-care	14,891 (73.1)	650 (72.3)	<.001
Hospice	498 (2.4)	1 (0.1)	
Skilled nursing facility	2,347 (11.5)	94 (10.5)	
Other facility	2,639 (13.0)	154 (17.1)	

[a] Values are number (percentage) unless otherwise indicated. Where null values existed, index hospitalizations were removed from binary analysis. Null values for each are lives alone (n = 23), homelessness (n = 7), sex (n = 2), insurance (n = 1), admission (n = 15), and assistive device (n = 49).
[b] ICU days indicates number of days spent in an intensive care unit.
[c] The severity of illness weight assigned by Centers for Medicare & Medicaid Services on the basis of a patient’s principle diagnoses.
[d] Requires a device to aid with mobility (eg, wheelchair, cane, walker).

Table 2. Multivariable Logistical Model Predicting Having a 30-Day Potentially Preventable Hospital Readmission Following an Index Hospitalization (N = 21,124), Two Urban Hospitals, Hawai‘i, May 2015–April 2017[a]

Variable	Odds Ratio (95% Confidence Interval)
Lives alone	
Yes	1.17 (0.96–1.42
No	1 [Reference]
Homeless	
Yes	0.87 (0.71–1.07)
No	1 [Reference]
Admission source	
Emergency	1 [Reference]
Referral	0.73 (0.58–0.92)
Transfer	1.04 (0.80–1.07)
Age, y	
<65	1.13 (0.96–1.32)
≥65	1 [Reference]
Sex	
Male	0.93 (0.81–1.07)
Female	1 [Reference]
Race/ethnicity	
Caucasian	1 [Reference]
Chinese	1.14 (0.81–1.60)
Filipino	0.95 (0.76–1.18)
Hawaiian	1.12 (0.90–1.40)
Japanese	1.01 (0.82–1.23)
Other Pacific Islander	0.94 (0.80–1.11)
Other	1.12 (0.85–1.48)
Insurance	
Private	1 [Reference]
Public	1.29 (1.09–1.53)
Other	0.61 (0.22–1.66)
Admission source	
Emergency	1 [Reference]
Referral	0.73 (0.58–0.92)
Transfer	1.04 (0.80–1.07)
Surgery	
Yes	0.94 (0.80–1.11)
No	1 [Reference]
Uses assistive device[b]	

[a] Excludes 150 patients with missing response or explanatory variables.
[b] Requires a device to aid with mobility (eg, wheelchair, cane, walker).

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Table 2. Multivariable Logistical Model Predicting Having a 30-Day Potentially Preventable Hospital Readmission Following an Index Hospitalization (N = 21,124), Two Urban Hospitals, Hawaiʻi, May 2015–April 2017[a]

Variable	Odds Ratio (95% Confidence Interval)
Yes	0.72 (0.62–0.84)
No	1 [Reference]
Elixhauser comorbidity score (number of co-occurring disorders in addition to primary diagnosis)	
0	1 [Reference]
1–3	2.77 (1.24–5.72)
4–6	3.98 (1.86–8.51)
7–9	5.91 (2.75–12.70)
≥10	9.30 (4.30–20.00)
Discharged to	
Home/self-care	1 [Reference]
Hospice	0.03 (0–0.21)
Skilled nursing facility	0.65 (0.51–0.82)
Other facility	1.10 (0.91–1.33)

[a] Excludes 150 patients with missing response or explanatory variables.
[b] Requires a device to aid with mobility (eg, wheelchair, cane, walker).

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ORIGINAL RESEARCH

Attitudes, Beliefs, and Cost-Related Medication Nonadherence Among Adults Aged 65 or Older With Chronic Diseases

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PEER REVIEWED

Abstract

Introduction

Cost-related medication nonadherence (CRN) can negatively affect chronic disease prevention and management in an aging population. Limited data are available on the interacting influences among such factors as availability of financial resources, attitudes and beliefs of patients, and CRN. The objective of this study was to examine the causal paths among financial resource availability, patient attitudes and beliefs, and CRN.

Methods

We used a nationally representative sample (n = 4,818) from the 2015 National Health Interview Survey; selected respondents were aged 65 or older, had a diagnosis of hypertension or diabetes or both, and were prescribed medication for at least 1 of these conditions. We performed structural equation modeling to examine whether perceived medication affordability, access to health care, and patient satisfaction influenced the effects of financial resource availability on CRN (skipped doses, took less medicine, or delayed filling a prescription to save money).

Results

Six percent of respondents reported CRN in the previous 12 months. The model showed a good to fair fit, and all paths were significant ($P < .05$) except for age. The effects of financial resource availability on CRN was mediated through perceived medication affordability, access to health care, and patient satisfaction with health care services.

Conclusion

This study suggests that patients' attitudes and beliefs can mediate the effects of financial resource availability on CRN. We call for senior-friendly public health interventions that can address these modifiable barriers to reduce CRN among older adults with chronic conditions.

Introduction

Medication nonadherence is a persistent public health issue that can influence management of chronic conditions, especially among older adults (aged ≥65), who are more likely to bear a greater disease burden than their younger counterparts. Although many reasons exist for medication nonadherence, older adults may forgo medications because of cost-related concerns, such as lack of adequate prescription coverage by insurance programs and out-of-pocket costs (1–3). This type of medication nonadherence is called cost-related medication nonadherence (CRN). CRN has been observed among approximately 10% to 40% of noninstitutionalized older adults (4–6). The adverse consequences of medication nonadherence include poorer health, increased risk of mortality, and greater health care costs (7–9).

Beyond financial factors, CRN is also associated with patient-related factors (eg, sociodemographic characteristics, health status, attitudes) (10–13) and the relationship between patients and their health care providers (14). For example, patient satisfaction, an attitude associated with the evaluation of a patient's experience with health care services (15–17), has a strong positive association with medication adherence (18). Medication affordability is a proximal driver of medication nonadherence in the proximal–distal continuum of adherence drivers (PDCAD) model (19). The PDCAD model is a conceptual framework that maps the determinants of medication adherence along a continuum of impacts, such that the proximal drivers have the strongest effect on medication nonadherence (19). Medication affordability is not necessarily bound by the cost of prescriptions or financial resource availability (20). Additionally, physical access to health care may have some effect, but a small one, on CRN (21,22).

By using the extended PDCAD model (19), we hypothesized that patient satisfaction with health care, physical access to health care, and medication affordability would mediate the relationship between CRN and financial resource availability, age, and mental health status. The objective of this study was to describe the effects of patient attitudes and beliefs on CRN and the mediating effects of patient attitudes and beliefs on the relationship between financial resource availability and CRN.

Methods

Our data source was the 2015 National Health Interview Survey (NHIS). The NHIS is a cross-sectional household interview survey conducted by the National Center for Health Statistics; it collects health and health-related information via face-to-face interviews among the civilian noninstitutionalized population living in United States (23). We selected participants according to the following self-reported criteria: 1) having a diagnosis of hypertension or diabetes, 2) having prescription medication for those conditions, and 3) being aged 65 or older at the time of the assessment. Proxy-reported data were excluded. We conducted our analysis from April 2017 through April 2018.

Variables

Data were collected on 3 types of CRN behaviors in the previous 12 months: skipping medication to save money, taking less medicine to save money, or delaying filling a prescription to save money. Each item was scored as yes or no. A participant who answered yes to any of the 3 items was categorized as reporting CRN, and a participant who answered no to all 3 items was categorized as not reporting CRN. Reliability tests of the measures showed high test–retest reliability ($\kappa \geq 0.6$) (24).

We assessed medication unaffordability by using a single item: “During the past twelve months, was there any time when you needed [prescription medicine] but didn’t get it because you couldn’t afford it?” The item was scored as yes or no.

Patient satisfaction with health care services was assessed by using a single item: “In general, how satisfied are you with the healthcare you received in the past twelve months?” Responses ranged from 1 (“very dissatisfied”) to 4 (“very satisfied”). Twenty-six (0.5%) of the 4,818 study-eligible participants did not report on this variable because they had not received any health care in the previous 12 months.

We used data on 5 areas of physical access to health care in the previous 12 months. All 5 items asked about delays in getting health care. Participants were asked about delays because of 1) difficulty in getting through on the telephone, 2) difficulty in getting an appointment in a timely manner, 3) long wait times at the health care setting, 4) the clinic or doctor’s office not being open when the participant could get there, and 5) lack of access to transportation. Each item was scored as yes or no. A participant who answered yes to any of the 5 items was categorized as having poor physical access to care, and a participant who reported no to all 5 items was categorized as not having poor physical access to health care.

We categorized the study sample into 4 groups based on the ratio of family income to the 2014 federal poverty thresholds (<1.00, 1.00–1.99, 2.00–3.99, ≥4.00). A ratio of less than 1 indicates that family income is below the federal definition of poverty (ie, <$11,670 for a household size of 1 in 2014).

The 2015 NHIS used the K6 screening scale for assessing the presence of serious mental illness. The K6 screening scale comprises six 5-point Likert items on how often respondents felt nervous, hopeless, restless or fidgety, depressed, or worthless or needed effort on everything in the past 30 days. For each item, the possible response ranges from 1 (all of the time) to 5 (none of the time); hence, the sum of the 6 items can range from 6 to 30. Using the dichotomous scoring approach described by Kessler et al (25), we classified participants who had a summary score of less than 19 as not having serious mental illness and participants who had a summary score of 19 or higher as having serious mental illness. The Cronbach α for the scale was 0.84.

Demographic and sociodemographic information. The 2015 NHIS collected data on age, sex, race, ethnicity, region of residence, education, and self-rated health. We categorized age into less than 75 years and 75 years or older. The dichotomization was guided by distribution of the data, such that about half of the study sample was assigned to each category. Sex was categorized as male and female. Ethnicity was categorized as Hispanic and non-Hispanic. Race was dichotomized as white and nonwhite. Region was classified into Northeast, Midwest, South, and West.

Analysis

The final study sample consisted of 4,818 adults aged 65 or older with hypertension or diabetes or both, accounting for 11.4% of all 2015 NHIS participants (N = 42,288). We calculated mean and standard deviation or frequency and percentage to describe characteristics of the study participants. We used listwise deletion for handling missing data. Of the 4,818 adults, 1,254 (26%) had missing values for at least one of the variables included in the structural equation model (SEM). We found few missing values (<5%) for most variables, but 85% (1,063 of 1,254) of participants who had missing values did not report all the income-related information to estimate the financial resource availability. Because of this missing information, we tested the final hypothesized model by using alternative measures of financial resources (eg, ever concerned about not having enough food in the past 12 months) that had lower rates of missing data. Although we did not tabulate these data for this study, we found no meaningful difference between the analysis using the income variables and the analysis using the alternative variables. By using χ^2 tests, we found a positive association with having 1 or more missing values for the SEM variables for being 75 or older, female, or nonwhite; living in the Midwest; not having poor physical access to health care; or having a serious mental illness. Similarly, being 75 or older, female, or nonwhite or living in the Midwest were positively associated with missing data on financial resource availability. Using quantile regression for interval variables and χ^2 tests for categorical variables, we compared study participants who reported CRN with study participants who did not report CRN.

After conducting the preliminary analyses, we used the SEM to examine patient attitudes and beliefs as potential mediators of the relationship between financial resource availability and CRN. We followed conventional SEM steps: model identification, parameter estimation, fit evaluation, and model re-identification. We used the robust maximum likelihood estimation method to account for nonnormal categorical endogenous variables. SEM can also evaluate fit of the mediated model relative to unmediated and saturated models. We used the χ^2 test, the confirmatory factor index, the root mean square error of approximation (RMSEA), and the standardized root mean square residual (SRMR) for the fit evaluation. We considered the following to indicate a good fit: a nonsignificant ($P \geq .05$) χ^2 test result, a confirmatory factor index greater than 0.95, an RMSEA less than 0.05, and a SRMR less than 0.05. We considered an RMSEA between 0.05 and 0.08 to indicate a fair fit. Furthermore, we used modification indices to identify potential areas of the model that had a poor fit. The direct path between physical access to care and CRN was dropped to obtain the better fit. The final model for testing included 3 exogenous variables (aged 75 or older, serious mental illness, and financial resource availability) and 4 endogenous variables (CRN, patient satisfaction with health care, poor physical access to care, and medication unaffordability) (Figure 1).

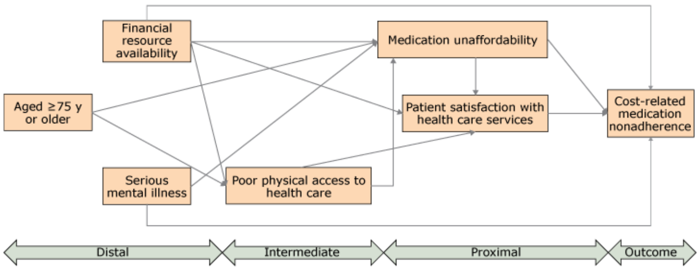

Figure 1. Hypothesized model depicting factors influencing cost-related medication nonadherence (CRN) among adults aged 65 years or older, National Health Interview Survey, 2015. The final hypothesized model included 3 exogenous variables (aged 75 or older, serious mental illness, and financial resource availability) and 4 endogenous variables (CRN, patient satisfaction with health care services, poor physical access to health care, and medication unaffordability). Arrow indicates "effects on"; for example, effects of poor physical access to health care on medication unaffordability.

We performed all statistical analyses in SAS version 9.4 (SAS Institute Inc). As instructed in the NHIS data guide, we conducted the subset analyses by using the complete data file to ensure correct estimation of variance and use of appropriate sampling weights. We confirmed with the Texas A & M University institutional review board that the study did not require approval because it used a public use data set.

Results

The median age of the study sample was 73, and most participants were female (54.7%), non-Hispanic (91.7%), and white (83.0%) (Table 1). Of 4,818 participants, 269 (5.9%) (weighted percentage, 5.7%) reported CRN in the previous 12 months. Compared with those who did not report CRN, those who reported CRN were younger (71 y vs 73 y), were more likely to be female (61.3% vs 54.0%) and have had a diagnosis of both hypertension and diabetes (36.5% vs 26.7%), and were less likely to be white (78.6% vs 83.7%), non-Hispanic (89.4% vs 92.0%), and married or living with a partner (47.8% vs 56.7%). Responses to the question on satisfaction with health care services were highly skewed, such that 72.7% reported being very satisfied with health care services.

The tested model had a good to fair fit based on the 3 fit indices: a confirmatory factor index of 0.97, an RMSEA of 0.06, and an SRMR of 0.03. The χ^2 test of fit was significant ($\chi^2_5 = 66.7$; $P < .001$), indicating a poor fit. However, this test can be sensitive to trivial deviations from the perfect fit with a sufficiently large sample size. Despite the adequate fit of the model, the model explained only 34.3% of the variance in CRN.

A greater likelihood of CRN was associated with greater medication unaffordability ($\beta = 0.55$; standard error [SE], 0.01; $P < .001$), lower levels of patient satisfaction with health care ($\beta = -0.06$; SE, 0.01; $P < .001$), less financial resource availability ($\beta = -0.07$; SE, 0.01; $P < .001$), and serious mental illness ($\beta = 0.04$; SE, 0.01; $P = .001$). Medication unaffordability was associated with poor physical access to health care ($\beta = 0.13$; SE, 0.02; $P < .001$), lower levels of financial resource availability ($\beta = -0.12$; SE, 0.02; $P < .001$), serious mental illness ($\beta = 0.11$; SE, 0.02; $P < .001$), and being younger than 75 ($\beta = -0.07$; SE, 0.02; $P < .001$). Lower levels of patient satisfaction were associated with greater medication unaffordability ($\beta = -0.10$; SE, 0.02; $P < .001$), poorer physical access to health care ($\beta = -0.14$; SE, 0.02; $P < .001$), and less financial resource availability ($\beta = 0.11$; SE, 0.02; $P < .001$). Poor physical access to health care was negatively associated with financial resource availability ($\beta = -0.13$; SE, 0.02; $P < .001$). Effect of age on physical access to health care was not significant ($\beta = 0.003$; SE, 0.02; $P = .84$) (Figure 2).

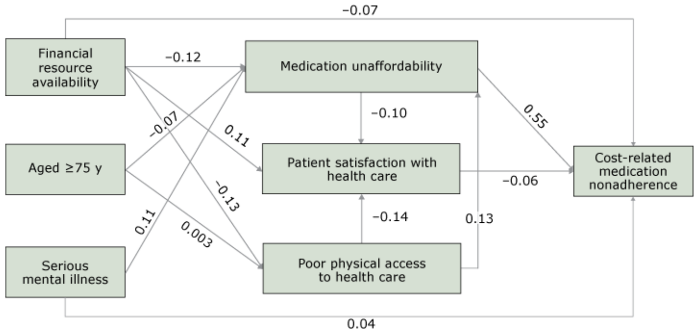

Figure 2. Path diagram of the final structural equation modeling among adults aged 65 years or older, National Health Interview Survey, 2015. The path diagram describes the magnitudes and significance of the hypothesized relationship between age, serious mental illness, financial resource availability, patient's attitudes and beliefs, and cost-related medication nonadherence (CRN). Arrow indicates "effects on"; for example, effects of poor physical access to health care on medication unaffordability.

Medication unaffordability had the strongest total effects on CRN, followed by financial resource availability, serious mental illness, poor physical access to health care, and patient satisfaction with health care services (Table 2). Age had the least total effect on CRN. Approximately half of the effects of financial resource availability on CRN were mediated through medication unaffordability, poor physical access to health care, and patient satisfaction with health care (direct effects = −0.072; indirect effects = −0.084).

Discussion

Approximately 6% of our sample of adults aged 65 or older with diabetes or hypertension or both reported CRN. This prevalence of CRN is similar to the 8% reported in the Health, Aging and Body Composition Study (26), but it is lower than the prevalence reported in other studies (4–6). CRN could be influenced by multiple factors (eg, disease type, disease duration), which might explain the broad range of CRN rates observed among older adults. Our study demonstrated that the effects of financial resource availability on CRN were mediated through patient's attitudes and beliefs on such factors as medication unaffordability, physical access to health care, and patient satisfaction with health care services. Our study expands understanding of the mechanisms driving CRN among older adults and suggests potential intervening points for enhancing CRN in this population.

Our findings are in line with the findings of studies showing that the relationship between financial pressure and CRN is complex and that financial pressure alone cannot explain CRN. For example, one study (27) observed CRN in both low-income and high-income populations and found that having low levels of concern about medication use (eg, side effects) was associated with lower levels of CRN in both populations. The difference between that study and our study is that the former focused on the independent effects of patients' attitudes on CRN by the degree of financial pressure, whereas our study focused on the causal paths that link these multiple factors together.

As hypothesized under our conceptual framework, medication unaffordability was the strongest predictor of CRN, and this finding is consistent with previous research (19,28). One study of a national sample of adults with at least 1 chronic condition found that medication affordability was the most common reason for medication nonadherence (28). More than half of study respondents who engaged in medication nonadherence reported that medication affordability was their reason for nonadherence (28). Another study found that adults who had the lowest levels of perceived medication affordability had a significantly greater likelihood of medication nonadherence than those with the highest levels of perceived medication affordability (19). Our study confirms these previous findings and strengthens the evidence on reasons for CRN among older adults.

Our study showed that patient satisfaction with health care services was adversely associated with CRN. Similarly, another study indicated a weak positive correlation between patient satisfaction and medication adherence among patients with HIV/AIDS ($r = 0.178$, $P < .05$) (29). However, that study did not examine the independent effects of patient satisfaction on medication nonadherence, and the study population was different from the population in our study.

As hypothesized in the PDCAD model, age had weaker effects on CRN than did other variables in the model. This observation is not surprising given the conflicting findings of previous studies

(30,31). For example, in 2 studies of medication adherence to adjuvant hormonal therapy among breast cancer patients, 1 study indicated that older age (>70 y) was a potential barrier to medication adherence (30), whereas the other study indicated that younger age (<70 y) was a potential barrier (31).

Our study has several limitations. First, the cross-sectional data precluded examination of cause and effect. However, previous studies support the hypothesized causal paths among financial resource availability, patient attitudes and beliefs, and CRN. Second, our study relied on self-reported data, which are subject to social desirability bias and recall bias, and these data could not be verified. However, self-reported data on medication nonadherence can provide contextual information and enable researchers to identify types of medication nonadherence (eg, intentional vs unintentional, cost-related vs not cost-related). Third, this survey had only a single item on patient satisfaction with health care, and responses to the items were highly skewed. Fourth, our model did not include some potentially important drivers, such as perceived need for medication and perceived concerns about medication use. The model explained only about one-third of the variance of CRN, and the inclusion of other important determinants could improve the model's explanatory power. Finally, we used listwise deletion for handling missing data, and we omitted records for more than 25% of the participants by using this approach. Study participants who did not report any problems with physical access to health care were more likely to be omitted from the analysis, and, therefore, the likelihood of having access to health care services was potentially biased downward. In addition, using listwise deletion tends to result in large standard errors and wide confidence intervals. To overcome this limitation, we tested the final model by using alternative measures of financial resources (eg, concerns about running out of food) that had low rates of missingness, and we found no meaningful change in the results (ie, no changes in significance and minimal changes in regression coefficients).

Despite these limitations, our study has some strengths. Our study is one of the few studies that attempted to explore the causal paths between financial resource availability and CRN and to understand the potential effects of patient attitudes and beliefs on the relationship. Another strength is that we used a nationally representative data set.

Our study aimed to explain the relationship among financial resource availability, patients' attitudes and beliefs (eg, perceived medication affordability, physical access to health care, and patient satisfaction with health care services), and CRN, a relationship that had not been examined previously. Our findings suggest that perceived medication affordability is the key driver of CRN and that the effects of financial resource availability on CRN is mediated through medication affordability, physical access to health care, and patient satisfaction with health care services. Although several possible pharmaceutical policy reforms (eg, the involvement by government in determining the prices of prescription drugs) should be considered in addressing the financial-related factors that drive medication nonadherence, many uncertainties exist at this stage of health policy reform. Meanwhile, our study suggests that rates of CRN among older adults can be reduced by decreasing financial pressure as well as by modifying attitudes and beliefs among this population. It also points to the need for public health interventions that address these modifiable barriers for older adults. Future research should test more comprehensive models by including other important attitudinal variables, such as the perceived need for medications and concern about their use. Future models should also include factors related to health care providers, prescriptions, and the health care system.

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Tables

Table 1. Characteristics of a Sample of Participants (n = 4,818) in Study on Cost-Related Medication Nonadherence[a,b,c] Among Adults Aged 65 Years or Older

Characteristic	Overall		Cost-Related Medication Nonadherence,[b] Weighted[d] %		*P* Value[e]
	Unweighted No. (%)	Weighted[d] %	Yes	No	
Age, y[c]	73	73	71	73	.006
Sex					
Female	2,828 (58.7)	54.7	61.3	54.0	<.001
Male	1,990 (41.3)	45.3	38.7	46.0	
Ethnicity					
Non-Hispanic	4,343 (90.1)	91.7	89.4	92.0	<.001
Hispanic	475 (9.9)	8.3	10.6	8.0	
Race					
White	3,814 (79.2)	83.0	78.6	83.7	<.001
Black or African American	713 (14.8)	11.1	14.7	10.4	
Asian	177 (3.7)	4.0	3.0	4.2	
Other races	38 (0.8)	0.6	1.6	0.5	
Multiple races	76 (1.6)	1.3	2.1	1.3	
Marital status					
Married or living with a partner	1,972 (40.9)	55.9	47.8	56.7	<.001
Not married or living with a partner	2,846 (59.1)	44.1	52.2	43.3	
Diagnosis					
Hypertension only	3,290 (68.3)	68.1	59.2	68.5	<.001
Diabetes only	214 (4.4)	5.0	4.4	4.8	
Both hypertension and diabetes	1,312 (27.2)	27.0	36.5	26.7	
Reported cost-related medication nonadherence[b]	269 (5.9)	5.7	—[f]	—[f]	—[f]

[a] Data source: 2015 National Health Interview Survey (23).

[b] Data were collected on 3 types of cost-related medication nonadherence behaviors in the previous 12 months: skipping medication to save money, taking less medication to save money, or delaying filling a prescription to save money. Each item was scored as yes or no. A participant who answered yes to any of the 3 items was categorized as reporting CRN, and a participant who answered no to all 3 items was categorized as not reporting CRN.

[c] Units in column heads apply to cells in all rows, except for row indicating age, which is reported in years.

[d] Weighted by sampling weights.

[e] Comparison between participants who reported CRN and participants who did not report CRN. Age was compared by using quantile regression, and categorical variables were compared by using χ^2 tests.

[f] Not applicable.

Table 2. Standardized Total, Direct, and Indirect Effects in the Hypothesized Structural Equation Model of Cost-Related Medication Nonadherence (CRN) Among Adults Aged 65 Years or Older[a,b]

Predictor	Mediated Through . . .	Causal Effect[c]		
		Total	Direct	Indirect
Medication unaffordability[d]	No mediator	—	0.550	—
	Patient satisfaction with health care	—	—	0.006
	Total	0.556	0.550	0.006
Financial resource availability[e]	No mediator	—	−0.072	—
	Medication unaffordability	—	—	−0.067
	Patient satisfaction with health care	—	—	−0.007
	Medication unaffordability → patient satisfaction with health care	—	—	−0.001
	Poor physical access to health care → medication unaffordability	—	—	−0.009
	Poor physical access to health care → medication unaffordability → patient satisfaction with health care services	—	—	<0[f]
	Poor physical access to health care → patient satisfaction with health care	—	—	−0.001
	Total	−0.156	−0.072	−0.084
Serious mental illness[g]	No mediator	—	0.044	—
	Medication unaffordability	—	—	0.059
	Medication unaffordability → patient satisfaction with health care services	—	—	0.001
	Total	0.103	0.044	0.059
Poor physical access to health care[h]	Patient satisfaction with health care	—	—	0.009
	Medication unaffordability	—	—	0.069
	Medication unaffordability → patient satisfaction with health care services	—	—	0.001
	Total	0.079	—	0.079

Abbreviation: →, effects on.

[a] Data source: 2015 National Health Interview Survey (23).

[b] Data were collected on 3 types of CRN behaviors in the previous 12 months: skipping medication to save money, taking less medication to save money, or delaying filling a prescription to save money. Each item was scored as yes or no. A participant who answered yes to any of the 3 items was categorized as reporting CRN, and a participant who answered no to all 3 items was categorized as not reporting CRN.

[c] Direct effect refers to the direct relationship between the 2 variables (ie, predictor variable and outcome variable). Indirect effects refer to the effect of a predictor variable on an outcome variable via one or more mediator variables. Total effect of a predictor variable on an outcome variable is the sum of direct and indirect effects. For example, approximately half of the total effects of financial resource availability on CRN were the indirect effects through medication unaffordability, poor physical access to health care, and patient satisfaction with health care services.

[d] Assessed by using single yes–no item: “During the past twelve months, was there any time when you needed [prescription medicine] but didn’t get it because you couldn’t afford it?”

[e] We categorized the study sample into 4 groups based on the ratio of family income to the 2014 federal poverty threshold (<1.00, 1.00–1.99, 2.00–3.99, ≥4.00).

[f] Less than 0, but greater than −0.001.

[g] Assessed by Kessler’s K6 screening scale and dichotomous scoring approach (25).

[h] Five yes–no items asked about delays in getting health care in previous 12 months: delays because of 1) difficulty in getting through on the telephone, 2) difficulty in getting an appointment in a timely manner, 3) long wait times at the health care setting, 4) the clinic or doctor’s office not being open when the participant could get there, and 5) lack of access to transportation. A participant who answered yes to any of the 5 items was categorized as having poor physical access to care, and a participant who reported no to all 5 items was categorized as not having poor physical access to health care.

[i] Assessed by using a single item: “In general, how satisfied are you with the healthcare you received in the past twelve months?” Responses ranged from 1 (“very dissatisfied”) to 4 (“very satisfied”).

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(continued)

Table 2. Standardized Total, Direct, and Indirect Effects in the Hypothesized Structural Equation Model of Cost-Related Medication Nonadherence (CRN) Among Adults Aged 65 Years or Older[a,b]

Predictor	Mediated Through . . .	Causal Effect[c]		
		Total	Direct	Indirect
Patient satisfaction with health care services[i]	No mediator	—	−0.063	—
	Total	−0.063	−0.063	—
Aged ≥75 y	Medication unaffordability	—	—	−0.038
	Medication unaffordability → patient satisfaction with health care services	—	—	<0[f]
	Total	−0.038	—	−0.038

Abbreviation: →, effects on.

[a] Data source: 2015 National Health Interview Survey (23).

[b] Data were collected on 3 types of CRN behaviors in the previous 12 months: skipping medication to save money, taking less medication to save money, or delaying filling a prescription to save money. Each item was scored as yes or no. A participant who answered yes to any of the 3 items was categorized as reporting CRN, and a participant who answered no to all 3 items was categorized as not reporting CRN.

[c] Direct effect refers to the direct relationship between the 2 variables (ie, predictor variable and outcome variable). Indirect effects refer to the effect of a predictor variable on an outcome variable via one or more mediator variables. Total effect of a predictor variable on an outcome variable is the sum of direct and indirect effects. For example, approximately half of the total effects of financial resource availability on CRN were the indirect effects through medication unaffordability, poor physical access to health care, and patient satisfaction with health care services.

[d] Assessed by using single yes–no item: "During the past twelve months, was there any time when you needed [prescription medicine] but didn't get it because you couldn't afford it?"

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ORIGINAL RESEARCH

Higher Breast Cancer Risk Among Immigrant Asian American Women Than Among US-Born Asian American Women

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PEER REVIEWED

Summary

What is already known on this topic?

Research in the United States has found that among Asian Americans, risk for female breast cancer was higher among US-born women than among women born outside the United States.

What is added by this report?

This report finds that this trend, in a more recent cohort of Asian Americans, may be shifting, such that breast cancer risk is higher among women who are immigrants compared with those who are US-born.

What are the implications for public health practice?

There may be an increased need for breast cancer treatment services for immigrant Asian Americans as well as for continued efforts to increase access to mammograms among all Asian American women.

Abstract

Introduction

Given rising rates of breast cancer in parts of Asia, immigrant Asian American women in the United States may have higher rates of breast cancer than previously anticipated. This study examined breast cancer risk among Asian American women by nativity and percentage of life lived in the United States, accounting for established breast cancer risk factors.

Methods

We analyzed a breast cancer case-control data set of Asian American women living in the San Francisco Bay Area; this data set included 132 cases of women with breast cancer selected from a Surveillance, Epidemiology, and End Results cancer registry and 438 Asian American women without diagnosed breast cancer matched to cases by age and country of origin. We used logistic regression to compare 3 Asian American groups: US-born, immigrants who lived 50% or more of their life in the United States, and immigrants who lived less than 50% of their life in the United States.

Results

In the minimally adjusted and fully adjusted models, both groups of immigrant Asian American women had higher risk of breast cancer than US-born Asian American women. In the fully adjusted model, compared with US-born Asian American women, immigrant Asian American women who lived more than 50% of their life in United States were on average 3 times as likely (odds ratio = 3.00; 95% confidence interval, 1.56–5.75) and immigrants who lived less than 50% of their life in United States were on average 2.46 times as likely (odds ratio = 2.46; 95% confidence interval, 1.21–4.99) to have breast cancer. We found no difference in fully adjusted odds ratios of having breast cancer between the 2 immigrant groups.

Conclusion

This study provides preliminary evidence that breast cancer risk among immigrant Asian American women may be higher than among their US-born counterparts.

Introduction

Research in the United States has consistently found that for racial/ethnic minority populations such as Asian Americans, those not born in the United States have lower rates of female breast cancer than their US-born counterparts (1,2). However, this trend may be shifting among recent waves of Asian American immigrants.

Worldwide, breast cancer incidence is high in North America and relatively low in Asia (3). Although breast cancer rates in the United States have stabilized since the 2000s, rates are increasing rapidly in East and Southeast Asia, with the highest rates found in urban and affluent areas (3–6). These trends are possibly due to the effects of globalization and economic development on increased screening, lower parity, delayed childbirth, decreased breastfeeding, and sedentary lifestyles — all factors that increase breast cancer rates (3,7,8).

Current US immigration policies have led to the influx of highly skilled Asian immigrants who perhaps have a higher socioeconomic status than previous immigrant groups. In 2013, 51% of recent East and South Asian immigrants in the United States had at least a college degree; in 1970, only 20% of all immigrant arrivals had this level of education (9). High socioeconomic status is related to increased risk for breast cancer in numerous populations (10). Consistent with these observations, a recent analysis showed that breast cancer rates are increasing among most Asian American groups in California (11). Asian immigrants may arrive in the United States with higher risk for latent breast cancer than previous immigrant cohorts (12).

Our study adds to the existing literature by describing how breast cancer risk among Asian American women varies by nativity status and percentage of life lived in the United States, accounting for established breast cancer risk factors, and it is among the first to do so. We hypothesized that 1) breast cancer risk would differ by nativity, 2) a greater percentage of life lived in the United States would be associated with higher breast cancer risk, and 3) modifiable risk factors, including reproductive history and body mass index (BMI) (7,13), would attenuate these differences by nativity and percentage of life in the United States.

Methods

We used a population-based case-control data set of Asian American women. We collected data from the Asian Community Health Initiative, a case-control study of breast cancer among Asian American women in the San Francisco Bay Area (14). The San Francisco Bay Area is an appropriate study location because it has the highest concentration of Asian Americans in the United States outside Hawai‘i, with 29% of the population (1.7 million) identifying as Asian American in the 2010 US census (15). Asian American women with breast cancer diagnosed during 2005–2009 were sampled from a population-based source — the Greater Bay Area Cancer Registry — part of the Surveillance, Epidemiology, and End Results (SEER) Program and the state-mandated California Cancer Registry. In a comparison of women with breast cancer in our sample with women in the California Cancer Registry, our sample was found to be representative of the source population.

Because selection bias can result from relying on a single recruitment method, the Asian Community Health Initiative used several methods to recruit women for the control sample (16). The Initiative used 5 strategies to recruit participants without breast cancer; these controls were used to represent the population of Asian American women at risk for breast cancer in the San Francisco Bay Area. The first strategy recruited participants from community health centers. The second strategy recruited participants by using email blasts through Army of Women, a volunteer registry of women with and without breast cancer who are interested in participating in breast cancer research (www.armyofwomen.org). The third strategy used monthly advertisements and posts on Craigslist, Facebook, Twitter, and listservs reaching Asian Americans. A fourth strategy used traditional address-based sampling of a randomly generated sample of 3,000 residential addresses of people with Asian American surnames; this strategy yielded a response rate of less than 2%. The fifth strategy involved disseminating flyers at health fairs, senior centers, community events, and fundraisers.

Initiative researchers frequency-matched controls to cases by Asian country of origin (Chinese, Filipina, and other Asian) and age (20–39, 40–59, and ≥60 y) in a 3:1 ratio of controls to cases. Researchers found the control sample to be representative of the overall population of Asian American women in the San Francisco Bay Area in comparisons of key demographic characteristics with data from the California Health Interview Survey (CHIS) (14).

Recruitment took place from March 2013 through October 2014 and yielded an analytical sample of 570 Asian American women consisting of 132 cases and 438 controls. Survey data were collected through telephone interviews and self-administered questionnaires in English, Chinese, or Tagalog. Written materials for Chinese and Tagalog were translated and independently back-translated. Participants received a $30 check for completing the telephone interview. Participants in the second-phase self-administered survey received an additional $15. Participants consisted of Chinese (53%), Filipina (20%), and other Asian American (27%)

women aged 22 to 87 (mean age, 52). Among immigrant women, the average age at immigration was 22 (standard deviation, 19). All study procedures were approved by the ethical review boards at the Cancer Prevention Institute of California, University of California–Los Angeles, and the University of California–Riverside.

Study variables

The outcome was breast cancer (1 = clinical diagnosis of breast cancer; 0 = no diagnosis). The independent variable of interest was nativity and percentage of life lived in the United States (US-born, immigrant with ≥50% of life lived in the United States; immigrant with <50% of life lived in the United States).

We adjusted for the following established breast cancer risk factors: pregnancy history (age at first birth <25 y, age at first birth 25–29 y, age at first birth 30–34 y, age at first birth ≥35 y, never had a pregnancy that lasted ≥7 months), family history of breast cancer (1 = mother, sister, or daughter had breast cancer; 0 = no immediate family member [mother, sister, or daughter] had breast cancer), and menopausal status and use of hormone replacement therapy (HRT) (premenopausal, postmenopausal and no history of using HRT, postmenopausal and history of using HRT). We also adjusted for BMI, calculated as the respondents' reported weight in kilograms divided by the square of their height in meters. We adjusted for BMI because it is positively associated with higher risk of breast cancer among postmenopausal women (13) and because higher BMI is also commonly associated with greater acculturation among immigrant groups (17). We chose BMI cutoff points (<23, 24–26, or ≥27) that are based on research that found higher risk of chronic disease at lower BMIs among Asian populations than among the general population (18).

Additional covariates were socioeconomic status, operationalized as education level (college graduate, some college, high school diploma or less), home ownership (1 = homeowner; 0 = renter or non-homeowner), and health insurance status (1 = public insurance or not insured; 0 = private insurance). All study variables were self-reported.

Statistical analysis

For each study variable, we calculated frequency and percentage by breast cancer status. We then used unconditional logistic regression to estimate odds ratios (ORs) and 95% confidence intervals (CIs) of breast cancer risk. Models were minimally adjusted for age group (20–39, 40–59, and ≥60) and country of origin (Chinese, Filipina, and other) (19). Fully adjusted models included measures of socioeconomic status and known breast cancer risk factors: education, home ownership, health insurance status, pregnancy history, family history of breast cancer, menopausal status and HRT use, and BMI. We conducted analyses by using Stata version 15 (StataCorp LLC). We conducted an additional sensitivity analysis, replacing percentage of life lived in the United States with other measures that used age at immigration (data available upon request). The results were similar when percentage of life lived in the United States was replaced with immigration before and after age 18. We also examined the association between breast cancer and immigration before or after menarche. However, too few women in the sample immigrated before menarche for these results to be conclusive.

Additionally, we analyzed whether other risk factors were associated with breast cancer, including physical activity, smoking status, alcohol use, and oral contraceptive use. In this sample none of these variables were associated with having breast cancer, and they were excluded from the final model.

Results

A lower percentage of Asian American women with breast cancer (17% [22 of 132]) were US-born compared with controls (33% [144 of 438]) (Table). A greater percentage of Asian American women with breast cancer (42% [56 of 132]) were immigrants and lived more than 50% of their lives in the United States compared with controls (25% [110 of 438]). The percentage of home ownership was higher among Asian American women with breast cancer (77% [102 of 132]) than among controls (63% [276 of 438]). Compared with controls, Asian American women with breast cancer also had a slightly higher percentage of private insurance, a lower percentage of never being pregnant, a higher percentage of a family history of breast cancer, and a higher percentage of being premenopausal or being postmenopausal and having used HRT.

Minimally adjusted ORs show that immigrant Asian American women had higher risk of breast cancer than US-born Asian American women (OR = 2.94 [95% CI, 1.65–5.21] for immigrant Asian American women who lived ≥50% of their life in the United States; OR = 1.87 [95% CI, 1.03–3.37] for immigrant Asian American women who lived <50% of their life in the United States). The risk of breast cancer was only slightly higher among immigrant Asian American women who lived ≥50% of their life in the United States compared with immigrant Asian American women who lived <50% of their life in the United States (OR = 1.57 [95% CI, 0.99–2.50], *P* = .06), but the lower limit of the CI just included the null. After we adjusted for potential confounders in the fully adjusted model, immigrant Asian American women still had higher risk of breast cancer than US-born Asian American women (OR = 3.00 [95% CI, 1.56–5.75] for immigrant Asian American women who lived ≥50% of their life in the United States; OR = 2.46 [95% CI, 1.21–4.99] for immigrant Asian American women who lived <50% of their life in the United States). We found no difference in fully adjusted odds ratios of having breast cancer between the 2 immigrant groups (OR = 1.22 [95% CI, 0.70–2.15]).

In the fully adjusted model, home ownership and having a high school diploma or less were associated with greater breast cancer risk. The association between education and breast cancer risk was significant only after we adjusted for menopausal status, because premenopausal women had higher levels of education than postmenopausal women. Excluding either menopausal status or education did not change the main estimated effect between breast cancer and nativity with percentage of life lived in the United States, so we included both variables in the final model. Women who gave birth to their first child when they were 35 or older had higher breast cancer risk than those who gave birth to their first child when they were younger than 25. Having an immediate family member with breast cancer was associated with higher odds of having breast cancer. Premenopausal women had higher risk of breast cancer than postmenopausal women who had never used HRT.

Discussion

This study provides preliminary evidence that immigrant Asian American women have a higher risk of breast cancer than US-born Asian American women. This finding confirms our first hypothesis that breast cancer risk among Asian American women would differ by nativity. However, this finding is contrary to earlier studies of Asian American populations in California showing that immigrants had lower rates of breast cancer than US-born women (1,2).

Our findings did not fully support the second hypothesis, that greater percentage of life lived in the United States would be associated with greater breast cancer risk among women who were immigrants, as suggested by prior research (1,20,21). The result for the logistic regression model that controlled only for age and Asian country of origin showed that greater percentage of life lived in the United States was not significantly associated with greater breast cancer risk, although the direction of the odds ratio suggested that there might be a slight association. Nevertheless, percentage of life lived in the United States was not associated with greater breast cancer risk after controlling for other variables in the model.

The third hypothesis was that modifiable risk factors for breast cancer — including pregnancy history, use of HRT, and BMI — would attenuate the differences in breast cancer risk by nativity and percentage of life lived in the United States. The association between immigrant status and greater breast cancer risk remained, even after adjusting for these known breast cancer risk factors. Modifiable risk factors are often cited as possible reasons for increased breast cancer risk that occurs with greater acculturation (1,3,7). Our findings indicate that yet-unidentified risk factors may exist among Asian American immigrants, leading to higher breast cancer risk than among their US-born counterparts.

Questions remain about why immigrant Asian American women had higher risk of breast cancer than US-born Asian American women in our sample. Data from CHIS 2012 in the same geographic area found that among Asian Americans, immigrant women were more likely than US-born women to have had a mammogram in the previous 2 years (63.2% vs 37.9%) (22), suggesting that our findings may be in part due to higher rates of detection among immigrant women.

Secular changes in breast cancer risk factors and the resulting increases in breast cancer rates in Asian countries, especially in affluent areas, may further explain our finding (3,4). The current Asian American immigrant population in the San Francisco Bay Area may reflect trends among populations in Asia. CHIS data show that the percentage of naturalized Asian Americans in the San Francisco Bay Area with household incomes greater than $135,000 increased from 18% in 2005 to 42% in 2016 (23). Several studies have found higher socioeconomic status, measured by income and education, to be associated with greater risk for breast cancer (10,24). Therefore, recent Asian immigrants to the San Francisco Bay Area may be arriving in the United States with higher risk for breast cancer than was found previously.

Other findings in our study coincide with previous findings on breast cancer among Asian American women. Greater breast cancer risk was associated with higher socioeconomic status, measured as home ownership and health insurance status (10,24). Giving birth to one's first child when aged 35 or older, compared with giving birth for the first time when younger than 25, was associated with higher risk for breast cancer (7,25). Having a family history of breast cancer was associated with higher risk of breast cancer (26). Premenopausal women, compared with postmenopausal women who had never used HRT, had higher risk of breast cancer, which reflects research showing higher rates of breast cancer among premenopausal Asian American women (1).

Our study had several limitations. One limitation was the relatively small sample size. A second was that the case and control subsamples were matched according to Asian country of origin, so we were unable to disaggregate the various Asian American subpopulations. A third limitation was the case-control design, which did not allow us to examine trends over time. Lastly, our study was conducted only in the San Francisco Bay Area, so our results may not be generalizable to the larger population of Asian American women in the United States. The San Francisco Bay Area is unique in its relative affluence and the characteristics of the Asian immigrants it attracts, so our findings may not apply to other areas of the United States, especially less affluent areas. Nevertheless, as with the research on breast cancer in Marin County in the San Francisco Bay Area (27,28), the unique demographics of the region can point to important disease associations and lead to the discovery of new risk factors. A major strength of this study was the use of a population-based survey conducted in multiple languages that was designed to examine breast cancer risk among Asian American women in the San Francisco Bay Area.

Clinicians who serve Asian American patients should be aware of the potential trend of higher breast cancer risk among immigrant Asian American women and allocate resources for breast cancer treatment among this demographic accordingly. Interventions are needed to increase breast cancer screening among both immigrant and US-born Asian American women to prevent breast cancer from progressing. Immigrant Asian American women likely have different barriers to screening and treatment than US-born Asian American women, including language and culturally appropriate care.

Future studies are needed to corroborate the novel findings of our research. Studies using larger samples in broader geographic areas should compare breast cancer risk among Asian Americans by nativity and explore possible explanations for differences. Cross-national studies that examine breast cancer risk in the country of origin and upon immigrating to the United States would be useful. Such research could illuminate our understanding of how breast cancer risk changes over time, especially in an environment of international migration and changing contextual risk factors. Such investigations can lead to better breast cancer prevention activities, especially among immigrant groups living in the United States.

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Table

Table. Characteristics and Associations of Breast Cancer Risk With Nativity and Percentage of Life Lived in the United States Among a Sample (N = 570) of Asian American Women in the San Francisco Bay Area, Asian Community Health Initiative, 2013–2014

Characteristic	No. (%)[a]		Risk of Breast Cancer, OR (95% CI)	
	Breast Cancer Cases (n = 132)	Controls[b] (n = 438)	Adjusted for Age and Country of Origin[c]	Fully Adjusted[d]
Nativity and percentage of life lived in United States[e]				
US-born	22 (17)	144 (33)	1 [Reference]	1 [Reference]
Immigrant, ≥50% of life in United States	56 (42)	110 (25)	2.94 (1.65–5.21)	3.00 (1.56–5.75)
Immigrant, <50% of life in United States	54 (41)	184 (42)	1.87 (1.03–3.37)	2.46 (1.21–4.99)
Education				
College graduate	81 (61)	275 (63)	1 [Reference]	1 [Reference]
Some college	21 (16)	87 (20)	0.71 (0.41–1.23)	1.10 (0.59–2.06)
High school diploma or less	30 (23)	76 (17)	1.01 (0.60–1.71)	2.27 (1.12–4.58)
Home ownership[e]				
Renter or non-homeowner	30 (23)	162 (37)	1 [Reference]	1 [Reference]
Homeowner	102 (77)	276 (63)	2.37 (1.48–3.81)	2.21 (1.23–3.97)
Health insurance				
Private insurance	102 (77)	310 (71)	1 [Reference]	1 [Reference]
Public insurance or not insured	30 (23)	128 (29)	0.47 (0.28–0.77)	0.50 (0.26–0.98)
Pregnancy history[e]				
Age at first birth <25 y	18 (14)	81 (18)	1 [Reference]	1 [Reference]
Age at first birth 25–29 y	46 (35)	101 (23)	2.34 (1.23–4.48)	1.90 (0.93–3.85)
Age at first birth 30–34 y	24 (18)	95 (22)	1.54 (0.74–3.18)	0.91 (0.41–2.04)
Age at first birth ≥35 y	21 (16)	41 (9)	3.21 (1.46–7.05)	3.14 (1.29–7.63)
Never had a pregnancy that lasted ≥7 months	23 (17)	120 (27)	1.24 (0.60–2.56)	1.15 (0.51–2.59)
Any family history of breast cancer[e,f]				
No	100 (76)	384 (88)	1 [Reference]	1 [Reference]
Yes	32 (24)	54 (12)	2.05 (1.24–3.38)	2.45 (1.38–4.36)
Menopausal status and use of HRT				
Postmenopausal, no HRT	41 (31)	196 (45)	1 [Reference]	1 [Reference]
Premenopausal	71 (54)	213 (49)	9.27 (3.86–22.2)	10.9 (4.40–26.9)
Postmenopausal, used HRT	20 (15)	29 (7)	2.15 (1.06–4.36)	2.04 (0.93–4.48)

Abbreviation: HRT, hormone replacement therapy.

[a] Percentages may not add to 100% because of rounding.

[b] Asian American women in the San Francisco Bay Area without a diagnosis of breast cancer.

[c] Each variable entered individually into a logistic regression model adjusted for age group (20–39, 40–59, or ≥60 years) and country of origin (Chinese, Filipina, or other Asian).

[d] Logistic regression model adjusted for age group, country of origin, and all variables in the table.

[e] Number of breast cancer cases and controls differed significantly on this variable on the basis of χ^2 test ($P < .05$).

[f] Family history was defined as a mother, sister, or daughter with breast cancer.

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(continued)

Table. Characteristics and Associations of Breast Cancer Risk With Nativity and Percentage of Life Lived in the United States Among a Sample (N = 570) of Asian American Women in the San Francisco Bay Area, Asian Community Health Initiative, 2013–2014

Characteristic	No. (%)[a]		Risk of Breast Cancer, OR (95% CI)	
	Breast Cancer Cases (n = 132)	Controls[b] (n = 438)	Adjusted for Age and Country of Origin[c]	Fully Adjusted[d]
Body mass index, kg/m^2				
<23	61 (46)	221 (50)	1 [Reference]	1 [Reference]
23–26	53 (40)	143 (33)	1.29 (0.83–1.98)	1.47 (0.90–2.41)
≥27	18 (14)	74 (17)	0.84 (0.46–1.55)	1.02 (0.52–2.02)

Abbreviation: HRT, hormone replacement therapy.

[a] Percentages may not add to 100% because of rounding.

[b] Asian American women in the San Francisco Bay Area without a diagnosis of breast cancer.

[c] Each variable entered individually into a logistic regression model adjusted for age group (20–39, 40–59, or ≥60 years) and country of origin (Chinese, Filipina, or other Asian).

[d] Logistic regression model adjusted for age group, country of origin, and all variables in the table.

[e] Number of breast cancer cases and controls differed significantly on this variable on the basis of χ^2 test ($P < .05$).

[f] Family history was defined as a mother, sister, or daughter with breast cancer.

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ORIGINAL RESEARCH

Medicaid Claims for Contraception Among Women With Medical Conditions After Release of the US Medical Eligibility Criteria for Contraceptive Use

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PEER REVIEWED

Abstract

Introduction

The US Medical Eligibility Criteria for Contraceptive Use (MEC) identified 20 medical conditions that increase a woman's risk for adverse outcomes in pregnancy. MEC recommends that women with these conditions use long-acting, highly effective contraceptive methods. The objective of our study was to examine provision of contraception to women enrolled in Medicaid who had 1 or more of these 20 medical conditions

Methods

We used Medicaid Analytic Extract claims data to study Medicaid-enrolled women who were of reproductive age in the 2-year period before MEC's release (2008 and 2009) (N = 442,424) and the 2-year period after its release (2011 and 2012) (N = 533,619) for 14 states. We assessed 2 outcomes: provision of family planning management (FPM) and provision of highest efficacy methods (HEMs) for the entire study population and by health condition. The ratio of the after-MEC rate to the before-MEC rate was used to determine significance in MEC's uptake.

Results

Outcomes increased significantly from the before-MEC period to the after-MEC period for both FPM (1.06; lower bound confidence interval [CI], 1.05) and HEM (1.37; lower bound CI, 1.36) for a 1-sided hypothesis test. For the 19 of 20 conditions we were able to test for FPM, contraceptive use increased significantly for 12 conditions, with ratios ranging from 1.05 to 2.14. For the 16 of 20 conditions tested for HEM, contraception use increased significantly for all conditions, with ratios ranging from 1.19 to 2.80.

Conclusion

Provision of both FPM and HEM increased significantly among women with high-risk health conditions from the before-MEC period (2008 and 2009) to the after-MEC period (2011 and 2012). Health policy makers and clinicians need to continue promotion of effective family planning management for women with high-risk conditions.

Introduction

In 2010, the Centers for Disease Control and Prevention (CDC) released the US Medical Eligibility Criteria for Contraceptive Use (MEC) to guide health care providers in making evidence-based decisions on contraception. MEC focused on 20 medical conditions that present an increased risk for adverse outcomes during pregnancy, stating that long-acting, highly effective contraception methods may be the best choice for women with these medical conditions (1). Such methods include reversible options, such as intrauterine devices (IUDs) and implants, and permanent options, such as sterilization. Sole use of behavior-based methods, such as condoms, was not recommended because of their typically high failure rates.

CDC disseminated MEC guidelines through mobile applications, publications, and presentations (2). Nevertheless, a recent survey found that providers' knowledge of MEC was low (3). Some studies of women with the 20 MEC medical conditions found low levels of use of highly effective contraception, high levels of unintended pregnancy, and provider-imposed limitations to effective contraception options (4–7).

MEC guidelines may be particularly relevant for providers who serve low-income women, including women enrolled in Medicaid.

Such women are most likely to have unintended pregnancies (8) and associated medical conditions (9). In 2016 over 20% of reproductive-aged women in the United States were insured by Medicaid (10), and in 2010 Medicaid covered health care for nearly half of all US births (11). However, information comparing provision of contraception before and after MEC's release is unavailable. The objective of our study was to examine provision of contraception to women enrolled in Medicaid who had 1 or more of the 20 MEC-highlighted medical conditions by 1) determining the provision of family planning for these women and 2) comparing the use of highly effective contraception methods in the 2-year period before MEC's release (2008 and 2009) with their use in the 2 years after its release (2011 and 2012) to see if an increase occurred.

Methods

Data sources

We used Medicaid Analytical Extract (MAX) medical claims acquired from the Centers for Medicare and Medicaid Services (CMS) for the years 2008 through 2012. The MAX data set consists of individual-level claims data for all Medicaid-enrolled beneficiaries. We examined enrollees from 14 states, which accounted for more than 50% of all Medicaid enrollees in the United States: 10 southeastern states (Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, and Texas) and 4 states from other regions of the country (California, Minnesota, New York, and Pennsylvania). The Southeast was chosen as a focal point because its states are similar to each other in contraception health policy (12) and spending levels for Medicaid (13), and the health rankings of these states are among the lowest in the country (14). The other 4 states chosen were highly populous states from regions of the country that have various health policies and reimbursement levels that represent differences across the United States.

We obtained approvals to perform our research from CMS and from the institutional review board of the Georgia Institute of Technology. The study infrastructure to safeguard identifiable data followed the CMS-approved data use agreement, which allows publication of results from populations of 11 or more people (eg, patients).

Study population

We assessed the overall population of reproductive-aged women who were enrolled in Medicaid in 2008, 2009, 2011, and 2012 in all 14 states. We investigated 2 periods: the 2 years before MEC's release (2008 and 2009) and the 2 years after MEC's release (2011 and 2012). Our study population was a subset of the overall population and consisted of women aged 15 to 44 who had 1 or more of the 20 conditions listed in MEC (Appendix A). We did not count women more than once if they had multiple conditions. We stratified the study population by 1) age group (15–24 y, 25–34 y, 35–44 y) (15), 2) medical condition, and 3) state of residence. We obtained the age of each woman by using the date of birth in MAX's Personal Summary table. A woman was assigned to an age group on the basis of her age at the beginning of each period (2008 and 2011).

Medical condition was defined as 1 of the 20 MEC-identified conditions. A woman with a nonsurgical MEC condition was identified as having at least 3 Medicaid claims for that condition recorded on 3 different days in the before-MEC period (2008 and 2009) or the after-MEC period (2011 and 2012) (16). The Medicaid claim could be a claim from MAX's Other Therapy table or MAX's Inpatient table. Diagnosis codes of the *International Classification of Disease*, ninth edition (ICD-9) were used to identify nonsurgical conditions (Appendix A) (17). Different approaches were needed to identify women with surgical MEC conditions (bariatric surgery and solid organ transplant). To identify these women, we queried the Inpatient table of the MAX data for claims that contained the corresponding surgery condition procedure codes (Appendix A). We screened for the procedure codes in the inpatient claims that occurred in the 2 periods and assigned women to the period in which the surgery occurred. When identifying patients, we considered each condition separately, to account for comorbidities.

We identified the woman's state of residence by the state listed on her claim. This ensured that a woman was counted in each state in which she received service.

Outcome analysis

We considered 2 outcome measures, family planning management (FPM) and highest efficacy methods (HEMs). We documented the number of women for both outcome measures for both periods and for each medical condition.

Family planning management. We defined an FPM claim as one containing a diagnosis code beginning with V25, the overarching code for "encounter for contraceptive management" (17). The FPM measure includes many forms of contraception claims, ranging from discussion of contraception options with the clinician to procedures, such as inserting IUDs and sterilization. We aggregated the number of women with V25 claims for each period and each condition and compared the study population with the overall population. We considered 19 of the 20 MEC medical conditions; we excluded schistosomiasis because the number of women with these conditions was less than 11.

Highest efficacy method, aggregate and condition-level analysis. The HEM outcome consisted of contraception claims for IUDs, contraceptive implants, and sterilizations. MEC recommends HEMs for women with high-risk conditions. We used the diagnosis codes for IUD insertion (V25.1), IUD surveillance (V25.42), and implant surveillance (V25.43) and searched through both inpatient and other therapy claims. Because of the nature of the procedure, we searched for sterilizations (V25.2) through inpatient claims only.

We calculated HEM provision for the overall population, the study population, and each medical condition, including the number of women in the HEM outcome for each condition, the percentage rates of HEM, and the results of a 1-sided test for significance, including the lower bound of a 99% confidence interval. We considered 16 of the 20 MEC medical conditions; we excluded malignant gestational trophoblastic disease, liver cancer, schistosomiasis, and solid organ transplant because the number of women with these conditions was less than 11.

Rate analysis

Because rates for FPM and HEM use increased nationally during the years of our study, we used rates in the overall population as a scaling factor for the study population. The scaling factor was applied to the study population use rate to accurately determine the change in rates before and after the introduction of MEC.

A 1-sided exact Poisson test was used to determine whether provision of contraception increased significantly in the study population. The alternative hypothesis was defined as the before-MEC rate being smaller than the after-MEC rate. A ratio greater than 1 indicates an increase in provision; a ratio of 1.1 indicates a 10% increase in the rate.

The test statistic comparing before-MEC and after-MEC outcome measures was scaled by the rates in each of the 2 periods by the corresponding outcome measure of the overall population (Appendix B). The test procedure was applied to all conditions together and to each MEC condition separately. For the condition-level analysis, we corrected for the testing of multiple outcomes simultaneously by using the Bonferroni correction.

Results

Study population

Our sample consisted of more than 12 million women in 14 states who were covered by Medicaid in both study periods (Table 1). Most reproductive-aged women enrolled in Medicaid did not have claims for these conditions; less than 5% were identified as having 1 of the 20 high-risk MEC conditions. Though low, we saw an increase from 3.5% in the before-MEC period to 3.9% in the after-MEC period. More than half of the women with high-risk conditions were in the 35-to-44 age group, 53.5% in the before-MEC period and 66.9% in the after-MEC period. The 4 most common conditions made up 83% of the study population; in order of frequency, they were hypertension, diabetes, epilepsy, and HIV.

Outcome analysis

FPM outcome: aggregate and condition-level analysis. Provision of FPM for all reproductive-aged women in Medicaid increased from 17.9% before MEC to 18.2% after MEC. We saw a comparable increase for women in the study population, from 16.7% before MEC to 17.8% after MEC (Table 2) (estimate: 1.06; lower bound CI: 1.05). Provision of FPM varied by medical condition, ranging from 4.4% before MEC and 6.7% after MEC for those with liver cancer to 46.6% before MEC and 44.8% after MEC for those with peripartum cardiomyopathy. The conditions with the highest rates of FPM provision for both periods were peripartum cardiomyopathy, sickle cell disease, and thrombogenic heart disease (Figure 1). Gestational trophoblastic disease had the second highest provision of FPM before MEC.

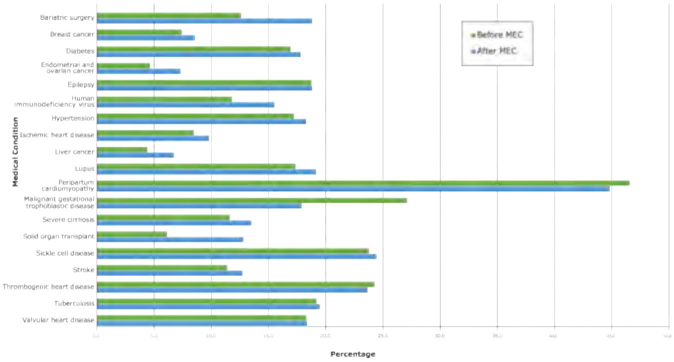

Figure 1. Changes in percentage of women, by medical condition, with a Medicaid claim for family planning management from the 2-year period before (2008 and 2009) to the 2-year period after (2011 and 2012) the 2010 release of the US Medical Eligibility Criteria for Contraceptive Use (MEC) by the Centers for Disease Control and Prevention (1). Percentage is number of women with each medical condition and an FPM Medicaid claim relative to the total population for that condition.

Before and after the MEC release, 12 of the 19 conditions examined showed a significant increase at the 1% significance level. After accounting for the increase at the overall population level, 5 conditions showed a greater than 30% increase in FPM: bariatric surgery, endometrial and ovarian cancer, HIV, liver cancer, and solid organ transplant (Table 2). The 7 conditions that did not show a significant increase in FPM were epilepsy, malignant gestational trophoblastic disease, peripartum cardiomyopathy, sickle cell disease, thrombogenic heart disease, tuberculosis, and valvular heart disease (Table 2).

HEM outcome: aggregate and condition-level analysis. Of the 12,422,899 reproductive-aged women insured by Medicaid, 437,036 had a HEM claim (3.5%) before MEC's release; 679,230 of the 13,597,612 women (5.0%) insured by Medicaid had a HEM claim after MEC (Table 3) (estimate: 1.37; lower bound CI: 1.36). We saw a comparable increase for women in the study population, from 4.1% to 5.7%. Provision of HEM varied by medical condition in both periods, ranging from 0.9% before MEC for endometrial or ovarian cancer to 25.6% after MEC for peripartum cardiomyopathy (Figure 2). After accounting for the increase at the overall population level, all 16 conditions showed a significant increase at the 1% significance level (Table 3). HEM provision more than doubled for 2 conditions: bariatric surgery and endometrial and ovarian cancer.

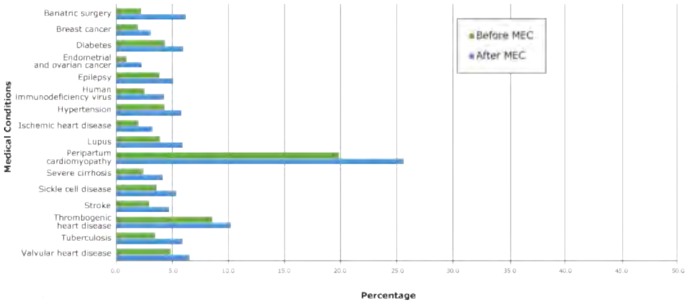

Figure 2. Changes in percentage of women, by medical condition, with a Medicaid claim for a highest efficacy contraception method from the 2-year period before (2008 and 2009) to the 2-year period after (2011 and 2012) the 2010 release of the US Medical Eligibility Criteria for Contraceptive Use (MEC) by the Centers for Disease Control and Prevention (1). Highest efficacy methods are contraceptive implants, intrauterine devices, and sterilization. Percentage is number of women with each medical condition and an HEM Medicaid claim relative to the total population for that condition.

Discussion

Our study showed an overall increase in provision of FPM and HEM from the 2-year period before MEC's release to the 2-year period after its release for women with 1 or more of the 20 medical conditions MEC identified as high risk for pregnant women. When all conditions were considered together, the difference was significant for both FPM and HEM. For individual conditions, significance was found for FPM for most medical conditions and for HEM for all medical conditions. The increase in HEM provision mirrors national trends. According to an analysis by the National Survey of Family Growth, the use of IUDs and contraceptive implants among reproductive-aged American women increased from 6% in 2008 to 12% in 2012 (18). Although our study accounted for the increase seen in the overall population and documented an increase across medical conditions, HEM rates for women with 1 or more of the 20 conditions were below the national average. Champaloux and colleagues had a similar finding in their review of claims of women with medical conditions from a privately insured population (19).

HEMs are particularly important for women with MEC-identified medical conditions, because pregnancy can result in severe adverse health outcomes for this population. The physiologic changes of pregnancy affect nearly every organ system in the body. For example, normal pregnancy creates a state of anemia, increased oxygen demand and cardiac output, hypercoagulability, immune compromise, and insulin resistance. These necessary changes support gestation and are generally well tolerated by healthy women. However, women with underlying medical conditions may experience amplification of their condition or predisposition to complications and illness, including death (20). The maternal death rate in the United States is the highest in the developed world (21). A recent review of maternal deaths from 9 states identified hemorrhage, cardiovascular and coronary conditions, infection, and cardiomyopathy as the most common causes (22). The review identified age-related differences underlying the cause of death and estimated that 63.2% of these deaths were preventable. One step proximal to preventing maternal death is preventing maternal illness. To prevent increased risk associated with pregnancy, a woman with a high-risk medical condition should have ready access to the most effective methods of contraception until she desires pregnancy. Then, when planning to conceive, a woman should have access to preconception care to optimize her health, manage medications, and transition her to and through pregnancy. This approach will help women with high-risk conditions to attain their reproductive goals while decreasing their health risk (23).

Our study found that provision of FPM and HEM varied by medical condition. For example, we found lower rates for FPM and HEM relative to other medical conditions among women with cancer (breast, endometrial, and ovarian cancer). One explanation is the nature of these conditions and the methods used to treat them. For example, hysterectomies or bilateral oophorectomies are common forms of treatment for endometrial and ovarian cancer, eliminating the need for contraception. Where the ability to conceive remains intact, cancers can limit women's contraceptive options. For example, IUDs are contraindicated for women with endometrial cancer as are hormonal IUDs and implants for women with breast cancer (1). On the other hand, we found that peripartum cardiomyopathy had the highest rates of FPM and HEM. One possible reason is that this condition is associated with high rates of illness and death rates as high as 14% for a subsequent pregnancy (24). Second, by definition, peripartum cardiomyopathy is diagnosed in the last month of pregnancy or the first few months after delivery. The timing of the diagnosis may create the opportunity for a health care provider to educate a woman on the importance of contraception because of the high risk associated with a subsequent pregnancy. However, the medical conditions affecting most women fall in between these extremes. Hypertension, diabetes, epilepsy, and HIV affected more than 430,000 women in our study, and these conditions also put women at high risk for adverse health outcomes with pregnancy. Therefore, additional focus should also be placed on these conditions.

Our study had several limitations. CMS data restricted us to the clinician’s diagnosis and procedure coding during the visit. Therefore, we may not have captured data on women using contraception methods that did not require a clinician or using methods for uncoded services. For example, we may not have captured data on women with previously placed IUDs or implants if surveillance of these devices was not coded during an annual or other visit. Similarly, we were only able to reliably capture data on sterilization procedures that occurred during the years of our study. Hence, data were not captured on women who used tubal sterilization and partner vasectomy as a form of birth control. For these reasons, we believe our findings to be underestimates. Because claims data do not include sexual or relationship history, we were unable to ascertain whether a woman was at risk for pregnancy on the basis of sexual activity with a male partner, nor were we able to assess whether her medical condition precluded sexual activity or fertility. Medicaid eligibility criteria for women vary by state, and women who become pregnant may be eligible for Medicaid for a limited amount of time. For 2 common conditions, hypertension and diabetes, MEC guidelines apply to women with severe disorders; our analysis was more inclusive by showing all women with the disorders. Finally, our statistical analysis shows associations but cannot directly address causality or reasons for a change.

Overall, our study found a limited, but encouraging, change in clinical practice in the 2 years after the release of MEC guidelines. The relatively low rate of FPM and provision of HEM that we found suggests that access to highly effective contraceptives was a barrier. Access issues for contraception can arise from financial and systems issues as well as from provider bias (25). Such barriers may also present opportunities for ongoing and future steps toward full implementation of MEC guidelines. Historically, access to contraception has been limited, especially for low-income women (26). Several efforts were made to lessen financial and system barriers to accessing contraception after the 2010 release of the MEC. After the Affordable Care Act mandate for contraceptive coverage went into effect, the percentage of women using IUDs and implants increased among sexually active women, whereas the use of oral contraception remained flat (27). The 6|18 Initiative (28) of CDC and its partners outlined 4 interventions for reducing financial and logistic barriers for public and private payers and providers. For women with no insurance coverage, family planning services can be obtained from the Federal Title X grant (29). These multilevel and collaborative approaches to reducing barriers may serve to increase the uptake of the MEC guidelines (30). In addition to these interventions, parallel programs have been working to ensure provider knowledge and application of MEC in practice. These include endorsement and implementation support of MEC by several medical associations, including the American College of Obstetricians and Gynecologists and the American Academy of Family Physicians (31,32). Focusing future efforts on specialist health care providers may help ensure that women with high-risk medical conditions receive evidence-based care and referrals to contraception counseling.

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Tables

Table 1. Reproductive-Aged Women in Medicaid Study Population Before and After MEC, by Age, State of Residence, and Health Condition

Variable	State Population Before MEC, 2008–2009, N = 442,424	State Population After MEC, 2011–2012, N = 533,619
Overall population, N	12,422,899	13,597,612
Study population[a]	437,018 (3.5)	527,660 (3.9)
Age[b], y		
15–24	69,050 (15.8)	87,797 (16.6)
25–34	134,267 (30.7)	200,909 (38.1)
35–44	233,701 (53.5)	352,833 (66.9)
State[b]		
Alabama	16,312 (3.7)	18,721 (3.5)
Arkansas	10,310 (2.3)	11,750 (2.2)
California	84,653 (19.1)	96,830 (18.1)
Florida	41,298 (9.3)	54,755 (10.3)
Georgia	31,543 (7.1)	32,481 (6.1)
Louisiana	23,031 (5.2)	25,568 (4.8)
Minnesota	11,389 (2.6)	16,844 (3.2)
Mississippi	17,284 (3.9)	18,888 (3.5)
New York	70,602 (16.0)	97,243 (18.2)
North Carolina	40,180 (9.1)	41,878 (7.8)
Pennsylvania	10,374 (2.3)	18,615 (3.5)
South Carolina	15,134 (3.4)	20,439 (3.8)
Tennessee	32,329 (7.3)	34,784 (6.5)
Texas	37,985 (8.6)	44,823 (8.4)
Medical conditions[c]		
Bariatric surgery	5,158 (1.0)	6,726 (1.1)
Breast cancer	11,072 (2.1)	13,016 (2.1)
Diabetes	159,042 (30.4)	190,648 (30.1)
Endometrial and ovarian cancer	2,259 (0.4)	2,557 (0.4)
Epilepsy	43,213 (8.3)	55,666 (8.8)

[a] Values are number (percentage) unless otherwise indicated. Percentage is the study population (women with a high-risk condition) relative to the overall population. Denominators of percentages vary because some women had more than one disorder.

[b] The Southeastern states were chosen as a focal point because of their similarity to each other in contraception health policy (12) and spending levels for Medicaid (13). In addition, the health rankings of these states are among the lowest in the country (14). The other 4 states chosen (California, Minnesota, New York, and Pennsylvania) were highly populous states from regions of the country that have various health policies and reimbursement levels that represent differences across the United States.

[c] Percentage is stratification group relative to sum of women in that strata. The sum of all categories in the stratification group may be greater than the total study population; women can belong to more than 1 category in the same stratification. Medical conditions totals used are 522,556 and 634,107, before and after MEC phases respectively. Medical conditions are the 20 disorders identified in the 2010 Centers for Disease Control and Prevention's US Medical Eligibility Criteria for Contraceptive Use that increase risk for adverse outcomes in pregnancy (1).

[d] Total population was fewer than 11. The Centers for Medicare and Medicaid Services data use agreement does not allow publication of results when study population (eg, patients) is fewer than 11 participants.

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Table 1. Reproductive-Aged Women in Medicaid Study Population Before and After MEC, by Age, State of Residence, and Health Condition

Variable	State Population Before MEC, 2008–2009, N = 442,424	State Population After MEC, 2011–2012, N = 533,619
Malignant gestational trophoblastic disease	118 (0.0)	123 (0.0)
Human immunodeficiency virus	23,865 (4.6)	22,894 (3.6)
Hypertension	207,286 (39.7)	259,571 (40.9)
Ischemic heart disease	12,357 (2.4)	13,577 (2.1)
Liver cancer	273 (0.1)	342 (0.1)
Lupus	15,750 (3.0)	20,014 (3.2)
Schistosomiasis	120 (0.0)	—[d]
Solid organ transplant	588 (0.1)	578 (0.1)
Peripartum cardiomyopathy	2,817 (0.5)	3,024 (0.5)
Sickle cell disease	8,395 (1.6)	9,564 (1.5)
Severe cirrhosis	6,626 (1.3)	9,451 (1.5)
Stroke	8,090 (1.5)	9,612 (1.5)
Thrombogenic heart disease	4,944 (0.9)	5,645 (0.9)
Tuberculosis	2,938 (0.6)	2,469 (0.4)
Valvular heart disease	7,645 (1.5)	8,630 (1.4)

[a] Values are number (percentage) unless otherwise indicated. Percentage is the study population (women with a high-risk condition) relative to the overall population. Denominators of percentages vary because some women had more than one disorder.

[b] The Southeastern states were chosen as a focal point because of their similarity to each other in contraception health policy (12) and spending levels for Medicaid (13). In addition, the health rankings of these states are among the lowest in the country (14). The other 4 states chosen (California, Minnesota, New York, and Pennsylvania) were highly populous states from regions of the country that have various health policies and reimbursement levels that represent differences across the United States.

[c] Percentage is stratification group relative to sum of women in that strata. The sum of all categories in the stratification group may be greater than the total study population; women can belong to more than 1 category in the same stratification. Medical conditions totals used are 522,556 and 634,107, before and after MEC phases respectively. Medical conditions are the 20 disorders identified in the 2010 Centers for Disease Control and Prevention's US Medical Eligibility Criteria for Contraceptive Use that increase risk for adverse outcomes in pregnancy (1).

[d] Total population was fewer than 11. The Centers for Medicare and Medicaid Services data use agreement does not allow publication of results when study population (eg, patients) is fewer than 11 participants.

Table 2. Provision of Family Planning Management (FPM) for Reproductive-Aged Women with Medical Conditions Enrolled in Medicaid in the 2-Year Period Before (2008 and 2009) and 2-Year Period After (2011 and 2012) the 2010 Release of the US Medical Eligibility Criteria for Contraceptive Use (MEC)

Family Planning Management[a]	Total Before MEC, 2008–2009[a]	FPM Provision Before MEC, 2008–2009[a]	Total After MEC, 2011–2012[a]	FPM Provision After MEC, 2011–2012[a]	Estimate[b] (Lower Bound CI[c])	P Value[d]
Overall population	12,422,899	2,221,325 (17.9)	13,597,612	2,477,023 (18.2)	NA	NA
Study population	437,018	87,115 (16.7)	527,660	112,851 (17.8)	1.06 (1.05)	<.001
Medical conditions						
Bariatric surgery	5,158	650 (12.6)	6,726	1,265 (18.8)	1.49 (1.42)	<.001
Breast cancer	11,072	822 (7.4)	13,016	1117 (8.6)	1.16 (1.13)	<.001
Diabetes	159,042	26,915 (16.9)	190,648	33,928 (17.8)	1.05 (1.04)	<.001
Endometrial and ovarian cancer	2,259	105 (4.6)	2,557	187 (7.3)	1.58 (1.48)	<.001
Epilepsy	43,213	8,104 (18.8)	55,666	10,469 (18.8)	1.00 (0.98)	.55
Human immunodeficiency virus	23,865	2,816 (11.8)	22,894	3,549 (15.5)	1.31 (1.28)	<.001
Hypertension	207,286	35,681 (17.2)	259,571	47,465 (18.3)	1.07 (1.06)	<.001
Ischemic heart disease	12,357	1,049 (8.5)	13,577	1,331 (9.8)	1.15 (1.12)	<.001
Liver cancer	273	12 (4.4)	342	23 (6.7)	1.52 (1.25)	<.001
Lupus	15,750	2,731 (17.3)	20,014	3,830 (19.1)	1.10 (1.07)	<.001
Malignant gestational trophoblastic disease	118	32 (27.1)	123	22 (17.9)	0.66 (0.49)	.99
Peripartum cardiomyopathy	2817	1,312 (46.6)	3.024	1,355 (44.8)	0.96 (0.90)	.95
Severe cirrhosis	6626	769 (11.6)	9,451	1,275 (13.5)	1.16 (1.12)	<.001
Sickle cell disease	8,395	1,996 (23.8)	9,564	2,337 (24.4)	1.03 (1.00)	.02
Solid organ transplant	588	36 (6.1)	9,612	74 (12.8)	2.14 (1.86)	<.001
Stroke	8,090	922 (11.4)	5,645	1,224 (12.7)	1.12 (1.08)	<.001
Thrombogenic heart disease	4,944	1,200 (24.3)	2,469	1,335 (23.6)	0.97 (0.93)	.94
Tuberculosis	2,938	564 (19.2)	8,630	481 (19.5)	1.02 (0.96)	.24
Valvular heart disease	7,645	1,399 (18.3)	9,612	1,584 (18.4)	1.00 (0.96)	.52

Abbreviation: CI, confidence interval; NA, not applicable.

[a] Values are number (percentage). Percentage is number of women with an FPM claim relative to women in that disease category. FPM claim includes all claims with an ICD-9 (*International Classification of Disease, Ninth Revision*)(17) code that begins with V25.

[b] The estimate is the ratio of the after-MEC scaled rate to the before-MEC scaled rate. A ratio greater than 1 indicates an increase in provision; a ratio of 1.1 indicates a 10% increase in the rate.

[c] 1-sided 99% confidence interval.

[d] *P* values are based on 1-sided Poisson test at a 99% confidence level. Bonferroni adjustment for *P* value threshold is .003.

Table 3. Provision of Highest Efficacy Contraception Methods (HEM)[a] for Reproductive-Aged Women with Medical Conditions Enrolled in Medicaid in the 2-Year Period Before (2008 and 2009) and 2-Year Period After (2011 and 2012) the 2010 Release of the US Medical Eligibility Criteria for Contraceptive Use (MEC)

Conditions Requiring Highest Efficacy Methods	Total Before MEC, 2008–2009[a]	HEM Provision Before MEC, 2008–2009[a]	Total After MEC, 2011–2012[a]	HEM Provision After MEC, 2011–2012[a]	Estimate[b] (Lower Bound CI[c])	*P* Value[d]
Overall population	12,422,899	437,036 (3.5)	13,597,612	679,230 (5.0)	NA	NA
Study population	437,018	21,413 (4.1)	527,660	36,176 (5.7)	1.37 (1.36)	.001
Bariatric surgery	5,158	114 (2.2)	6,726	416 (6.2)	2.8 (2.68)	.001
Breast cancer	11,072	214 (1.9)	13,016	400 (3.1)	1.59 (1.55)	.001
Diabetes	159,042	6,892 (4.3)	190,648	11,377 (6.0)	1.38 (1.37)	.001
Endometrial and ovarian cancer	2,259	21 (0.9)	2,557	58 (2.3)	2.43 (2.27)	.001
Epilepsy	43,213	1,658 (3.8)	55,666	2,813 (5.1)	1.32 (1.30)	.001
Human immunodeficiency virus	23,865	602 (2.5)	22,894	976 (4.3)	1.69 (1.65)	.001
Hypertension	207,286	8,902 (4.3)	259,571	15,072 (5.8)	1.35 (1.34)	.001
Ischemic heart disease	12,357	242 (2.0)	13,577	439 (3.2)	1.65 (1.60)	.001
Lupus	15,750	615 (3.9)	20,014	1,187 (5.9)	1.52 (1.48)	.001
Peripartum cardiomyopathy	2,817	559 (19.8)	3,024	775 (25.6)	1.29 (1.21)	.001
Severe cirrhosis	6,626	159 (2.4)	9,451	391 (4.1)	1.72 (1.66)	.001
Sickle cell disease	8,395	302 (3.6)	9,564	511 (5.3)	1.49 (1.44)	.001
Solid organ transplant	588	—[e]	578	24 (4.2)	NA	NA
Stroke	8,090	237 (2.9)	9,612	452 (4.7)	1.60 (1.55)	.001
Thrombogenic heart disease	4,944	423 (8.6)	5,645	576 (10.2)	1.19 (1.14)	.001
Tuberculosis	2,938	102 (3.5)	2,469	146 (5.9)	1.71 (1.61)	.001
Valvular heart disease	7,645	371 (4.9)	8,630	563 (6.5)	1.35 (1.30)	.001

Abbreviations: CI, confidence interval; NA, not applicable.

[a] Values are number (percentage). Percentage is number of women with an HEM Medicaid claim relative to the population in that disease category. HEM claims for contraception are for intrauterine devices, contraceptive implants, and sterilization.

[b] Estimated ratio of the after-MEC scaled rate to the before-MEC scaled rate. A ratio greater than 1 indicates an increase in provision; a ratio of 1.1 indicates a 10% increase in the rate.

[c] 1-sided 99% confidence interval.

[d] *P* values are based on 1-sided Poisson test at 99% confidence level. Bonferroni adjustment for *P* value threshold is $P < .006$.

[e] Total population was fewer than 11. The Centers for Medicare and Medicaid Services Data Use Agreement does not allow publication of results when study population (eg, patients) is fewer than 11 participants.

Appendix A. ICD-9[a] Codes for 20 High-Risk Medical Conditions Identified by the US Medical Eligibility Criteria for Contraceptive Use

Condition	ICD-9 Code
Breast cancer	174
Diabetes	250
Endometrial and ovarian cancer	179, 182, 183
Epilepsy	345
History of bariatric surgery (past 2 years) [a]	V45.86
Human immunodeficiency virus	042
Hypertension	401–405
Ischemic heart disease	410, 412–414
Malignant gestational trophoblastic disease	181
Malignant liver tumors and hepatocellular carcinoma of the liver	155
Peripartum cardiomyopathy	674.5
Schistosomiasis with fibrosis of the liver	120.9
Severe cirrhosis	571
Sickle cell disease	282.6
Solid organ transplant in the past 2 years[b]	V42.0, V42.1, V42.6, V42.7, V42.83, V42.9
Stroke	430–434, 436–438
Systemic lupus erythematosus	710.0
Thrombogenic mutations	286.
Tuberculosis	010–018
Valvular heart disease	424

[a] *International Classification of Disease, Ninth Revision* (17).
[b] Current Procedural Terminology code; used to identify surgical medical conditions (16).

Appendix B. Poisson Ratio Test Model to Determine an Increase in Family Planning Management and Provision of the Highest Efficacy Contraception Methods

Setting up the problem, we define:

C_i^k: Total number of women in overall population in time period *i* for outcome *k*

C_i = Sum of C_i^k for all k = Total overall population in time period *i*
π_i^k = *Rate of outcome k in time period in for overall population* = C_i^k *over* C_i

M_i^k = Total number of women in study population in time period *i* for outcome *k*

M_i = Sum of M_i^k for all *k* = Total study population in time period *i*

Given that M_i is a subset of the overall population, the expected number of women in the study population with outcome *k* is $E[M_i^k] = \pi_i^k \times M_i^k$

Furthermore, let

μ_{ij}^k: *Scaled proportion of the study population for time period i and medical condition j*

where:

phase $i \in (0,1)$

medical condition $j \in (1,2,\ldots 20)$

outcome $k \in (1,2)$

We determined the rate for each time-period as:

- Outcome 1: family planning management (FPM) ratio
- Counseling, insertions, and surveillance for contraceptive methods
  μ_{ij}^1 = (scaled number of women from study population with FPM claim) over (total study population) = $(M_i^1 - E[M_i^1])/M_i$
- Outcome 2: highest efficacy method (HEM) ratio
- Intrauterine device (IUD): insertion and surveillance
- Implants: insertion
  μ_{ij}^2 = (scaled number of women from study population with HEM claim)/(total study population) = $(M_i^2 - E[M_i^2]) / M_i$

The ratio of rates in time period 0 and time period 1 were assessed by using a 1-sided exact Poisson test.

$H_0: (\mu_{1j}^k/\mu_{0j}^k) = 1$

$H_1: (\mu_{1j}^k/\mu_{0j}^k) > 1$

All analysis was completed by using R version 3.4.3 (https://www.r-project.org/).

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ORIGINAL RESEARCH

Inpatient Medicaid Usage and Expenditure Patterns After Changes in Supplemental Nutrition Assistance Program Benefit Levels

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PEER REVIEWED

Abstract

Introduction

Food insecurity worsens health outcomes and is associated with increased health care usage and expenditures. The Supplemental Nutrition Assistance Program (SNAP) reduces but does not eliminate recipients' food insecurity. We sought to determine whether inpatient Medicaid usage and expenditure patterns responded to an April 2009 increase in SNAP benefit levels and a subsequent November 2013 decrease.

Methods

Interrupted time series models estimated responses to the 2009 and 2013 SNAP changes in the Medicaid population, compared responses between Medicaid and Medicare recipients, and compared responses between Medicaid recipients with different likelihoods of having a disability. Analyses used 2006 through 2014 Healthcare Cost and Utilization Project National (previously Nationwide) Inpatient Sample data.

Results

After the 2009 SNAP increase, Medicaid admission growth fell nationally from 0.80 to 0.35 percentage points per month (a difference of –0.45; 95% CI, –0.72 to –0.19), adjusting for enrollment. After the 2013 SNAP decrease, admission growth rose to 2.42 percentage points per month (a difference of 2.07; 95% CI, 0.68 to 3.46). Inflation-adjusted monthly Medicaid expenditures followed similar patterns and were associated with $26.5 billion (in 2006 dollars) in reduced expenditures over the 55 months of the SNAP increase, and $6.4 billion (in 2006 dollars) in additional expenditures over the first 14 months after the SNAP decrease. Effects were elevated for Medicaid compared with Medicare recipients and among people with a high likelihood of having a disability.

Conclusion

Although alternative causal explanations warrant consideration, changes in SNAP benefit levels were associated with changes in inpatient Medicaid usage and cost patterns.

Introduction

Food insecurity is a determinant of population health (1) associated with multiple health problems (2) and elevated health care usage and expenditures (3). In 2016, 12% of US households experienced food insecurity (4). The Supplemental Nutrition Assistance Program (SNAP), serving 44 million Americans in 2016 (5), partially alleviates recipients' food insecurity (6). It follows that fluctuations in SNAP benefit levels may affect food insecurity and in turn health care usage and expenditures. Conceptual models for these hypotheses propose that food insecurity increases the risk of developing chronic diseases in the long term and exacerbating these conditions in the short term (7). These effects occur via skipped meals (8), poor nutrition quality (9), stress and depression (10), impaired decision-making capacity (11), and tradeoffs with key resources such as medication and housing (11,12).

Recent policy changes provide a unique opportunity for studying these pathways. The American Recovery and Reinvestment Act increased monthly SNAP benefits by a minimum of 13.6% per SNAP household in April 2009 (13), and this increase expired in November 2013 (13). Both the 2009 and 2013 changes were immediate and affected all recipients across the United States. Moreover, the post–Great Recession recovery did not reach those eligible for SNAP during much of this time period, leading to a poor but stable economic environment; wealth grew for higher-income families during this period but was stagnant for lower-income families (14).

One study of the 2009 SNAP increase found it was associated with decreased growth in inpatient Medicaid admissions and expenditures in Massachusetts, particularly among people with chronic illnesses (15). Another report examining both the 2009 and 2013 SNAP changes found no effect on health outcomes, though it did not adjust for enrollment and used limited data points (16). Our objective was to build on these approaches by examining changes in nationwide usage, expenditure, and enrollment data at multiple time points. We compared effects among Medicaid and Medicare populations and among recipients with varying likelihoods of having a disability. Effects should be greater in Medicaid versus Medicare, because Medicaid recipients have greater exposure to SNAP benefits (13). Effects of SNAP should also be magnified for people with disabilities, who have elevated exposure to food insecurity and elevated SNAP and health care usage (17,18).

Methods

Data

We used data from the 2006 through 2014 Healthcare Cost and Utilization Project's Nationwide Inpatient Sample (renamed National Inpatient Sample in 2012), which provide all-payer inpatient discharge data covering of 97% of the United States population (19), including detailed medical, expenditure, and demographic data for each hospital admission (19). The Inpatient Sample was redesigned in 2012; however, by using "trend weights" for years before 2012 and original weights for later years, nationally representative trends spanning periods before and after 2012 can be calculated (19).

Analytic samples

Three analytic samples were identified. In the first, data from discharges for which the primary payer was Medicaid were collapsed by month. This made the 108 months from January 2006 through December 2014 the units of observations. Summary data for each month (eg, total admissions) were included as model covariates. This sample allowed for interrupted time series analyses examining the Medicaid population as a whole.

For the second analytic sample, we replicated the procedures used for the overall Medicaid sample with the Medicare sample and then combined them. The payer was assigned based on the primary payer listed, which was typically Medicare for inpatient stays for dual eligible individuals. Summary data for each payer for each month were again the covariates, in addition to a variable identifying the payer for each observation. This sample allowed for analyses comparing the Medicaid and Medicare populations.

For the final analytic sample, each Medicaid discharge was identified as being for someone with no, low, moderate, or high likelihood of having a disability. To identify disability likelihood, we used a modified version (20) of the Access Risk Classification System (version 2) algorithm (21), which uses information from *International Classification of Diseases, Ninth Revision, Clinical Modification*, codes and Healthcare Common Procedure Coding System codes.

This modified algorithm has a sensitivity for identifying people with disabilities of 49% to 83% and a specificity of 30% to 80% when dichotomizing individuals into no/low and moderate/high disability likelihood categories (20,21). To increase the specificity of this algorithm, as done previously (22), we identified the individuals with the highest likelihood of having a disability and compared them to the other groups. After each discharged person was assigned a likelihood for having a disability, data for each group was collapsed by month. Consequently, each month had 4 observations, 1 for each group (no, low, moderate, and high). Summary data for each group for each month were the covariates in addition to a variable identifying the likelihood group for each observation. This sample allowed for analyses comparing the different disability likelihood subsets of the Medicaid population.

Dependent variables

We used 3 dependent variables: total monthly admissions, monthly average length of stay per admission, and total monthly inflation-adjusted inpatient costs. When collapsing monthly data, as in the prior study examining effects of the 2009 SNAP increase in Massachusetts (15), we generated the total number of admissions (the weighted sum of the number of discharges) and the weighted average length of stay per admission. Before totaling monthly costs, we multiplied hospital charges for each admission by the cost-to-charge ratio provided by the National Inpatient Sample (23). Hospitals charge differently for similar procedures, so each has a different cost-to-charge ratio. Multiplying charges by cost-to-charge ratios yielded actual costs (23). We used the provided weights to produce nationally representative estimates (trend weights for the 2006–2011 data and original weights for the 2012–2014 data) (19). Weighted total cost figures were then summed to obtain total monthly costs.

Medical care inflation was significantly higher than general inflation during the study period (24), but Medicaid inflation was also lower than overall medical inflation (25). To estimate Medicaid-specific inflation and generate inflation-adjusted costs, we calculated the monthly change in the average cost per day of admission. Because this inflation measure was internal to the data, we could estimate inflation figures specific to Medicaid, to the different disability likelihood groups, and to Medicare.

As was done in the Massachusetts study (15), we scaled each dependent variable to be the percentage change from the value in the first month, January 2006. This scaling standardized interpretations across dependent variables and comparison groups.

Covariates

For covariates, weighted monthly demographic figures were calculated. These figures included the average age of patients and the percentages of discharges for which the individual discharged was female, non-Hispanic white, or lived in a zip code with a median annual income in the lowest quartile (below $36,000 to $39,000, depending on the year). Enrollment per month was another covariate. Medicaid and Medicare enrollment numbers were available for June of each year of the study period through 2013 and on a monthly basis for 2014 (26,27). Enrollment numbers for months other than June for 2006 through 2013 were projected using linear interpolation based on the available numbers. Enrollment was not a covariate when comparing disability likelihood groups because such numbers are not available by disability likelihood.

We also created variables for the purposes of the interrupted time series approach. First was a “month” counter variable, with a value of 1 for January 2006 and 108 for December 2014. The interruption points, which each had dichotomous post variables and post-counter variables, were April 2009 (month 40) and November 2013 (month 95), coinciding with the increase and subsequent decrease in SNAP benefits. For the Medicare comparison, there was a dichotomous payer variable and interaction terms between this variable and all time-related variables. Similarly, for the disability analyses, there was also a dichotomous disability variable and interaction terms between this variable and all time-related variables.

Statistical analysis

Single-group interrupted time series models test for 2 potential data pattern changes after a policy change (“interruption”): changes in trends (slope) and immediate changes in level (intercept) (28). Multiple interruptions can be tested in 1 model (28). Multigroup interrupted analyses are similar, but they also allow for comparisons of how the patterns of different groups change after interruptions (28). Inferences from multigroup analyses are thus analogous to those from difference-in-differences models. The statistical models used here are provided in the Appendix. We used Stata software, version 14.0 (StataCorp LLC), and its ITSA package to account for autocorrelation and heteroskedasticity via Newly-West standard errors. We allowed consideration of up to 12 months of lag in the autocorrelation structure.

Results

Medicaid population as a whole

During January 2006 through March 2009, adjusting for enrollment and other covariates, the number of monthly Medicaid admissions across the United States rose by an average of 0.80 percentage points per month over the baseline January 2006 number (Table 1). This growth slowed to 0.35 percentage points per month (a difference of –0.45; 95% CI, –0.72 to –0.19) from April 2009 to October 2013, and then rose again to 2.42 percentage points per month (a difference of 2.07; 95% CI, 0.68 to 3.46) starting in November 2013 (Table 1). Monthly inpatient Medicaid expenditures followed a similar pattern: initial growth of 0.85 percentage points per month, a slowdown in growth to 0.36 percentage points per month (a difference of –0.49; 95% CI, –0.73 to –0.25) after the April 2009 SNAP increase, and a subsequent increase in this growth to 2.09 percentage points per month (1.73; 95% CI, 0.37 to 3.09) after the November 2013 SNAP decrease (Table 1, Figure). The changes in expenditure patterns were associated with a total savings of $26,465,103,280 (in January 2006 dollars) over the 55 months of the SNAP increase and a total cost of $6,374,326,245 (in January 2006 dollars) over the first 14 months after the SNAP decrease. The immediate changes in overall levels of monthly admissions and expenditures after the SNAP policy changes were not significant. Patterns for the average length of stay differed, because they did not change significantly after the April 2009 SNAP increase. After the November 2013 SNAP decrease, there was an immediate 1.33 percentage point increase (95% CI, 0.40 to 2.26) in the average length of stay, but this was offset over time by a slowdown in growth of –0.30 percentage points per month (95% CI, –0.55 to –0.05) (Table 1).

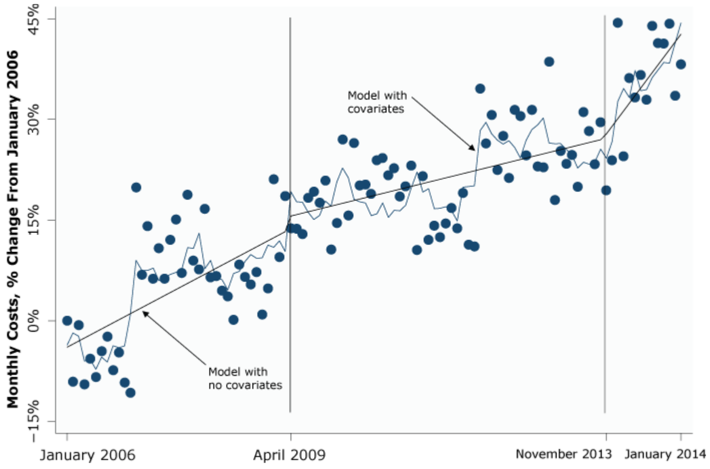

Figure. Interrupted time series analysis of changes in nationwide inpatient Medicare expenditures in response to changes in the Supplemental Nutrition Assistance Program (SNAP), January 2006–January 2014. SNAP benefits increased monthly by a minimum of 13.6% per SNAP household in April 2009, and this increase expired in November 2013.

Medicaid-Medicare comparison

Before the April 2009 SNAP increase, expenditure growth did not differ significantly between the 2 groups (Table 2). After the April 2009 SNAP increase, admission growth slowed significantly more for Medicaid than for Medicare (–0.26 percentage points per month; 95% CI, –0.48 to –0.04), though Medicaid also had a larger immediate change at the time (22.30 percentage points; 95% CI, 8.43 to 36.18) (Table 2). After the November 2013 SNAP decrease, admission growth increased significantly more for Medicaid than for Medicare (2.26 percentage points per month; 95% CI, 0.84 to 3.67) (Table 2). Differences in Medicaid and Medicare expenditure patterns paralleled the differences in admission patterns, though differences in average length of stay patterns were minimal (Table 2).

Comparing disability likelihood groups

Differences in admission patterns between the group with a high likelihood of having a disability and the group with no likelihood of having a disability were in the hypothesized directions but not significant (Table 3), although differences in admission patterns between the high likelihood and the low likelihood groups and the high likelihood and moderate likelihood groups were significant. Expenditure results also were in the hypothesized directions and varied in terms of significance across comparisons. Before the April 2009 SNAP increase, expenditures for the high likelihood group rose faster than they did for all other groups. Greater expenditure slowdowns for the high versus no groups after the April 2009 SNAP increase were not significant (Table 3), but they were in the comparisons of the high versus low groups and the high versus moderate groups. After the November 2013 SNAP decrease, expenditures for the high group had a larger immediate jump than both the no group (Table 3) and the low group, but not the moderate group. Results for average length of stay were less consistent in terms of direction and significance.

Discussion

In the Medicaid population, monthly hospital admissions were increasing from January 2006 until the April 2009 SNAP increase. The rate of this growth fell significantly after the April 2009 SNAP increase and rose significantly after the November 2013 SNAP decrease. Expenditure patterns matched admission patterns closely and were associated with $26.5 billion in savings over the 55 months of the SNAP decrease and $6.4 billion in added costs during the first 14 months of the SNAP decrease. Cost growth slowed more after April 2009 and increased more after November 2013 for the Medicaid population than it did for the Medicare population, whose recipients have less exposure to SNAP. This difference indicates an effect beyond general health care patterns. Further, using a rough identifier of disability likelihood, moderate evidence suggested that Medicaid recipients with a high likelihood of having a disability, a group with greater food insecurity exposure and sensitivity, were more responsive to SNAP changes than were Medicaid recipients with a lower likelihood of having a disability. Interrupted time series models involving a comparison group and both the introduction and removal of a policy are among the most robust quasi-experimental designs (28). These findings thus offer support for the hypothesis that inpatient Medicaid cost and usage patterns are responsive to changes in SNAP benefit levels.

Several limitations must be considered. SNAP and Medicaid populations do not overlap perfectly. Many Medicaid recipients do not receive SNAP benefits, meaning they would not have been affected by changes in SNAP benefit levels. This likely made the results conservative, however, because it reduced our ability to detect the effects of the SNAP changes precisely. Another potential limitation was the use of internal inflation data. By using the average costs per day of admission, we may have captured both changes in inpatient Medicaid inflation and changes in the quantity and intensity of services provided per day. If so, and if fluctuations in the daily quantity and intensity of services differed substantially from changing patterns in admissions and lengths of stay, then these results could have been biased. This possibility was likely small, as the inflation figures used here were consistent with previous Medicaid inflation research (25), and the lack of changes in length of stay per admission do not suggest changes in case mix. Separately, results were limited to inpatient data and could be offset by changes in other types of care that were not measured. Additionally, although the comparison to Medicare data was a strength, further studies with more detailed claims data might allow for more nuanced comparisons with additional payers. Privately insured individuals are even less likely to receive SNAP than Medicare recipients are, but they made for a less feasible comparison here because of large changes in private insurance markets during the study period. Finally, the study period included multiple other policy changes, including at the state level, that we could not control for here given the lack of state indicators in recent Healthcare Cost and Utilization Project inpatient sample data. However, the immediacy and uniformity of the SNAP changes and the general lack of economic growth for SNAP-eligible populations during the study period (14) offer some buffering against this limitation.

Increases in admissions and expenditure trends after the November 2013 SNAP decrease were markedly larger than the decreases following the April 2009 SNAP increase, despite the 2009 change being larger (the expiration of the SNAP increase coincided with a cost-of-living adjustment, partially offsetting the decrease [13]). Although we adjusted for Medicaid enrollment, state Medicaid expansions starting in 2014 could explain part of the difference if the expansion population had significantly greater medical needs than the pre-expansion population. Pent-up demand is also possible, though it would be unlikely to fully explain the large change in cost and admission patterns, especially given the higher income of the expansion population. Another possibility is that people may be more sensitive to increases in food insecurity than to alleviations of food insecurity. This would be consistent with concepts from ecosocial theory positing that harms can build up in people's bodies over time and may be easier to exacerbate than to expunge (29). If true, food benefit cuts may lead to larger health effects than increases in food benefits. Further examination of these alternatives is warranted.

Findings from the multigroup models comparing those with high likelihood of disability to other groups were less uniform, though still broadly consistent with the hypothesis that people with disabilities are especially responsive to changes in SNAP benefit levels. One potential limitation to clearer findings was the low specificity of the Access Risk Classification System (version 2) algorithm. It is unlikely that this low specificity differentially affected groups with different sensitivities to changes in SNAP benefits, however, so the resulting misclassification bias was likely nondifferential and made our results more conservative. Another potential explanation is the large diversity within the disability population. Parts of this population may be less sensitive to changes in food security than others. If true, broad comparisons between those with and without disabilities would yield weaker associations. Study of more nuanced stratifications of the disability population may clarify this issue.

Although alternative causal explanations warrant consideration, particularly those related to state policy changes that could not be examined here, our findings overall suggest that proposed cuts to the SNAP program (30) may increase Medicaid usage and expenditures. Proposed Medicaid coverage cuts would offset Medicaid-specific costs, but such cuts will likely amplify associated negative health effects. Moreover, if low-income people experience worsening health and reduced health care access simultaneously, burdens on hospitals may rise if they are forced to provide more unreimbursed emergency care. Financial costs for the health care system may rise overall as a result, even if Medicaid-specific costs are lowered.

The public health consensus is that social factors drive health outcomes (1), but few studies have explored the effects on health care of alleviating or exacerbating social ills such as hunger. Our findings suggest that health care usage and expenditures may be responsive to changes in certain social policies.

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Tables

Table 1. Changes in Nationwide Inpatient Medicaid Trends in Response to an April 2009 Increase and November 2013 Decrease in SNAP Benefit Levels, 2006–2014[a]

Category	Monthly Admissions in Percentage Points[b] (95% CI)	Monthly Expenditures[c] in Percentage Points[b] (95% CI)	Monthly Average Length of Stay per Admission in Percentage Points[b] (95% CI)
Variable			
Change in percentage points[d] per month before SNAP increase	0.80[e] (0.31 to 1.29)	0.85[e] (0.36 to 1.34)	0.03 (−0.05 to 0.11)
2009 SNAP increase, immediate change in level that month	11.17 (−0.02 to 22.36)	9.86 (−1.45 to 21.17)	−0.99 (−2.46 to 0.49)
Change in slope[d] after SNAP increase	−0.45[e] (−0.72 to −0.19)	−0.49[f] (−0.73 to −0.25)	−0.02 (−0.07 to 0.02)
2013 SNAP decrease, immediate change in level that month	−3.90 (−11.87 to 4.06)	−2.12 (−9.69 to 5.44)	1.33[e] (0.40 to 2.26)
Change in slope[d] after SNAP decrease	2.07[e] (0.68 to 3.46)	1.73[g] (0.37 to 3.09)	−0.30[g] (−0.55 to −0.05)
Covariates			
Medicaid enrollment, in millions	−1.81 (−3.92 to 0.31)	−1.94 (−4.13 to 0.25)	−0.04 (−0.47 to 0.38)
Percentage of female admissions	−1.85 (−4.70 to 1.01)	−3.28[g] (−6.10 to −0.47)	−1.17[f] (−1.60 to −0.74)
Percentage of non-Hispanic white admissions	0.27 (−1.38 to 1.92)	0.02 (−1.54 to 1.58)	−0.21[g] (−0.37 to −0.05)
Percentage of lowest income quartile admissions[h]	3.78[f] (1.89 to 5.67)	3.70[e] (1.66 to 5.75)	−0.03 (−0.38 to 0.33)
Average age, y	−1.70 (−4.22 to 0.83)	−0.57 (−2.94 to 1.79)	0.90[f] (0.49 to 1.31)

Abbreviations: CI, confidence interval; SNAP, Supplemental Nutrition Assistance Program.

[a] Single group interrupted time series models using Newey-West standard errors (constant omitted).

[b] All dependent variables scaled by dividing by the value in January 2006, subtracting 1, and multiplying by 100 (this produces coefficients that can be read as percentage points of the January 2006 value).

[c] Monthly expenditures adjusted for inflation.

[d] Slope can be interpreted as the changes in percentage points per month (for example, a coefficient of 2 on a slope term would indicate a change in 2 percentage points per month; this would mean that after 3 months the value would have increased by 6% of the January 2006 value).

[e] $P < .01$.

[f] $P < .001$.

[g] $P < .05$.

[h] This was equivalent to annual income less than $36,000 to $39,000, depending on the year.

Table 2. Comparison of Nationwide Inpatient Medicaid and Medicare Trends Before and After an April 2009 Increase and November 2013 Decrease in SNAP Benefit Levels, 2006–2014[a]

Variable	Monthly Admissions in Percentage Points[b] (95% CI)	Monthly Expenditures[c] in Percentage Points[b] (95% CI)	Monthly Average Length of Stay per Admission in Percentage Points[b] (95% CI)
Medicare			
Change in percentage points[d] per month before SNAP increase	0.65[e] (0.41 to 0.88)	0.59[e] (0.36 to 0.82)	−0.05[f] (−0.09 to 0)
2009 SNAP increase, immediate change in level that month	−8.5[g] (−14.23 to −2.77)	−10.42[e] (−15.97 to −4.87)	−1.99[e] (−2.78 to −1.21)
Change in slope[d] after SNAP increase	−0.14 (−0.38 to 0.11)	−0.16 (−0.40 to 0.09)	0 (−0.03 to 0.03)
2013 SNAP decrease, immediate change in level that month	−3.31 (−6.73 to 0.11)	0.75 (−2.95 to 4.45)	2.99[e] (2.16 to 3.83)
Change in slope[d] after SNAP decrease	−0.14 (−0.47 to 0.18)	−0.24 (−0.57 to 0.09)	−0.09 (−0.20 to 0.01)
Medicaid			
Difference in slope[d] before SNAP increase	0.08 (−0.25 to 0.40)	0.23 (−0.08 to 0.54)	0.12[e] (0.07 to 0.17)
Difference in immediate change[g] in level for the month of the 2009 SNAP increase	22.30[h] (8.43 to 36.18)	22.64[h] (8.66 to 36.62)	0.88 (−0.68 to 2.44)
Difference in change in slope[d,g] after SNAP increase	−0.26[f] (−0.48 to −0.04)	−0.29[f] (−0.52 to −0.07)	−0.05 (−0.11 to 0)
Difference in immediate change in level for the month of the 2013 SNAP decrease	−0.29 (−7.15 to 6.57)	−3.18 (−9.27 to 2.90)	−2.24[f] (−4.01 to −0.47)
Difference in change in slope[d,g] after SNAP decrease	2.26[h] (0.84 to 3.67)	2.07[h] (0.69 to 3.44)	−0.16 (−0.46 to 0.13)
Covariates			
Medicaid enrollment, in millions	−1.94 (−4.27 to 0.40)	−2.27 (−4.54 to 0)	−0.24 (−0.64 to 0.15)
Percentage of female admissions	−0.23 (−3.56 to 3.10)	−1.87 (−5.19 to 1.44)	−1.36[e] (−1.79 to −0.93)
Percentage of non-Hispanic white admissions	0.81 (−1.00 to 2.62)	0.55 (−1.22 to 2.31)	−0.20[f] (−0.36 to −0.05)
Percentage of lowest income quartile admissions[i]	3.98[e] (2.68 to 5.28)	3.87[e] (2.49 to 5.25)	0.05 (−0.18 to 0.28)
Average age, y	0.07 (−2.55 to 2.68)	1.63 (−1.03 to 4.29)	1.4[e] (0.89 to 1.99)

Abbreviations: CI, confidence interval; SNAP, Supplemental Nutrition Assistance Program.

[a] Multigroup interrupted time series models using Newey-West standard errors (constant and term comparing initial intercept between groups omitted).

[b] Dependent variable scaled by dividing by the value in January 2006, subtracting 1, and multiplying by 100 (this produces coefficients that can be read as percentage points of the January 2006 value).

[c] Monthly expenditures adjusted for inflation.

[d] Slope can be interpreted as the changes in percentage points per month (for example, a coefficient of 2 on a slope term would indicate a change in 2 percentage points per month; this would mean that after 3 months the value would have increased by 6% of the January, 2006 value).

[e] $P < .001$.

[f] $P < .05$.

[g] All “difference in change” terms should be interpreted as difference-in-differences terms (for example, a difference in change in slope indicates how the change in the slope for the Medicaid population differed from the change in slope for the Medicare population).

[h] $P < .01$.

[i] This was equivalent to annual income less than $36,000 to $39,000, depending on the year.

Table 3. Comparison of Nationwide Inpatient Medicaid Trends Among Individuals With No Likelihood of Having a Disability and With High Likelihood of Having a Disability Before and After an April 2009 Increase and November 2013 Decrease in SNAP Benefit Levels, 2006–2014[a]

Variable	Monthly Admissions in Percentage Points[b] (95% CI)	Monthly Expenditures[c] in Percentage Points[b] (95% CI)	Monthly Average Length of Stay per Admission in Percentage Points[b] (95% CI)
No likelihood of having a disability			
Change in percentage points[d] per month before SNAP increase	0.41[e] (0.13 to 0.69)	0.33[f] (0.07 to 0.58)	−0.08[e] (−0.12 to −0.03)
2009 SNAP increase, immediate change in level that month	4.33 (−3.28 to 11.94)	3.36 (−4.00 to 10.72)	−0.40 (−1.67 to 0.88)
Change in slope[d] after SNAP increase	−0.61[g] (−0.94 to −0.29)	−0.50[e] (−0.79 to −0.21)	0.09[g] (0.05 to 0.14)
2013 SNAP decrease, immediate change in level that month	−4.05 (−8.77 to 0.67)	−2.96 (−7.30 to 1.37)	0.92[f] (0.08 to 1.76)
Change in slope[d] after SNAP decrease	0.70[e] (0.26 to 1.15)	0.57[e] (0.15 to 0.99)	−0.09[f] (−0.16 to −0.02)
High likelihood of having a disability			
Difference in slope[d] before SNAP increase	0.33 (−0.05 to 0.71)	0.36[f] (0.02 to 0.70)	0.03 (−0.01 to 0.08)
Difference in immediate change[h] in level for the month of the 2009 SNAP increase	6.00 (−6.19 to 18.19)	3.35 (−8.12 to 14.82)	−2.10[e] (−3.33 to −0.87)
Difference in change in slope[d,h] after SNAP increase	0.26 (−0.20 to 0.71)	0.06 (−0.35 to 0.48)	−0.13[g] (−0.18 to −0.07)
Difference in immediate change in level for the month of the 2013 SNAP decrease	8.71 (−2.14 to 19.56)	9.68[f] (0.68 to 18.68)	0.41 (−1.38 to 2.19)
Difference in change in slope[d,h] after SNAP decrease	1.00 (−0.20 to 2.20)	0.45 (−0.45 to 1.34)	−0.24[f] (−0.45 to −0.03)
Covariates			
Percentage of female admissions	1.36 (−1.77 to 4.49)	0.28 (−2.69 to 3.26)	−0.91[e] (−1.29 to −0.53)
Percentage of non-Hispanic white admissions	0.11 (−1.23 to 1.46)	−0.04 (−1.29 to 1.21)	−0.10 (−0.27 to 0.07)
Percentage of lowest income quartile admissions[i]	2.81[f] (0.50 to 5.11)	2.57[f] (0.42 to 4.71)	−0.10 (−0.35 to 0.15)
Average age, y	−2.80 (−8.20 to 2.60)	−1.61 (−6.46 to 3.25)	0.84[f] (0.14 to 1.53)

Abbreviations: CI, confidence interval; SNAP, Supplemental Nutrition Assistance Program.

[a] Multigroup interrupted time series models using Newey-West standard errors (constant and term comparing initial intercept between groups omitted).

[b] Dependent variable scaled by dividing by the value in January 2006, subtracting 1, and multiplying by 100 (this produces coefficients that can be read as percentage points of the January 2006 value).

[c] Monthly expenditures adjusted for inflation.

[d] Slope can be interpreted as the changes in percentage points per month (for example, a coefficient of 2 on a slope term would indicate a change in 2 percentage points per month; this would mean that after 3 months the value would have increased by 6% of the January, 2006 value).

[e] $P < .01$.

[f] $P < .05$.

[g] $P < .001$.

[h] All "difference in change" terms should be interpreted as difference-in-differences terms (for example, a difference in change in slope indicates how the change in the slope for the group with a high likelihood of disability differed from the change in slope for the group with no likelihood of disability).

[i] This was equivalent to annual income less than $36,000 to $39,000, depending on the year.

Appendix

The single-group and multigroup interrupted times series models used in this study were as follows:

Single-group

$$\text{Admissions}_t = \beta_0 + \beta_1 \times (\text{Months})_t + \beta_2 \times (\text{Post\_April\_2009})_t + \beta_3 \times (\text{Months\_Post\_April\_2009})_t$$

$$+ \beta_4 \times (\text{Post\_November\_2013})_t + \beta_5 \times (\text{Months\_Post\_November\_2013})_t + \beta_{6\text{–}9} \times (\text{Covariates})$$

$$+ e_t$$

Multigroup

$$\text{Admissions}_t = \beta_0 + \beta_1 \times (\text{Months})_t + \beta_2 \times (\text{Post\_April\_2009})_t + \beta_3 \times (\text{Months\_Post\_April\_2009})_t$$

$$+ \beta_4 \times (\text{Post\_November\_2013})_t + \beta_5 \times (\text{Months\_Post\_November\_2013})_t + \beta_6 \times (\text{Disability})$$

$$+ \beta_7 \times (\text{Months}) \times (\text{Disability})_t + \beta_8 \times (\text{Post\_April\_2009}) \times (\text{Disability})_t$$

$$+ \beta_9 \times (\text{Months\_Post\_April\_2009}) \times (\text{Disability})_t + \beta_{10} \times (\text{Post\_November\_2013}) \times (\text{Disability})_t$$

$$+ \beta_{11} \times (\text{Months\_Post\_November\_2013}) \times (\text{Disability})_t + \beta_{12\text{–}15} \times (\text{Covariates}) + e_t$$

The coefficients of interest for testing the research hypotheses described in the text were β_2 through β_5 in the single-group models and β_7 through β_{11} in the multigroup models.

The dependent variable listed in the models is admissions, but the same model formulations were used for expenditures and average length of stay. Also, the comparison group listed is disability, but the same model formulations were used for the Medicaid-Medicare comparisons.

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ORIGINAL RESEARCH

Racial/Ethnic Differences in Influenza and Pneumococcal Vaccination Rates Among Older Adults in New York City and Los Angeles and Orange Counties

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PEER REVIEWED

Abstract

Introduction

Disparities in vaccination rates exist among racial/ethnic minority adults. This study examined factors associated with influenza (flu) and pneumococcal vaccination rates among non-Hispanic black, Hispanic, and Asian American adults aged 50 or older living in New York City or Los Angeles and Orange counties in California.

Methods

We used data collected by the REACH US Risk Factor Survey 2009–2012 in New York City and California. We analyzed data on 14,139 adults aged 50 or older who were categorized as non-Hispanic black (New York City [n = 1,715], California [n = 530]), Hispanic (New York City [n = 2,667], California [n = 1,099]), Chinese American (New York City [n = 1,656]), Korean American (New York City [n = 310]), Filipino American (California [n = 1,515]), or Vietnamese American (California [n = 3,435]). Bivariate analyses examined difference across race/ethnicity and location, and multivariable logistic regression models, adjusting for sociodemographic and health variables, examined flu and pneumococcal vaccination rates.

Results

Among adults aged 50 or older, the flu vaccination rate was lower among non-Hispanic black respondents (New York City, 53.3%; California, 40.5%) than among Hispanic (New York City, 61.0%; California, 49.4%), Chinese (New York City, 67.6%), Korean (New York City, 60.5%), Filipino (California, 66.2%), and Vietnamese (California, 68.0%) respondents. Among adults aged 65 or older, pneumococcal vaccination rates were lowest among Chinese and Korean respondents in New York City (51.7% and 49.1%, respectively), compared with non-Hispanic black (New York City, 62.0%, California, 65.6%), Hispanic (New York City, 60.0%; California 62.7%), Filipino (California, 63.4%), and Vietnamese (California, 63.8%) respondents. Older age, having had a checkup in the past year, and diabetes diagnosis were significantly associated with flu and pneumococcal vaccination in both locations. Additional variables were significant for some vaccinations and locations.

Conclusion

When compared with Asian American respondents, non-Hispanic black respondents were least likely to receive the flu vaccine in New York City and California. We found no racial/ethnic differences in pneumococcal vaccination rates. Our findings highlight the need for targeted efforts to increase vaccination rates among racial/ethnic minority older adults.

Introduction

Influenza (flu) and pneumococcal vaccinations offer important protection against flu complications and pneumococcal diseases, which can become life threatening in vulnerable populations such as children, persons with chronic conditions, and older adults. The Centers for Disease Control and Prevention (CDC) recommends that everyone aged 6 months or older receive a flu vaccination every season (1). CDC also recommends that everyone aged 65 or older receive both conjugate and polysaccharide pneumococcal vaccines (2). Healthy People 2020 goals include increasing the percentage of noninstitutionalized adults aged 65 or older receiving the seasonal flu vaccine and pneumococcal vaccine to 90.0% (3).

Overall vaccination rates among adults aged 65 or older were below the goal of 90%, according the 2014 National Health Interview Survey, and national and state studies demonstrate differences in vaccination rates by race/ethnicity. For instance, according to various surveys in recent years, non-Hispanic white adults had the highest rates of annual flu vaccination nationally (range, 68.0%–75.1%), compared with non-Hispanic black (range, 53.0%–64.3%), Hispanic (range, 57.5%–64.1%), and Asian American (range 65.2%–83.5%) adults (4–7). Similarly, rates of ever receiving a pneumococcal vaccination were higher among non-Hispanic white adults (range, 61.1%–71.1%) than among non-Hispanic black (range, 38.9%–57.7%), Hispanic (range, 32.0%–51.9%), and Asian American adults (range, 41.3%–49.0%) (4,5,7–9). State data demonstrate additional disparities. Flu vaccination rates in California among adults aged 65 or older were highest among Asian American adults (range, 64.9%–80.1%), followed by Hispanic (range, 52.6%–67.5%), non-Hispanic white (59.1%), and non-Hispanic black (range, 46.2%–59.5%) adults; whereas rates of ever receiving a pneumococcal vaccination among adults aged 65 or older were highest among non-Hispanic white adults (range, 67.0%–77.8%), followed by Asian American (range, 56.0%–73.0%), non-Hispanic black (range, 61.8%–68.3%), Hispanic (range, 48.2%–58.3%), and Vietnamese American adults (41.0%) (10–12). Among adults aged 50 or older, Vietnamese Americans had higher annual flu vaccination rates (60.6%) than non-Hispanic white (51.7%) and Asian American adults (45.3%) (11). Flu vaccination rates in New York State among adults aged 65 or older were highest among Asian Americans (range, 62.1%–83.4%), followed by non-Hispanic white (60.5%), Hispanic (range, 58.3%–67.6%), and non-Hispanic black adults (range, 52.1%–63.2%), whereas rates of ever receiving a pneumococcal vaccination among adults aged 65 or older were highest among non-Hispanic white (72.9%), followed by Hispanic (59.9%–66.1%), Asian American (52.4%–57.0%), and non-Hispanic black (52.7%–53.2%) adults (10–12).

These studies consistently showed that racial/ethnic minority groups have lower vaccination rates than non-Hispanic white adults. In the aggregate, Asian Americans are often found to have vaccination rates similar to rates among non-Hispanic white adults. This aligns with the “model minority” stereotype that pos- its Asian Americans are doing well socioeconomically and are adhering to healthy behaviors compared with other racial/ethnic groups (7,9,13). Aggregated data on Asian American health, however, mask large and significant differences that exist across Asian subgroups (14,15). Asian Americans comprise more than 50 ethnicities, each of which has unique health behaviors, cultural values, and varying degrees of access to health care resources (15–17). The limited data available on vaccination rates among older Asian Americans indicate that pneumococcal vaccination differs by subgroup: Japanese Americans (59.8%), Asian Indian Americans (26.2%), Korean Americans (24.7%), and Filipino Americans (22.9%) (9). Although flu vaccination rates have not been published for Asian American subgroups aged 65 or over, variation exists among adult Asian American subgroups overall. Annual flu vaccination rates among Asian American adults aged 18 or older are the following: Japanese Americans (range, 30.7%–44.1%), Chinese Americans (range, 26.5%–36.6%), Filipino Americans (range, 26.1%–35.9%), Korean Americans (range, 23.4%–48.9%), and Vietnamese Americans (range, 28.7%–46.7%).

To identify factors associated with persistent disparities in vaccination rates among racial/ethnic minority adults aged 50 or older, we compared flu and pneumococcal vaccination rates among older non-Hispanic black, Hispanic, and Asian American populations living in New York City and 2 counties in California, Los Angeles County and Orange County.

Methods

Racial and Ethnic Approaches to Community Health (REACH) is a national program administered by CDC, beginning in 2007, to mobilize local communities to implement community-based strategies for the elimination of health disparities in racial/ethnic minority populations. The REACH US Risk Factor Survey was conducted annually from 2009 to 2012 to evaluate program activities in 28 REACH communities (12). New York City and Los Angeles and Orange counties in California had large numbers of Asian American, non-Hispanic black, and Hispanic adults; therefore, we studied these locations. The NYU School of Medicine institutional review board policy indicated this research did not involve human participants and that institutional review board review was not required.

The survey used an address-based sampling design with geographical information systems technology to target US Census tracts with large numbers of Asian American, Hispanic, and non- Hispanic black adults. Questions were derived from the Behavioral Risk Factor Surveillance System (18). Data on 14,139 adults aged 50 or older were categorized as non-Hispanic black (New York City = 1,715, Los Angeles and Orange counties = 530), Hispanic (New York City = 2,667, Los Angeles and Orange counties = 1,099), Chinese American (New York City = 1,656), Korean

American (New York City = 310), Filipino American (Los Angeles and Orange counties = 1,515), or Vietnamese American (Los Angeles and Orange counties = 3,435). Details on methods are available elsewhere (12,19,20).

We selected adults aged 50 or older to examine rates of flu vaccination (to increase our sample size and power) and adults aged 65 or older to examine rates of pneumococcal vaccination. We excluded Asian American subgroups with fewer than 100 respondents among adults aged 65 or older.

Outcomes of interest included a flu vaccination in the past 12 months and a lifetime pneumonia vaccination. We used responses to the following 2 questions: "During the past 12 months, have you had a flu shot?" and "Have you ever had a pneumonia shot?"

Independent variables were age group (50–64 or ≥65); sex (male or female); nativity (US born or non-US born), education (<high school diploma, high school diploma/some college, or college graduate); self-reported health (good, fair/poor, or excellent/very good); health insurance (yes or no); most recent checkup (within past year or more than a year/never/do not know); smoking status (current, former, or never); ever received a diagnosis of stroke, angina, or coronary heart disease (yes, no/do not know); needed a physician but was too costly (yes or no); and ever received a diagnosis of diabetes (yes or no). We chose these variables on the basis of literature that identified associations between sociodemographic and health-related factors and vaccination outcomes (4,5,11,21).

Data analysis

We performed descriptive analyses for all independent variables stratified by location and racial/ethnic minority group. We performed bivariate analyses; we ran χ^2 tests (categorical variables) and independent samples *t* tests (continuous variables) to evaluate significant differences of sociodemographic and health-related variables affecting vaccination outcomes among non-Hispanic black respondents, Hispanic respondents, and Asian American subgroups, and to inform variables to be used in the models. Finally, we analyzed racial/ethnic and geographic differences in vaccination receipt by using multivariable logistic regression; we tabulated odds ratios (ORs) and 95% confidence intervals (CIs). Model 1 accounted for sociodemographic factors, and Model 2 (the full model) accounted for sociodemographic and health-related factors. We performed all data analyses by using SAS-callable SUDAAN version 11.0.2 (RTI International), and we used an α level of <.05. Because our study was secondary data analysis of cross-sectional data, we did not conduct a power analysis to determine sample size.

Results

The rate of receiving a flu vaccination among non-Hispanic black respondents was 53.3% in New York City and 40.5% in Los Angeles and Orange counties; among Hispanic respondents, 61.0% in New York City and 49.4% in Los Angeles and Orange counties; among Chinese American respondents in New York City, 67.6%; among Korean American respondents in New York City, 60.5%; among Filipino American respondents in Los Angeles and Orange counties, 66.2%; and among Vietnamese American respondents in Los Angeles and Orange counties, 68.0% (Table 1). The rate of receiving a pneumococcal vaccina- tion among non-Hispanic black respondents was 62.0% in New York City and 65.6% in Los Angeles and Orange counties; among Hispanic respondents, 60.0% in New York City and 62.7% in Los Angeles and Orange counties; among Chinese American respond- ents in New York City, 51.7%; among Korean American respond- ents in New York City, 49.1%; among Filipino American respond- ents in Los Angeles and Orange counties, 63.4%; and among Viet- namese American respondents in Los Angeles and Orange counties, 63.8%.

Most non-Hispanic black respondents were born in the United States, whereas most Hispanic respondents and Asian American respondents were non-US born. Rates of health insurance were lowest among Hispanic respondents in Los Angeles and Orange counties (71.7%) and Korean American respondents in New York City (76.8%); rates of having a checkup within the past year were lowest among these same 2 groups and not being able to see a physician because it was too costly were highest. Non-Hispanic black respondents, Hispanic respondents, and Korean American respondents in New York City were most likely to be current smokers, whereas Filipino American respondents in Los Angeles and Orange counties were least likely to be current smokers.

Flu vaccination in New York City

In Model 1 of multivariable logistic regression predicting receipt of flu vaccination in the past year, Chinese American respondents were 1.7 times as likely ($P < .001$), Korean American respondents were 1.6 times as likely ($P = .045$), and Hispanic respondents were 1.3 times as likely ($P = .01$) as non-Hispanic black respondents to have received a flu vaccination (Table 2). Older age was significantly associated with receiving a flu vaccination (OR = 1.04, $P < .001$), whereas respondents with less than a high school diploma were 1.6 times as likely ($P < .001$) and those with a high school diploma or some college education were 1.2 times as likely ($P = .02$) as college graduates to have received a flu vaccination.

In Model 2, both Chinese American respondents (OR = 1.8, $P < .001$) and Korean American respondents (OR = 2.2, $P = .003$)

were more likely than non-Hispanic black respondents to have received a flu vaccination; Hispanic ethnicity was no longer significant. Older age and having less than a high school diploma remained significant. Additional factors associated with receiving a flu vaccination were having health insurance (OR = 1.8, $P < .001$), having had a checkup within the past year (OR = 2.5, $P < .001$), self-reporting health as good (OR = 1.2, $P = .02$) or fair/poor (OR = 1.4, $P = .02$), and self-reported diabetes (OR = 2.0, $P < .001$).

Flu vaccination in Los Angeles and Orange counties

In Model 1, Vietnamese American respondents were 5.5 times as likely ($P < .001$), Filipino American respondents were 4.2 times as likely ($P < .001$), and Hispanic respondents were 2.3 times as likely ($P < .001$) as non-Hispanic black respondents to have received a flu vaccination. Similar to New York City findings, older age was significantly associated with receiving a flu vaccination (OR = 1.08, $P < .001$). In addition, women were 1.2 times as likely as men to have received a flu vaccination ($P = .04$), and US-born respondents were 1.3 times as likely as non–US-born respondents to have received a flu vaccination ($P = .007$).

In Model 2, Vietnamese American respondents were 5.6 times as likely ($P < .001$), Filipino American respondents were 4.0 times as likely ($P < .001$), and Hispanic respondents were 2.5 times as likely ($P < .001$) as non-Hispanic black respondents to have received a flu vaccination. Older age and US nativity remained significant. Additional factors associated with receiving a flu vaccination were having health insurance (OR = 2.1, $P < .001$); having had a checkup within the past year (OR = 2.0, $P < .001$); self-reporting health as good (OR = 1.2, $P = .003$) or fair/poor (OR = 1.4, $P < .001$); a diagnosis of stroke, angina, or coronary heart disease (OR = 1.4, $P = .03$); and self-reported diabetes (OR = 1.6, $P < .001$).

Pneumococcal vaccination in New York City

Racial/ethnic minority group was not significantly associated with pneumococcal vaccination in either multivariable logistic regression predicting pneumococcal vaccination in lifetime (Table 3). In Model 1, only older age was associated with ever receiving the pneumococcal vaccination (OR = 1.01, $P = .02$).

In Model 2, age was no longer significant. Additional factors associated with having ever received a pneumococcal vaccination were being non-US born (OR = 1.3, $P = .046$), having had a checkup within the past year (OR = 1.7, $P < .001$), self-reporting health as fair/poor (OR = 1.4, $P = .009$), self-reported stroke, angina, or coronary heart disease (OR = 1.4, $P = .008$), and self-reported diabetes (OR = 1.6, $P < .001$).

Pneumococcal vaccination in Los Angeles and Orange counties

Racial/ethnic subgroup was not significantly associated with pneumococcal vaccination in either model. In Model 1, older age was significantly associated with having ever received a pneumococcal vaccination (OR = 1.04, $P < .001$). Respondents with less than a high school diploma were less likely than respondents who were college graduates to have ever received a pneumococcal vaccination (OR = 0.6, $P < .001$).

In Model 2, age and education remained significant. Additional factors associated with having ever received the pneumococcal vaccine were having health insurance (OR = 1.8, $P = .006$), having had a checkup within the past year (OR = 1.7, $P < .001$), self-reporting health as good (OR = 1.2, $P = .03$), and self-reported diabetes (OR = 1.2, $P = .02$).

Discussion

Our study results indicate that among non-Hispanic black, Hispanic, and Asian respondents to the REACH US Risk Factor Survey 2009–2012, non-Hispanic black respondents were the least likely to receive a flu vaccination in New York City and Los Angeles and Orange counties; however, we found no significant association between pneumococcal vaccination rate and race/ethnicity in New York City or Los Angeles and Orange counties. Our study also identified 4 variables that are significantly associated with positive outcomes for both flu and pneumococcal vaccination in both locations: older age (not significant in pneumococcal vaccine Model 2, New York City), having had a checkup in the past year, self-reported fair/poor health, and self-reported diabetes. All these indicators were associated with flu and pneumococcal vaccination in previous studies (4,5,11,21). One possible explanation for the association between self-reported diabetes and higher rates of flu and pneumococcal vaccination is that people with diabetes, who may have a weaker immune response to infections, are at higher risk of developing serious complications caused by flu and pneumonia infections (22). Primary care providers may recommend these vaccines to prevent further illness.

In addition to identifying shared variables that are associated with positive vaccination outcomes, our findings also distinguished variables that are uniquely associated with each vaccination type in each geographic location. For example, lower educational attainment was significantly associated with flu vaccine receipt in New York City, and lower educational attainment was inversely associated with pneumococcal vaccine receipt in Los Angeles and Orange counties. Additionally, US birthplace was significantly associated with a positive flu vaccination outcome in Los Angeles and Orange counties, whereas a non-US birthplace was significantly associated with pneumococcal vaccination outcome in New York City. Lastly, health insurance coverage was significantly associated with a positive flu and pneumococcal vaccination outcome in Los Angeles and Orange counties and with a positive flu vaccination outcome in New York City. Insurance, particularly private insurance, is associated with flu and pneumococcal vaccination (4,5,21).

Similar to previous studies that showed racial/ethnic disparities in flu and pneumococcal vaccination rates among non-Hispanic black adults, compared with non-Hispanic white adults (4,5,21,23), our study findings also showed racial/ethnic differences in flu vaccination rates. Non-Hispanic black adults had the lowest flu vaccination rate when compared with Hispanic adults and Asian American subgroups. Unlike previous studies, our findings did not indicate a significant association between race/ethnicity and pneumococcal vaccination. However, our study did not include non-Hispanic white adults, who may report higher vaccination rates. Additionally, we focused only on adults aged 50 or older, whereas previous studies described overall flu vaccination rates among all adults (aged ≥18) or adults aged 65 or older.

Similar to a previous study comparing vaccination rates among Vietnamese American, Asian American, and non-Hispanic white adults aged 18 or older in Santa Clara County, California (11), our study also identified older age, having had a recent checkup, and self-reported diabetes to be significantly associated with a positive vaccination outcome. Conversely, the association between self-reported fair/poor health and vaccination outcome is unique to our study findings for Asian Americans, although it was significant in a study of non-Hispanic black and non-Hispanic white Medicare beneficiaries (4).

Our study has several limitations. First, we excluded from analysis Asian American subgroups with a sample size of fewer than 100; because Asian American subgroups differed by location, we were unable to compare data from the same subgroups in both locations. Larger sample sizes for Asian American subgroups are needed in future research. Second, our study used self-reported data; therefore, our findings may be subject to recall bias. Finally, we were not able to assess differences in vaccination rates among unique subgroups of non-Hispanic black and Hispanic respondents. Future research should expand options on surveys, allowing respondents to pinpoint their race/ethnicity, so that disparities can be further investigated across subgroups.

The strengths of this study include the comparison of multiple racial/ethnic groups, the disaggregation of data on Asian Americans, and the comparison of vaccination rates between 2 locations. Although previous studies established that disparities in vaccination rates exist between non-Hispanic white adults and non-Hispanic black adults, and between non-Hispanic white adults and Asian American adults, no previous studies compared non-Hispanic black adults with Asian American adults, Hispanic adults with Asian American adults, and most importantly, various Asian American subgroups. Our study disaggregated Asian American respondents into 4 subgroups, allowing for comparison across subgroups, as well as with Hispanic and non-Hispanic black respondents. Additionally, our data compared vaccination rates between New York City and Los Angeles and Orange counties, which may provide insights to differences and similarities in vaccination barriers.

Our study identified 4 variables that are strongly associated with positive vaccination outcomes; these factors may help guide implementation of health interventions to effectively reach target populations and communities. Treatment teams may consider age, most recent checkup, self-reported health, and diabetes diagnosis when developing primary interventions to maximize protection against vaccine-preventable diseases. CDC suggests increasing coverage by expanding access through nontraditional settings such as pharmacies and by improving the use of evidence-based practices such as reminder/recall notifications (24). These recommendations can also be modified to accommodate the needs of racial/ethnic minority older adults. For example, if these adults are unable to visit a traditional clinical setting, then immunizations can be offered at local community centers or through a home visit by a health care provider. Reminder/recall notifications are methods to identify and notify patients that immunizations are due or behind (25). Reminder messages can be recorded in multiple languages and designed to educate recipients on the importance of immunization regardless of health status. Finally, involving family members and caregivers who may have more advanced skills in the use of technological devices may help expand reminder/recall benefits among older adults.

Our study findings demonstrate that vaccination rates among older racial/ethnic populations living in New York City and Los Angeles and Orange counties are suboptimal and that disparities exist among these groups. More granular data on racial/ethnic subgroups are needed. Routine monitoring and reporting of disaggregated vaccine coverage by race, ethnicity, and sociodemographic factors are needed to identify cultural barriers that are unique to each race/ethnicity and factors associated with vaccination outcomes that may not be measureable when coverage data are aggregated (5).

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Tables

Table 1. Sociodemographic and Health Characteristics of Sample in Study on Racial/Ethnic Differences in Influenza (Flu) and Pneumococcal Vaccination Rates Among Adults Aged ≥50, by Location and Race/Ethnicity, 2009–2012[a]

Characteristic	% (95% Confidence Interval)							
	Non-Hispanic Black		Hispanic		Chinese American	Korean American	Filipino American	Vietnamese American
	New York City (n = 1,715)	Los Angeles and Orange Counties (n = 530)	New York City (n = 2,667)	Los Angeles and Orange Counties (n = 1,099)	New York City (n = 1,656)	New York City (n = 310)	Los Angeles and Orange Counties (n = 1,515)	Los Angeles and Orange Counties (n = 3,435)
Flu vaccine (aged ≥50)	53.3 (49.5–57.1)	40.5 (36.8–44.4)	61.0 (59.0–62.9)	49.4 (42.1–56.7)	67.6 (64.1–70.9)	60.5 (52.7–67.9)	66.2 (62.4–69.8)	68.0 (66.5–69.4)
Pneumococcal vaccine (aged ≥65)	62.0 (56.4–67.3)	65.6 (62.9–68.2)	60.0 (57.9–62.0)	62.7 (53.7–70.8)	51.7 (46.3–57.1)	49.1 (35.0–63.2)	63.4 (60.5–66.2)	63.8 (61.0–66.4)
Age group								
50–64	64.8 (61.3–68.1)	60.7 (53.3–67.7)	63.6 (55.4–71.2)	72.0 (66.2–77.1)	60.1 (57.2–63.0)	69.6 (65.6–73.3)	59.0 (54.2–63.5)	67.3 (64.7–69.7)
≥65	35.2 (31.9–38.7)	39.3 (32.3–46.7)	36.4 (28..8–44.7)	28.0 (22.9–33.8)	39.9 (37.0–42.8)	30.4 (26.8–34.4)	41.0 (36.5–45.8)	32.7 (30.3–35.3)
Sex								
Male	43.8 (39.2–48.5)	43.1 (36.9–49.6)	46.2 (40.0–52.5)	48.9 (45.7–52.1)	46.1 (42.8–49.4)	50.6 (48.7–52.5)	42.1 (40.2–44.2)	51.4 (48.5–54.2)
Female	56.2 (51.5–60.8)	56.9 (50.5–63.1)	53.8 (47.5–60.0)	51.1 (47.9–54.3)	53.9 (50.6–57.3)	49.4 (47.5–51.4)	57.9 (55.9–59.8)	48.6 (45.8–51.5)
Nativity								
Born in the United States	77.9 (69.7–84.4)	92.6 (86.6–96.0)	33.8 (27.8–40.3)	27.3 (23.4–31.6)	3.6 (2.6–4.9)	1.0 (0.3–2.8)	4.8 (3.7–6.1)	0.5 (0.3–0.7)
Education								
<High school diploma	24.0 (22.0–26.2)	6.3 (5.2–7.5)	49.9 (48.3–51.4)	49.8 (43.4–56.2)	50.9 (47.2–54.6)	12.6 (9.0–17.2)	3.6 (2.8–4.6)	25.3 (22.8–28.0)
High school diploma/some college	58.5 (56.1–60.9)	63.0 (57.2–68.5)	40.7 (38.8–42.5)	38.3 (33.8–43.0)	32.3 (30.6–34.0)	50.4 (44.8–56.0)	28.0 (26.3–29.9)	48.3 (45.9–50.7)
College graduate	17.5 (15.4–19.7)	30.7 (24.5–37.8)	9.5 (8.1–11.2)	11.9 (9.8–14.4)	16.8 (14.4–19.6)	37.0 (28.9–46.0)	68.3 (65.7–70.8)	26.4 (24.1–29.0)
Self-reported health								
Excellent/very good	27.1 (24.8–29.5)	36.0 (33.0–39.1)	16.9 (14.7–19.3)	23.6 (19.5–28.3)	17.8 (15.7–20.2)	32.2 (23.0–43.1)	32.1 (30.8–33.4)	21.7 (19.7–23.8)
Good	36.7 (34.4–39.2)	38.8 (35.0–42.6)	30.0 (28.0–32.1)	33.0 (27.8–38.6)	30.5 (24.3–37.4)	41.4 (33.3–50.0)	43.7 (42.9–44.5)	35.9 (33.8–38.0)
Fair/poor	36.2 (33.8–38.6)	25.3 (23.6–27.0)	53.1 (49.6–56.6)	43.4 (34.6–52.8)	51.7 (44.7–58.7)	26.4 (24.6–28.2)	24.3 (22.9–25.7)	42.5 (39.1–45.9)
Health insurance								
Yes	88.0 (86.5–89.3)	87.6 (84.1–90.4)	88.7 (87.2–90.1)	71.7 (67.3–75.8)	89.9 (87.4–91.9)	76.8 (74.7–78.8)	90.9 (89.6–92.0)	85.7 (83.9–87.2)
No	12.0 (10.7–13.5)	12.4 (9.6–15.9)	11.3 (9.9–12.8)	28.3 (24.2–32.7)	10.1 (8.1–12.6)	23.2 (21.2–25.3)	9.1 (8.0–10.4)	14.3 (12.8–16.1)
Most recent checkup								

[a] The REACH US Risk Factor Survey was conducted annually from 2009 to 2012 to evaluate program activities in 28 communities (12).

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(continued)

Table 1. Sociodemographic and Health Characteristics of Sample in Study on Racial/Ethnic Differences in Influenza (Flu) and Pneumococcal Vaccination Rates Among Adults Aged ≥50, by Location and Race/Ethnicity, 2009–2012[a]

	% (95% Confidence Interval)							
	Non-Hispanic Black		Hispanic		Chinese American	Korean American	Filipino American	Vietnamese American
Characteristic	New York City (n = 1,715)	Los Angeles and Orange Counties (n = 530)	New York City (n = 2,667)	Los Angeles and Orange Counties (n = 1,099)	New York City (n = 1,656)	New York City (n = 310)	Los Angeles and Orange Counties (n = 1,515)	Los Angeles and Orange Counties (n = 3,435)
Within the past year	83.9 (80.7–86.7)	79.4 (69.9–86.4)	83.7 (82.5–84.9)	71.2 (67.2–74.4)	84.3 (82.5–85.9)	65.6 (63.2–68.0)	80.8 (79.9–82.5)	77.9 (75.7–79.9)
More than a year/never/do not know	16.1 (13.3–19.3)	20.6 (13.6–30.1)	16.3 (15.1–17.5)	28.8 (25.6–32.3)	15.7 (14.1–17.5)	34.4 (32.0–36.9)	19.2 (17.5–21.1)	22.1 (20.2–24.3)
Smoking status								
Current	21.3 (19.4–23.3)	15.6 (12.7–18.8)	17.8 (16.0–19.8)	10.1 (8.6–11.9)	9.0 (7.4–10.8)	15.2 (12.1–19.0)	7.4 (5.5–9.3)	10.6 (9.6–11.6)
Former	30.6 (28.4–32.9)	33.5 (28.1–39.4)	26.7 (24.1–29.5)	26.1 (22.8–29.7)	15.5 (13.3–18.0)	25.9 (22.3–30.0)	19.9 (18.3–21.5)	18.5 (16.3–21.1)
Never	48.1 (45.0–51.3)	50.9 (47.1–54.7)	55.5 (53.0–58.0)	63.8 (59.1–68.2)	75.6 (73.1–77.9)	58.9 (58.3–59.5)	72.8 (70.3–75.1)	70.9 (67.6–74.0)
Ever received diagnosis of stroke, angina, or coronary heart disease								
Yes	15.7 (14.2–17.4)	14.6 (12.1–17.6)	18.2 (16.3–20.3)	11.4 (9.8–13.2)	11.6 (10.3–13.0)	10.8 (9.6–12.1)	11.6 (10.2–13.1)	10.6 (9.6–11.7)
No/do not know	84.3 (82.6–85.8)	85.4 (82.4–87.9)	81.8 (79.7–83.7)	88.6 (86.8–90.2)	88.4 (87.0–89.7)	89.2 (87.9–90.4)	88.4 (86.9–89.8)	89.4 (88.3–90.4)
Needed a physician but was too costly								
Yes	15.4 (12.8–18.3)	15.5 (13.6–17.5)	16.5 (15.0–18.0)	25.7 (21.4–30.7)	11.5 (10.8–12.2)	30.7 (26.7–35.0)	13.6 (11.9–15.5)	15.8 (14.3–17.5)
No	84.6 (81.7–87.2)	84.5 (82.5–86.4)	83.5 (82.0–85.0)	74.3 (69.4–78.6)	88.5 (87.8–89.2)	69.3 (65.0–73.4)	86.4 (84.5–88.1)	84.2 (82.5–85.7)
Ever received a diabetes diagnosis								
Yes	27.3 (25.1–29.7)	23.5 (21.6–25.4)	30.9 (27.8–34.3)	24.2 (21.7–26.9)	18.7 (16.9–20.6)	21.4 (18.1–25.0)	29.6 (28.3–31.0)	17.5 (16.7–18.3)
No	72.7 (70.3–74.9)	76.5 (74.6–78.4)	69.1 (65.7–72.2)	75.8 (73.1–78.3)	81.3 (79.4–83.1)	78.6 (75.0–81.9)	70.4 (69.0–71.7)	82.6 (81.7–83.3)

[a] The REACH US Risk Factor Survey was conducted annually from 2009 to 2012 to evaluate program activities in 28 communities (12).

Table 2. Multivariable Logistic Regression Predicting Receipt of Influenza Vaccination Within Previous Year Among Samples of Adults Aged ≥50 in New York City and Los Angeles and Orange Counties, 2009–2012[a]

	New York City		Los Angeles and Orange Counties	
	Model 1[b]	Model 2[c]	Model 1[b]	Model 2[c]
Characteristic	OR (95% CI) [*P* Value]	OR (95% CI) [*P* Value]	OR (95% CI) [*P* Value]	OR (95% CI) [*P* Value]
Race/ethnicity				
Hispanic	1.3 (1.1–1.6) [.01]	1.2 (1.0–1.5) [.06]	2.3 (1.9–2.8) [<.001]	2.5 (1.9–3.4) [<.001]
Chinese	1.7 (1.3–2.2) [<.001]	1.8 (1.3–2.5) [<.001]	—[d]	—[d]
Korean	1.6 (1.0–2.5) [.045]	2.2 (1.4–3.7) [.003]	—[d]	—[d]
Filipino	—[d]	—[d]	4.2 (2.9–6.0) [<.001]	4.0 (2.5–6.5) [<.001]
Vietnamese	—[d]	—[d]	5.5 (4.0–7.6) [<.001]	5.6 (3.6–8.8) [<.001]
Non-Hispanic Black	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
Age, continuous	1.04 (1.03–1.05) [<.001]	1.03 (1.02–1.04) [<.001]	1.08 (1.07–1.09) [<.001]	1.06 (1.05–1.07) [<.001]
Sex				
Female	1.1 (1.0–1.2) [.29]	0.9 (0.8–1.0) [.11]	1.2 (1.0–1.4) [.04]	1.2 (1.0–1.4) [.053]
Male	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
Nativity				
US born	1.0 (0.9–1.2) [.71]	1.0 (0.9–1.2) [.87]	1.3 (1.1–1.6) [.007]	1.2 (1.1–1.5) [.01]
Non-US born	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
Education				
<High school	1.6 (1.3–1.9) [<.001]	1.4 (1.2–1.7) [.001]	0.9 (0.7–1.1) [.42]	0.9 (0.8–1.1) [.45]
High school/some college	1.2 (1.0–1.4) [.02]	1.1 (0.9–1.4) [.20]	1.0 (0.9–1.2) [.82]	1.0 (0.9–1.2) [.75]
College graduate	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
Insurance coverage				
Yes	—[e]	1.8 (1.4–2.2) [<.001]	—[e]	2.1 (1.9–2.4) [<.001]
No		1 [Reference]		1 [Reference]
Most recent checkup				
Within the past year	—[e]	2.5 (2.1–2.9) [<.001]	—[e]	2.0 (1.8–2.3) [<.001]
More than a year/never/don't know		1 [Reference]		1 [Reference]
Self-reported health				
Good	—[e]	1.2 (1.0–1.3) [.02]	—[e]	1.2 (1.1–1.4) [.003]
Fair/poor		1.4 (1.1–1.7) [.02]		1.4 (1.3–1.6) [<.001]
Excellent/very good		1 [Reference]		1 [Reference]
Ever received diagnosis of stroke, angina, or coronary heart disease				
Yes	—[e]	1.2 (1.0–1.5) [.054]	—[e]	1.4 (1.0–1.9) [.03]
No/don't know		1 [Reference]		1 [Reference]
Ever received a diabetes diagnosis				
Yes	—[e]	2.0 (1.8–2.3) [<.001]	—[e]	1.6 (1.4–1.8) [<.001]
No		1 [Reference]		1 [Reference]

[a] The REACH US Risk Factor Survey was conducted annually from 2009 to 2012 to evaluate program activities in 28 communities (12).
[b] Model 1 accounted for sociodemographic variables.
[c] Model 2 (the full model) accounted for sociodemographic and health-related variables.
[d] Asian subgroups with <100 respondents were not included in analysis.
[e] Model 1 did not account for health-related variables.

Table 3. Multivariable Logistic Regression Predicting Receipt of Pneumococcal Vaccination In Lifetime Among Samples of Adults Aged ≥65 in New York City and Los Angeles and Orange Counties, 2009–2012[a]

	New York City		Los Angeles and Orange Counties	
	Model 1[b]	Model 2[b]	Model 1[b]	Model 2[c]
Characteristic	OR (95% CI) [*P* Value]	OR (95% CI) [*P* Value]	OR (95% CI) [*P* Value]	OR (95% CI) [*P* Value]
Race/ethnicity				
Hispanic	1.1 (0.8–1.3) [.67]	1.0 (0.8–1.4) [.88]	1.2 (0.8–1.9) [.40]	1.3 (0.8–2.1) [.37]
Chinese	0.7 (0.5–1.0) [.08]	0.7 (0.5–1.1) [.11]	—[d]	—[d]
Korean	0.8 (0.5–1.4) [.39]	0.8 (0.4–1.5) [.45]	—[d]	—[d]
Filipino	—[d]	—[d]	1.1 (0.8–1.5) [.67]	1.1 (0.7–1.7) [.62]
Vietnamese	—[d]	—[d]	1.2 (0.9–1.6) [.19]	1.2 (0.8–1.9) [.30]
Non-Hispanic Black	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
Age (continuous)	1.01 (1.00–1.03) [.02]	1.01 (1.00–1.03) [.09]	1.04 (1.02–1.07) [<.001]	1.04 (1.02–1.07) [<.001]
Sex				
Female	1.1 (1.0–1.3) [.11]	1.1 (0.9–1.3) [.38]	1.1 (1.0–1.2) [.06]	1.1 (1.0–1.2) [.20]
Male	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
Nativity				
Non-US born	1.2 (1.0–1.5) [.05]	1.3 (1.0–1.6) [.046]	1.1 (0.8–1.4) [.66]	1.1 (0.7–1.6) [.81]
US born	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
Education				
< High school	0.9 (0.8–1.2) [.50]	0.9 (0.7–1.1) [.22]	0.6 (0.5–0.7) [<.001]	0.6 (0.4–0.7) [<.001]
High school/Some college	0.9 (0.7–1.2) [.60]	0.9 (0.7–1.2) [.39]	0.9 (0.8–1.1) [.22]	0.9 (0.8–1.1) [.24]
College graduate	1 [Reference]	1 [Reference]	1 [Reference]	1 [Reference]
Health care coverage				
Yes	—[e]	1.5 (0.9–2.3) [.08]	—[e]	1.8 (1.2–2.8) [.006]
No		1 [Reference]		1 [Reference]
Most recent checkup				
Within the past year	—[e]	1.7 (1.3–2.1) [<.001]	—[e]	1.7 (1.4–2.1) [<.001]
More than a year/never/don’t know		1 [Reference]		1 [Reference]
Self-reported health				
Good	—[e]	1.3 (0.9–1.9) [.12]	—[e]	1.2 (1.0–1.4) [.03]
Fair/poor		1.4 (1.1–1.8) [.009]		1.2 (0.9–1.5) [.21]
Excellent/very good		1 [Reference]		1 [Reference]
Ever received diagnosis of stroke, angina, or coronary heart disease				
Yes	—[e]	1.4 (1.1–1.8) [.008]	—[e]	1.0 (0.7–1.5) [.86]
No/don’t know		1 [Reference]		1 [Reference]
Ever received a diabetes diagnosis				
Yes	—[e]	1.6 (1.4–1.8) [<.001]	—[e]	1.2 (1.0–1.5) [.02]
No		1 [Reference]		1 [Reference]

[a] The REACH US Risk Factor Survey was conducted annually from 2009 to 2012 to evaluate program activities in 28 communities (12).

[b] Model 1 accounted for sociodemographic variables.

[c] Model 2 (the full model) accounted for sociodemographic and health-related variables.

[d] Asian subgroups with <100 respondents were not included in analysis.

[e] Model 1 did not account for health-related variables.

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ORIGINAL RESEARCH

Disparities in Diabetes Prevalence Among Native Hawaiians/Other Pacific Islanders and Asians in Hawaiʻi

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PEER REVIEWED

Summary

What is already known about this topic?

The prevalence of diabetes varies significantly among racial/ethnic groups in Hawaiʻi. However, how prevalence varies by age for Asian subgroups and Native Hawaiian/Other Pacific Islanders (NHOPIs) is understudied.

What is added by this report?

We used the Hawaiʻi Behavioral Risk Factor Surveillance System to examine diabetes prevalence by age and race/ethnicity and assessed how socioeconomic status and lifestyle behaviors affected prevalence among Japanese, Filipino, Chinese, NHOPI, and white populations in Hawaiʻi.

What are the implications for public health practice?

NHOPIs and Filipinos have higher rates of diabetes compared with other races/ethnicities in Hawaiʻi. This study shows the importance of conducting age-specific analyses of racial/ethnic-subgroups for health disparities.

Abstract

Introduction

The prevalence of diabetes varies widely among racial/ethnic groups in Hawaiʻi. How prevalence varies by age for Asian subgroups and Native Hawaiian/Other Pacific Islanders (NHOPIs) is understudied. We examined diabetes prevalence by age and race/ethnicity and assessed how socioeconomic status and lifestyle behaviors affected prevalence among Japanese, Filipino, Chinese, NHOPI, and white populations in Hawaiʻi.

Methods

We studied 18,200 subjects aged 18 or older from the Hawaiʻi Behavioral Risk Factor Surveillance System. We performed Poisson regression analyses to examine the prevalence of diabetes by race/ethnicity, age, sex, marital status, education, income, health care coverage, obesity, smoking and drinking status, physical activity, and fruit and vegetable consumption and examined the interactions of these factors with age and race/ethnicity.

Results

We found disparities in diabetes prevalence among respondents aged 35 to 44 and among Asians and NHOPIs, and disparities increased with age. NHOPIs and Filipinos had the highest prevalence of diabetes after controlling for other demographic factors and lifestyle variables. Japanese adults were less likely than NHOPIs and Filipinos to have diabetes; however, whites had the lowest prevalence. Income, physical activity, and obesity were the strongest predictors of diabetes.

Conclusion

NHOPIs and Filipinos have higher rates of diabetes compared with other races/ethnicities in Hawaiʻi. More research is needed to reduce diabetes disparities among NHOPI and Filipino populations in Hawaiʻi. This study also shows the importance of conducting age-specific analyses of racial/ethnic-subgroups for health disparities.

Introduction

Diabetes has reached epidemic proportions in the United States (1). It affects approximately 30 million Americans (9.4%), 21.3 million diagnosed and another 7.2 million undiagnosed (2). Diabetes is more prevalent among racial/ethnic minority populations, especially those of indigenous origin, who have higher rates of complications and other disorders from diabetes than do nonminority populations (3,4). In the United States in 2017, 10.3% of the Asian population had diabetes compared with 7.3% of the white population (2).

Hawaiʻi is a multicultural state in which Asians, Native Hawaiians, and Other Pacific Islanders (NHOPIs) make up two-thirds of the population. In 2010, the state's population was 1,360,301, and the estimated racial/ethnic distribution was 21.3% Native Hawaiian, 2.7% Other Pacific Islander, 22.7% white, 16.3% Japanese, 17.2% Filipino, and 6.8% Chinese (5). Diabetes is most prevalent among racial/ethnic minority populations in Hawaiʻi. In 2014, an estimated 12.8% of Native Hawaiians, 10.0% of Chinese, 13.0% of Filipinos, 13.6% of Japanese, and 14.9% of Other Pacific Islanders were diagnosed with diabetes compared with 5.0% of white residents of the state (6). Previous research examined diabetes prevalence across Asian subpopulations; however, none examined interactions related to age or race/ethnicity (7–10). Such information is needed, because age distribution differs significantly across population groups, and diabetes risk increases with age. For example, although Native Hawaiians make up 21.3% of Hawaiʻi's population, they are only 10.9% of the population aged 60 or older. In contrast, Japanese make up 16.3% of the state's population but 37.6% of residents aged 60 or older (5).

Other reasons for diabetes-related disparities among NHOPI and Asian subgroups in Hawaiʻi are associated with biological, health care system, behavioral, socioeconomic, cultural, and environmental factors (8,10,11). For example, traditional NHOPI diets have shifted from locally sourced foods low in fat and high in fiber to processed foods that are high in fat, salt, calories, and sugar (11). NHOPIs have the lowest levels of educational attainment, lowest mean income, highest rates of poverty, and highest prevalence of being current, everyday smokers compared with white, Japanese, and Chinese adults in Hawaiʻi (12). NHOPIs also have more difficulty accessing Westernized health care services because of socioeconomic disparities, cultural preferences, and discrimination (13). Yet, no studies have examined diabetes prevalence across race/ethnicity by age and the extent to which lifestyle behaviors affect diabetes among those who reside in Hawaiʻi. Although eliminating diabetes disparities may not be possible (eg, because of genetic issues), such research may improve health disparities by enabling a better understanding of interactions related to age and race/ethnicity and the role of modifiable health behaviors.

By using 3 waves of population-representative data from the Hawaiʻi Behavioral Risk Factor Surveillance System (HBRFSS) (14), we aimed to 1) describe racial/ethnic differences in diabetes prevalence by age groups among NHOPI, white, and 3 Asian subgroups (Japanese, Chinese, and Filipino) and 2) assess the relationship between associated risk factors and the prevalence ratios of diabetes. We hypothesized that age, race/ethnicity, socioeconomic status, and risky health behaviors are strongly associated with diabetes.

Methods

Data source

The Behavioral Risk Factor Surveillance System (BRFSS), is an annual telephone survey and a collaborative project between US states and the Centers for Disease Control and Prevention. BRFSS collects data on health risk behaviors, chronic diseases, and access to health care. HBRFSS started in 1986 with results reported annually. Participants are noninstitutionalized residents of Hawaiʻi aged 18 or older. HBRFSS collects detailed racial/ethnic data, including a breakdown of Asian subgroups. Since 2011, participants are randomly selected from houses with listed and unlisted landline and cellular telephone numbers. HBRFSS uses the weighting methodology known as iterative proportional fitting or raking (15). Raking allows the introduction of more demographic variables into the statistical weighting process, and the resulting adjusted sample weights provide a closer match between the sample and the population. BRFSS provides valid national estimates, within-state estimates, and comparisons across states (16). This study was deemed exempt and approved by the University of Hawaiʻi Institutional Review Board.

Outcome variable — diabetes

To determine diabetes status, participants were asked if a doctor, nurse, or other health professional ever told them they had diabetes (yes/no). We described independent variables in 3 categories — demographics, obesity, and lifestyle factors.

Demographic variables were race/ethnicity, age, sex, marital status, education level, annual household income, and health care coverage. The Hawaiʻi Department of Health provides detailed information on categorizing race/ethnicity of HBRFSS respondents (17). Because of the limited number of respondents classified as Other Pacific Islander, we combined that population with those classified as Native Hawaiian into an NHOPI group. We focused on the 5 largest racial/ethnic groups in Hawaiʻi: 1) white, 2) NHOPI, 3) Filipino, 4) Japanese, and 5) Chinese. Participants were categorized into 7 age groups (18–24, 25–34, 35–44, 45–54, 55–64, 65–74, and ≥75 y). Sex was self-reported by the participant as male or female. Marital status was coded as married, divorced/separated, never married, or widowed. Educational attainment was based on the highest grade or year of school completed (eg, less than high school, high school/general equivalency diploma, 1–3 y of college, or ≥4 y of college). Health coverage was coded as yes (having any kind of health care coverage) or no. Income was based on the participant's annual household income from all sources (≤$14,999, $15,000–$24,999, $25,000–$49,999, $50,000–$74,999, ≥$75,000, or unknown). The category of "unknown" was kept in the model because of missing data for income.

Participants were asked questions about height and weight to calculate body mass index (weight in kg divided by height in m^2 [BMI]): About how much do you weigh without shoes?, About how tall are you without shoes?. Height and weight were used to estimate BMI, and participants whose BMI was greater than or equal to 30 kg/m^2 were categorized as obese (18).

Lifestyle variables were smoking status, heavy drinking status, physical activity per week, and daily fruit and vegetable consumption. Smoking status was coded as never, smoke some days, smoke every day, and former smoker (ie, participants who smoked at least 100 cigarettes in their entire life, but no longer smoke at all). Participants were asked to provide the number of days per week or per month during the past 30 days that they had at least one alcoholic beverage and the average number of alcohol drinks per day. We used only the "heavy drinking" variable, defined as more than 2 drinks per day for men or more than 1 drink per day for women (yes/no).

Participants reported the amount of time they spent per week participating in physical activities (eg, walking, gardening, running) outside of work. The physical activity variable was coded on the basis of US physical activity guidelines as nothing, less than guidelines (1–149 min/wk), meets guidelines (150–300 min/wk), and exceeds guidelines (>300 min/wk) (19). Participants were asked the number of times per day, week, or month they ate fruit (fresh, canned, frozen) and vegetables (dark green or orange-colored). Fruit and vegetable consumption variables were coded as none, 1 to 2 times per day, or 3 or more times per day.

Statistical analysis

HBRFSS reported physical activity and daily fruit and vegetable consumption only for odd years, therefore we used 2011, 2013, and 2015 data for our study. HBRFSS responses were 7,606 (44.8%) for 2011, 7,858 (40.2%) for 2013, and 7,163 (42.2%) for 2015 (14) for a total of 22,627. From these, we excluded those missing values for race/ethnicity (n = 1,966); diabetes (n = 36); age, sex, marital status, and health coverage (n = 261); smoking and drinking (n = 885); obesity (n = 469); and lifestyle variables (n = 810). The 3 years of survey data yielded a total sample size of 18,200. Sensitivity analysis was performed by including the missing values as separate "missing" categories, and results remained similar.

Sample characteristics by race/ethnicity were analyzed by accounting for complex survey weights and design strata. We conducted univariate analysis of the whole sample and bivariate analysis of frequency and weighted prevalence of diabetes by all independent variables. We performed weighted Poisson regression analyses of the crude model and 3 multivariate prevalence ratios (PRs) and the corresponding 95% confidence intervals (CIs). We estimated the PRs (direct estimate of the ratio between 2 groups) instead of odds ratios (ORs), because ORs tend to have a larger effect size when the outcome event is common (20–22).

We used 3 multivariate main effect models. Model 1 adjusted for demographic and socioeconomic variables, and model 2 added obesity and lifestyles. Because of potential interaction effects between age and other demographic variables (especially education and income), interactions effects were checked, and deviance testing showed a significant interaction effect for age and race/ethnicity ($P < .001$). Thus, Model 3 examined the age and race/ethnicity interaction effect while adjusting for all other variables. Statistical software R, version 3.4.1 (The R Foundation) and its libraries "survey," "effects," and "ggplot2" were used for the analyses. Significance was set at $P < .05$.

Results

NHOPIs had the highest weighted proportion of adults aged 18 to 34 but the lowest weighted proportion aged 75 or older (Table 1). They also had the lowest proportions of adults reporting a college education and an annual household income at or greater than $75,000. Japanese and Chinese participants had the lowest weighted proportions of adults aged 18 to 34 and the highest proportions aged 75 and older, and these groups also had the highest proportions of adults reporting any college education and an annual household income at or greater than $75,000.

Diabetes prevalence was 11.5% (95% CI, 10.2%–12.9%) for Japanese, 11.2% (95% CI, 9.5%–13.2%) for Filipinos, 9.9% (95% CI, 8.6%–11.3%) for NHOPIs, 9.1% (95% CI, 6.7%–12.1%) for Chinese, and 5.4% (95% CI, 4.8%–6.1%) for whites (Table 2). The weighted prevalence of diabetes was highest among adults aged 65 to 74 (18.6%; 95% CI, 16.6%–20.7%) and 75 or older (17.6%; 95% CI, 15.3%–20.0%), who were widowed (18.4%; 95% CI, 15.6%–21.4%), had less than a high school diploma or general equivalency diploma (13.1%; 95% CI, 10.1%–16.6%), had an annual household income of less than $15,000 (12.6%; 95% CI, 10.3%–15.3%), had health care coverage (9.1%; 95% CI, 8.5%–9.7%), were obese (16.5%; 95% CI, 15.0%–18.1%), were former smokers (11.8%; 95% CI, 10.6%–13.0%), participated in no physical activity (13.2%; 95% CI, 11.7%–14.8%), and consumed no vegetables (10.4%; 95% CI, 9.1%–11.8%).

In the crude model all variables were associated with diabetes prevalence except for sex, current smoking status, and daily fruit consumption (Table 3). Compared with whites, Japanese (PR = 2.12; 95% CI, 1.81–2.49) and Filipino (PR = 2.07; 95% CI, 1.69–2.52) had the highest crude PRs of diabetes. When all demographic variables were adjusted for, the PR for Japanese reduced to 1.69 (95% CI, 1.44–1.99) (model 1) and 1.77 (95% CI, 1.51–2.08) when all variables were adjusted for (model 2). The PR for NHOPI changed from 1.82 (95% CI, 1.52–2.17) in the crude model to 2.23 (95% CI, 1.87–2.66) in model 1 and 1.74 (95% CI, 1.46–2.08) in model 2. Marital status, education, and health insurance were no longer significant after adjusting for other demographics (model 1). After adjusting for all variables (model 2), race/ethnicity, age, household income, and obesity were strongly associated with diabetes. Physical activity and heavy drinking were significant for protective factors.

To illustrate variability by age and race/ethnicity, we graphically presented diabetes prevalence and 95% CIs (Figure) from model 3, results of which are available from the authors. Differences in diabetes prevalence appeared by age 35. For instance, whites had significantly lower diabetes prevalence from age 35 or older than Filipinos and NHOPIs (*P* < .05). Compared with Japanese participants, whites had significantly lower diabetes prevalence for ages 35 to 74 (*P* < .05). NHOPIs and Filipinos had higher diabetes prevalence than Japanese participants. For example, NHOPIs had a significantly higher diabetes prevalence at ages 45 to 54 (*P* = .01). However, NHOPIs aged 55 to 64 had higher prevalence in diabetes than Japanese participants (*P* = .06). Additionally, Filipinos aged 55 and older had significantly higher diabetes prevalence than Japanese participants (55–64 y, *P* = .03; 65–74 y, *P* = .008; ≥75, *P* = .006).

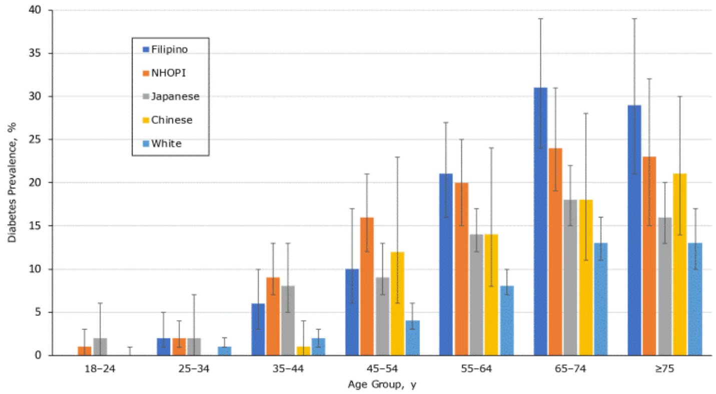

Figure. Interaction between age and race/ethnicity in diabetes prevalence among Native Hawaiian/Other Pacific Islanders and Asian subpopulations (N = 18,200), calculated as crude and multivariate prevalence ratios. Estimates are from weighted Poisson regression analyses (age–race/ethnicity interaction effect, *P* < .001). Nonoverlapping CIs indicate significant differences at 5. Source: Hawai‘i Behavioral Risk Factor Surveillance System, 2011, 2013, 2015 (14). Abbreviations: NHOPI, Native Hawaiian and Other Pacific Islander.

We saw minimal changes in PRs between models 2 and 3 for all other independent variables. We calculated PRs and 95% CIs of diabetes by risk factors calculated from model 3 (Table 3). The PRs of diabetes decreased as household income increased. For example, the PR of diabetes among participants whose annual household income was greater than or equal to $75,000 was 0.53 (95% CI, 0.42–0.67) compared with those with an annual household income of less than $15,000. Participants who were obese had the highest diabetes PR at 2.53 (95% CI, 2.22–2.89) compared with those who were not obese. Participants who drank heavily had a lower PR of 0.74 (95% CI, 0.55–0.98) compared with those who did not. Participants who participated in more physical activity also had a lower diabetes PR, and those who exceeded the US physical activity guidelines were 0.71 (95% CI, 0.61–0.83) times as likely to have diabetes compared with those who participated in no physical activity.

Discussion

We found that NHOPI, Filipino, Japanese, and Chinese residents of Hawai‘i all have significantly higher diabetes PRs than white residents. These disparities remain after adjusting for demographics and diabetes risk factors. Furthermore, we found that the association between age and diabetes varied by race/ethnicity, with diabetes prevalence increasing more rapidly with age among NHOPI, Filipino, and Japanese residents than among white residents. To our knowledge, this is the first study to examine relationships between age and race/ethnicity for diabetes among NHOPI and Asian subpopulations. Our results illustrate the need for researchers to disaggregate and further define terms like “ethnic” and “minority” in discussing populations. Our findings also highlight the large burden of diabetes and its associated risk factors among NHOPI and Asian residents of Hawai‘i.

Our findings affirm the importance of including age in analyses by race/ethnicity, because different racial/ethnic groups may have different age distributions. When only race/ethnicity was considered, Filipinos had the greatest PRs of diabetes after adjusting for demographics (model 1) and all risk factors (model 2). However, when age was included in the analyses by race/ethnicity, variations in diabetes prevalence were found. NHOPI and Filipino residents had significantly higher diabetes prevalence starting at age 35 than white residents of the state. Furthermore, NHOPIs and Filipinos had significantly higher diabetes prevalence than Japanese residents in specific age groups.

Our results are consistent with predominant findings that higher diabetes risk is associated with low household income, obesity, and lack of physical activity (23,24). Adults with greater household income who were not obese and who exceeded US physical activity guidelines were less likely to have diabetes. Although marital status, educational attainment, health coverage, former smoking, and vegetable consumption were significantly associated with diabetes prevalence in the bivariate analysis, these associations were no longer significant after adjusting for other demographics (model 1) and risk factors (model 2).

Strengths of this study are its focus on Hawai‘i, which allowed for obtaining a robust sample of NHOPI participants and Asian subgroups and for the examination of diabetes and other risk factors across Asian subgroups. In addition, this study focused on the differences in diabetes prevalence by age and race/ethnicity.

The study has limitations. First, BRFSS data are self-reported, and participants may not report accurate measures (ie, data can be over represented or underrepresented). Second, collapsing Native Hawaiians and Other Pacific Islanders into the one category limited our ability to compare them with separate Pacific Islander races/ethnicities, such as Samoans or Tongans. Third, categorizing each adult into a single ethnic group is problematic, because Hawai‘i has the highest proportion of multiracial residents in the United States (25). Fourth, this study did not have enough power to detect differences that may exist between racial/ethnic groups. The HBRFSS collects data on multiple races/ethnicities, and this should be a topic for future research. Lastly, we were unable to infer causation in the relationships between risk factors and diabetes because this was a cross-sectional study.

Future research is needed on how race/ethnicity is defined in health disparities research. Racial/ethnic-specific data collection and analyses are needed to investigate health disparities among heterogeneous groups that are often combined into one racial group (ie, Asian). Furthermore, demographic and risk factor variables did not account for all racial/ethnic disparities in diabetes prevalence. Future examination is needed of the role of genetic factors and body fat distribution in explaining high diabetes prevalence among NHOPI and Filipino populations in Hawai‘i (26). Public health programs are also needed to promote positive lifestyle behaviors before the high prevalence of obesity further increases diabetes rates among at-risk racial/ethnic populations. Public health programs in Hawai‘i should target education and early interventions, especially for Filipino and NHOPI residents by age 18 to 24, before diabetes disparities begin to appear.

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Tables

Table 1. Demographic Characteristics of Participants (N = 18,200) and Lifestyle Risk Factors for Diabetes, by Race/Ethnicity, Hawai‘i Behavioral Risk Factor Surveillance System, 2011, 2013, 2015[a]

Variable	White	Native Hawaiian/Other Pacific Islander	Filipino	Japanese	Chinese
Age, y					
18–24	306 (9.4)	335 (17.9)	217 (13.4)	161 (7.6)	67 (14.3)
25–34	685 (18.0)	503 (25.2)	310 (19.2)	258 (9.3)	85 (12.3)
35–44	801 (16.0)	485 (20.0)	363 (20.0)	314 (11.5)	117 (15.6)
45–54	1,254 (18.4)	487 (13.1)	411 (16.3)	594 (17.0)	166 (17.3)
55–64	2,156 (17.7)	486 (11.8)	435 (15.0)	960 (21.8)	219 (16.8)
65–74	1,823 (12.5)	373 (7.7)	351 (9.7)	813 (14.8)	179 (11.6)
≥75	1,024 (8.0)	184 (4.4)	209 (6.4)	885 (18.1)	184 (12.1)
Sex					
Female	4,156 (45.6)	1,639 (50.9)	1,303 (52.2)	2,198 (52.3)	551 (49.0)
Male	3,893 (54.4)	1,214 (49.1)	993 (47.8)	1,787 (47.7)	466 (51.0)
Marital status					
Married	4,436 (59.1)	1,388 (46.7)	1,310 (57.3)	2,117 (54.3)	564 (55.8)
Divorced/separated	1,520 (13.5)	403 (10.6)	209 (7.5)	453 (10.0)	124 (8.0)
Never married	1,290 (21.7)	798 (36.7)	530 (28.3)	863 (25.2)	214 (28.3)
Widowed	803 (5.70	264 (5.9)	247 (6.8)	552 (10.5)	115 (7.9)
Education level					
<High school	239 (7.0)	197 (16.1)	203 (15.0)	76 (3.8)	16 (3.20)
High school diploma or GED	1,648 (25.2)	1,300 (44.2)	805 (33.5)	929 (25.5)	178 (20.6)
College, 1–3 years	2,250 (34.2)	813 (28.5)	621 (33.6)	1,105 (35.9)	248 (32.3)
College, ≥4 years	3,912 (33.5)	543 (11.1)	667 (18.0)	1,875 (34.7)	575 (43.9)
Annual income, $					
≤14,999	711 (7.0)	427 (14.4	269 (8.5)	183 (3.6)	65 (6.0)
15,000–24,999	991 (11.7)	547 (19.7	394 (16.1)	411 (8.8)	80 (6.4)
25,000–49,999	1,774 (20.6)	754 (25.0	719 (30.8)	956 (22.3)	221 (21.8)
50,000–74,999	1,306 (16.4)	383 (13.3		706 (17.0)	181 (16.1)
≥75,000	2,747 (37.4)	533 (18.8	431 (20.7)	1,362 (39.1)	373 (38.5)
Unknown	520 (6.9)	209 (8.8	186 (10.5)	367 (9.2)	97 (11.2)
Health care coverage					
Yes	7,506 (92.7)	2,558 (86.8	2,096 (90.6)	3,843 (95.9)	960 (93.7)

Abbreviation: GED, general equivalency diploma.

[a] Values are number (weighted percentage). All *P* values are < .001 and were calculated by χ^2 test.

[b] Body mass index (weight in kg divided by height in m^2) ≥30.

[c] Participants who smoked at least 100 cigarettes in their entire life, but no longer smoke at all.

[d] Defined as more than 2 drinks per day for men or more than 1 drink per day for women.

[e] Less than guidelines = 1–149 min/wk, meets guidelines = 150–300 min/wk), and exceeds guidelines = >300 min/wk (19).

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Table 1. Demographic Characteristics of Participants (N = 18,200) and Lifestyle Risk Factors for Diabetes, by Race/Ethnicity, Hawai‘i Behavioral Risk Factor Surveillance System, 2011, 2013, 2015[a]

Variable	White	Native Hawaiian/Other Pacific Islander	Filipino	Japanese	Chinese
No	543 (7.3)	295 (13.2	200 (9.4)	142 (4.1)	57 (6.3)
Obese[b]					
Yes	1,540 (20.6)	1,228 (43.5	426 (18.8)	598 (16.6)	110 (9.9)
No	6,509 (79.4)	1,625 (56.5	1,870 (81.2)	3,387 (83.4)	907 (90.1)
Smoking status[c]					
Never smoker	4,176 (54.1)	1,534 (53.3	1,529 (66.5)	2,390 (60.1)	744 (75.8)
Former smoker	2,875 (31.8)	737 (23.0	492 (21.0)	1,215 (28.5)	216 (17.4)
Smoke some days	293 (4.5)	172 (6.9	96 (4.6)	87 (2.8)	10 (1.0)
Smoke every day	705 (9.6)	410 (16.9	179 (7.9)	293 (8.5)	47 (5.8)
Heavy drinking[d]					
Yes	807 (9.8)	283 (10.9	108 (5.7)	184 (5.1)	36 (3.2)
No	7,242 (90.2)	2,570 (89.1	2,188 (94.3)	3,801 (94.9)	981 (96.8)
Don’t drink	1,373 (16.7)	706 (25.0	615 (27.5)	888 (23.5)	194 (21.3)
Meets US guidelines for physical activity[e]					
No physical activity	1,373 (16.7)	706 (25)	615 (27.5)	888 (23.5)	194 (21.3)
Less than guidelines	1,203 (17.6)	473 (16.1	475 (22.6)	775 (22.6)	226 (23.6)
Meets guidelines	1,610 (21.7)	521 (17.0	405 (18.7)	749 (19.1)	206 (19.0)
Exceeds guidelines	3,863 (44.0)	1,153 (42.0	801 (31.2)	1,573 (34.9)	391 (36.1)
Daily servings of fruit					
None	2,394 (33.3)	1,276 (46.6	918 (42.8)	1,623 (44.9)	340 (39.5)
1–2	4,344 (52.3)	1,156 (38.5	1,024 (42.8)	2,006 (47.6)	551 (50.4)
≥3	1,311 (14.3)	421 (14.9	354 (14.4)	356 (7.5)	126 (10.2)
Daily servings of vegetables					
None	1,133 (17.1)	742 (27.4	608 (29.5)	839 (22.6)	196 (20.5)
1–2	4,999 (61.0)	1,541 (52.1	1,217 (51.6)	2,385 (61.0)	627 (62.4)
≥3	1,917 (21.9)	570 (20.5	471 (18.9)	761 (16.4)	194 (17.1)

Abbreviation: GED, general equivalency diploma.
[a] Values are number (weighted percentage). All *P* values are < .001 and were calculated by χ^2 test.
[b] Body mass index (weight in kg divided by height in m^2) ≥30.
[c] Participants who smoked at least 100 cigarettes in their entire life, but no longer smoke at all.
[d] Defined as more than 2 drinks per day for men or more than 1 drink per day for women.
[e] Less than guidelines = 1–149 min/wk, meets guidelines = 150–300 min/wk), and exceeds guidelines = >300 min/wk (19).

Table 2. Prevalence Ratios, by Demographic Characteristics and Lifestyle Risk Factors of All Participants (N = 18,200) and Participants With Diabetes (N = 1,882), Hawai‘i Behavioral Risk Factor Surveillance System, 2011, 2013, 2015[a]

Variable	All Participants, N (%)	Participants With Diabetes, N (%) [95% Confidence Interval]	*P* Value
Race/ethnicity			
White	8,049 (37.1)	570 (5.4) [4.8–6.1]	<.001
Native Hawaiian/Other Pacific Islander	2,469 (12.5)	326 (9.9) [8.6–11.3]	
Filipino	2,296 (17.4)	321 (11.2) [9.5–13.2]	
Japanese	3,985 (23.5)	519 (11.5) [10.2–12.9]	
Chinese	1,017 (6.8)	100 (9.1) [6.7–12.1]	
Age, y			
18–24	1,086 (11.3)	6 (0.5) [0.2–1.2]	<.001
25–34	1,841 (16.9)	33 (1.7) [1.0–2.5]	
35–44	2,080 (16.2)	110 (5.0) [3.8–6.3]	
45–54	2,912 (16.8)	246 (8.4) [7.0–10.1]	
55–64	4,256 (17.2)	496 (13.5) [11.9–15.1]	
65–74	3,539 (11.8)	576 (18.6) [16.6–20.7]	
≥75	2,486 (9.8)	415 (17.6) [15.3–20.0]	
Sex			
Female	9,847 (49.4)	996 (8.9) [8.1–9.8]	.60
Male	8,353 (50.6)	886 (8.6) [7.9–9.5]	
Marital status			
Married	9,815 (55.5)	1,004 (9.3) [8.5–10.1]	<.001
Divorced/separated	2,709 (10.8)	282 (9.9) [8.2–11.9]	
Never married	3,695 (26.4)	243 (4.7) [3.9–5.6]	
Widowed	1,981 (7.2)	353 (18.4) [15.6–21.4]	
Education level			
<High school	731 (8.8)	123 (13.1) [10.1–16.6]	<.001
High school diploma or GED	4,860 (29.3)	573 (9.1) [8.2–10.2]	
College, 1–3 y	5,037 (33.5)	532 (9.1) [8.1–10.2]	
College, ≥4 y	7,572 (28.4)	654 (6.7) [6.1–7.4]	
Annual household income, $			
≤14,999	1,655 (7.5)	242 (12.6) [10.3–15.3]	<.001
15,000–24,999	2,423 (12.6)	304 (9.8) [8.2, 11.7]	
25,000–49,999	4,424 (23.5)	496 (9.9) [8.7–11.2]	
50,000–74,999	2,873 (15.5)	259 (7.9) [6.5–9.4]	

Abbreviation: GED, general equivalency diploma.
[a] Percentages are weighted.
[b] Body mass index (weight in kg divided by height in m^2) ≥30.
[c] Participants who smoked at least 100 cigarettes in their entire life, but no longer smoke at all.
[d] Defined as more than 2 drinks per day for men or more than 1 drink per day for women.
[e] Less than guidelines = 1–149 min/wk, meets guidelines = 150–300 min/wk, and exceeds guidelines = >300 min/wk (19).

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Table 2. Prevalence Ratios, by Demographic Characteristics and Lifestyle Risk Factors of All Participants (N = 18,200) and Participants With Diabetes (N = 1,882), Hawai‘i Behavioral Risk Factor Surveillance System, 2011, 2013, 2015[a]

Variable	All Participants, N (%)	Participants With Diabetes, N (%) [95% Confidence Interval]	*P* Value
≥75,000	5,446 (32.1)	429 (6.8) [6.0–7.7]	
Unknown	1,379 (8.6)	152 (9.9) [7.7–12.5]	
Health care coverage			
Yes	16,963 (92.3)	1,802 (9.1) [8.5–9.7]	.001
No	1,237 (7.7)	80 (5.5) [3.9–7.4]	
Obese[b]			
Yes	3,902 (22.1)	770 (16.5) [15.0–18.1]	<.001
No	14,298 (77.9)	1,112 (6.6) [6.0–7.2]	
Smoking status[c]			
Never smoker	10,373 (59.0)	956 (7.9) [7.2–8.6]	<.001
Former smoker	5,535 (26.8)	711 (11.8) [10.6–13.0]	
Smoke some days	658 (4.2)	53 (5.9) [3.8–8.7]	
Smoke every day	1,634 (9.9)	162 (7.4) [5.8–9.2]	
Heavy drinking[d]			
Yes	1,418 (7.7)	86 (5.0) [3.7–6.6]	<.001
No	16,782 (92.3)	1,796(9.1) [8.5–9.7]	
Meets US guidelines for physical activity[e]			
No physical activity	3,776 (21.7)	568 (13.2) [11.7–14.8]	<.001
Less than guidelines	3,152 (19.8)	305 (7.7) [6.5–9.0]	
Meets guidelines	3,491 (19.7)	307 (7.3) [6.1–8.5]	
Exceeds guidelines	7,781 (38.8)	702 (7.7) [6.9–8.5]	
Daily servings of fruit			
None	6,551 (40.1)	724 (9.1) [8.2–10.1]	.11
1–2	9,081 (47.3)	910 (8.2) [7.4–9.0]	
≥3	2,568 (12.6)	248 (10.0) [8.2–12.0]	
Daily servings of vegetables			
None	3,518 (22.4)	462 (10.4) [9.1–11.8]	.001
1–2	10,769 (58.1)	1,048 (8.4) [7.7–9.2]	
≥3	3,913 (19.5)	372 (8.1) [7.0–9.3]	

Abbreviation: GED, general equivalency diploma.

[a] Percentages are weighted.

[b] Body mass index (weight in kg divided by height in m^2) ≥30.

[c] Participants who smoked at least 100 cigarettes in their entire life, but no longer smoke at all.

[d] Defined as more than 2 drinks per day for men or more than 1 drink per day for women.

[e] Less than guidelines = 1–149 min/wk, meets guidelines = 150–300 min/wk, and exceeds guidelines = >300 min/wk (19).

Table 3. Crude and Multivariate Prevalence Ratios of Diabetes (N = 18,200), Hawai'i Behavioral Risk Factor Surveillance System, 2011, 2013, 2015

Variable	Crude Model		Multivariate Model 1[a]		Multivariate Model 2[b]		Multivariate Model 3[c]	
	Prevalence Ratio (95% Confidence Interval)	*P* Value	Prevalence Ratio (95% Confidence Interval)	*P* Value	Prevalence Ratio (95% Confidence Interval)	*P* Value	Prevalence Ratio (95% Confidence Interval)	*P* Value
Race/ethnicity								
White	1 [Reference]							
Native Hawaiian/Other Pacific Islander	1.82 (1.52–2.17)	<.001	2.23 (1.87–2.66)	<.001	1.74 (1.46–2.08)	<.001	—[c]	—[c]
Filipino	2.07 (1.69–2.52)	<.001	2.12 (1.75–2.56)	<.001	2.16 (1.79–2.61)	<.001	—[c]	—[c]
Japanese	2.12 (1.81–2.49)	<.001	1.69 (1.44–1.99)	<.001	1.77 (1.51–2.08)	<.001	—[c]	—[c]
Chinese	1.68 (1.24–2.28)	<.001	1.69 (1.26–2.26)	<.001	1.90 (1.43–2.53)	<.001	—[c]	—[c]
Age, y								
18–24	0.10 (0.04–0.27)	<.001	0.08 (0.03–0.21)	<.001	0.10 (0.04–0.27)	<.001	—[c]	—[c]
25–34	0.34 (0.21–0.54)	<.001	0.31 (0.19–0.50)	<.001	0.34 (0.21–0.55)	<.001	—[c]	—[c]
35–44	1 [Reference]							
45–54	1.70 (1.27–2.29)	.004	1.82 (1.36–2.43)	<.001	1.85 (1.39–2.47)	<.001	—[c]	—[c]
55–64	2.72 (2.09–3.54)	<.001	2.88 (2.21–3.75)	<.001	3.04 (2.34–3.94)	<.001	—[c]	—[c]
65–74	3.75 (2.89–4.87)	<.001	3.91 (3.01–5.09)	<.001	4.14 (3.19–5.38)	<.001	—[c]	—[c]
≥75	3.56 (2.71–4.66)	<.001	3.42 (2.57–4.56)	<.001	4.04 (3.02–5.41)	<.001	—[c]	—[c]
Sex								
Female	1 [Reference]							
Male	0.97 (0.85–1.10)	.60	1.17 (1.03–1.32)	.01	1.12 (0.99–1.27)	.08	1.13 (0.99– 1.28)	.06
Marital status								
Married	1 [Reference]							
Divorced/separated	1.07 (0.87–1.31)	.51	0.91 (0.74–1.12)	.36	0.89 (0.74–1.09)	.26	0.89 (0.73– 1.08)	.25
Never married	0.50 (0.41–0.61)	<.001	1.11 (0.91–1.35)	.29	1.07 (0.88–1.29)	.49	1.06 (0.88– 1.28)	.56
Widowed	1.98 (1.66–2.36)	<.001	1.00 (0.83–1.20)	.997	1.00 (0.83–1.21)	.98	1.01 (0.84– 1.21)	.94
Education level								
<High school	1 [Reference]							
High school diploma or GED	0.70 (0.53–0.91)	.008	0.94 (0.73–1.21)	.61	0.99 (0.77–1.29)	.96	1.02 (0.78– 1.32)	.90
College, 1–3 years	0.70 (0.53–0.91)	.008	0.95 (0.73–1.23)	.70	1.02 (0.78–1.33)	.87	1.04 (0.79– 1.36)	.77
College, ≥4 years	0.51 (0.40–0.67)	<.001	0.75 (0.57–0.98)	.03	0.88 (0.67–1.16)	.37	0.88 (0.67– 1.16)	.38

Abbreviation: GED, general equivalency diploma.

[a] Weighted multivariate Poisson model adjusted for demographic and socioeconomic variables.

[b] Weighted multivariate Poisson model adjusted for all independent variables (including obesity and lifestyle variables).

[c] Weighted multivariate Poisson model with age and race/ethnicity interaction effects adjusted for all independent variables. Results for race/ethnicity and age are available from the authors.

[d] Body mass index (weight in kg divided by height in m^2) ≥30.

[e] Cells are blank because multivariate model 1 included only demographic variables.

[f] Participants who smoked at least 100 cigarettes in their entire life, but no longer smoke at all.

[g] Defined as more than 2 drinks per day for men or more than 1 drink per day for women.

[h] Less than guidelines = 1–149 min/wk, meets guidelines = 150–300 min/wk, and exceeds guidelines = >300 min/wk (19).

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Table 3. Crude and Multivariate Prevalence Ratios of Diabetes (N = 18,200), Hawai'i Behavioral Risk Factor Surveillance System, 2011, 2013, 2015

Variable	Crude Model		Multivariate Model 1[a]		Multivariate Model 2[b]		Multivariate Model 3[c]	
	Prevalence Ratio (95% Confidence Interval)	*P* Value	Prevalence Ratio (95% Confidence Interval)	*P* Value	Prevalence Ratio (95% Confidence Interval)	*P* Value	Prevalence Ratio (95% Confidence Interval)	*P* Value
Annual household income, $								
≤14,999	1 [Reference]							
15,000–24,999	0.78 (0.60–1.01)	.055	0.73 (0.57–0.94)	.01	0.72 (0.57–0.91)	.006	0.72 (0.57– 0.91)	.001
25,000–49,999	0.78 (0.62–0.98)	.04	0.66 (0.53–0.82)	..002	0.63 (0.51–0.79)	<.001	0.64 (0.51– 0.79)	<.001
50,000–74,999	0.62 (0.48–0.81)	.004	0.58 (0.45–0.75)	<.001	0.55 (0.43–0.71)	<.001	0.55 (0.43– 0.71)	<.001
≥75,000	0.54 (0.43–0.68)	<.001	0.54 (0.43–0.68)	<.001	0.53 (0.42–0.67)	<.001	0.53 (0.42– 0.67)	<.001
Unknown	0.78 (0.58–1.06)	.11	0.77 (0.58–1.01)	.06	0.74 (0.56–0.97)	.03	0.74 (0.56– 0.97)	
Health care coverage								
Yes	1 [Reference]							
No	0.61 (0.44–0.83)	.002	0.84 (0.62–1.14)	.26	0.91 (0.67–1.24)	.56	0.92 (0.68– 1.26)	.62
Obese[d]								
No	1 [Reference]							
Yes	2.51 (2.20–2.85)	<.001	—[e]	—[e]	2.55 (2.24–2.90)	<.001	2.53 (2.22– 2.89)	<.001
Smoking status[f]								
Never smoker	1 [Reference]							
Former smoker	1.50 (1.31–1.72)	<.001	—[e]	—[e]	1.10 (0.96–1.25)	.16	1.10 (0.96– 1.25)	.17
Smoke some days	0.76 (0.51–1.13)	.17	—[e]	—[e]	1.02 (0.72–1.46)	.89	1.02 (0.72– 1.45)	.92
Smoke every day	0.94 (0.74–1.20)	.61	—[e]	—[e]	0.97 (0.77–1.24)	.83	0.97 (0.76– 1.23)	.81
Heavy drinking[g]								
No	1 [Reference]							
Yes	0.55 (0.41–0.73)	<.001	—[e]	—[e]	0.75 (0.56–1.00)	.05	0.74 (0.55– 0.98)	.04
Physical activity, US guidelines[h]								
No physical activity	1 [Reference]							
Less than US. guidelines	0.58 (0.48–0.71)	<.001	—[e]	—[e]	0.82 (0.68–0.99)	.04	0.81 (0.67– 0.97)	.03
Meets guidelines	0.55 (0.45–0.67)	<.001	—[e]	—[e]	0.79 (0.65–0.95)	.02	0.79 (0.65– 0.96)	.02
Exceeds guidelines	0.58 (0.50–0.68)	<.001	—[e]	—[e]	0.71 (0.61–0.83)	<.001	0.71 (0.61– 0.83)	<.01
Daily servings fruit								
None	1 [Reference]							

Abbreviation: GED, general equivalency diploma.

[a] Weighted multivariate Poisson model adjusted for demographic and socioeconomic variables.

[b] Weighted multivariate Poisson model adjusted for all independent variables (including obesity and lifestyle variables).

[c] Weighted multivariate Poisson model with age and race/ethnicity interaction effects adjusted for all independent variables. Results for race/ethnicity and age are available from the authors.

[d] Body mass index (weight in kg divided by height in m^2) ≥30.

[e] Cells are blank because multivariate model 1 included only demographic variables.

[f] Participants who smoked at least 100 cigarettes in their entire life, but no longer smoke at all.

[g] Defined as more than 2 drinks per day for men or more than 1 drink per day for women.

[h] Less than guidelines = 1–149 min/wk, meets guidelines = 150–300 min/wk, and exceeds guidelines = >300 min/wk (19).

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Table 3. Crude and Multivariate Prevalence Ratios of Diabetes (N = 18,200), Hawai'i Behavioral Risk Factor Surveillance System, 2011, 2013, 2015

Variable	Crude Model		Multivariate Model 1[a]		Multivariate Model 2[b]		Multivariate Model 3[c]	
	Prevalence Ratio (95% Confidence Interval)	*P* Value	Prevalence Ratio (95% Confidence Interval)	*P* Value	Prevalence Ratio (95% Confidence Interval)	*P* Value	Prevalence Ratio (95% Confidence Interval)	*P* Value
1-2	0.90 (0.78–1.03)	.13	—[e]	—[e]	0.92 (0.80–1.06)	.25	0.92 (0.80– 1.06)	.27
≥3	1.09 (0.89–1.35)	.41	—[e]	—[e]	1.17 (0.95–1.44)	.13	1.17 (0.95– 1.44)	.13
Daily servings vegetables								
None	1 [Reference]							
1–2	0.81 (0.69–0.95)	.009	—[e]	—[e]	0.95 (0.81–1.11)	.49	0.95 (0.81– 1.11)	.49
≥3	0.78 (0.64–0.94)	.01	—[e]	—[e]	0.93 (0.76–1.14)	.49	0.94 (0.77– 1.15)	.55

Abbreviation: GED, general equivalency diploma.

[a] Weighted multivariate Poisson model adjusted for demographic and socioeconomic variables.

[b] Weighted multivariate Poisson model adjusted for all independent variables (including obesity and lifestyle variables).

[c] Weighted multivariate Poisson model with age and race/ethnicity interaction effects adjusted for all independent variables. Results for race/ethnicity and age are available from the authors.

[d] Body mass index (weight in kg divided by height in m^2) ≥30.

[e] Cells are blank because multivariate model 1 included only demographic variables.

[f] Participants who smoked at least 100 cigarettes in their entire life, but no longer smoke at all.

[g] Defined as more than 2 drinks per day for men or more than 1 drink per day for women.

[h] Less than guidelines = 1–149 min/wk, meets guidelines = 150–300 min/wk, and exceeds guidelines = >300 min/wk (19).

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ORIGINAL RESEARCH

A Qualitative Evaluation of Caregiver Support Services Offered at the Atlanta Veterans Affairs Health Care System

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Summary

What is already known about the topic?

Dementia affects a significant number of elderly US adults. Informal caregivers play a critical role in dementia care, offering uncompensated support to patients outside formal medical settings. To support these caregivers, research teams and agencies are developing evidence-based programs.

What is added by this report?

The Atlanta Veterans Affairs Health Care System implemented multicomponent caregiver support services, which included elements such as psychoeducational programs and resource referrals. We demonstrated how these services improved participants' daily caregiver experiences and identified caregiver-perceived program gaps.

What are the implications for public health practice?

By evaluating the utility of these services, we can enhance existing programs and inform other caregiver support strategies.

Abstract

Introduction

The Department of Veterans Affairs (VA) provides health care to approximately 300,000 patients with dementia. Recognizing the critical role caregivers play in veterans' health, the Cognitive Disorders Specialty Care Education Center of Excellence (COE) at the Atlanta VA Health Care System implemented a suite of caregiver support services, including formal programs and resource linkages. We evaluated the effectiveness of these services and identified caregiver-perceived gaps in them.

Methods

We conducted 11 semistructured interviews from November 2016 through February 2017 with caregivers of veterans seen in the COE who had participated in support services. After coding transcripts, we established a codebook of 9 major themes and conducted a thematic analysis of all transcripts.

Results

Caregivers spoke positively of COE caregiver services that offered information on dementia, social support, an emphasis on caregiver well-being and self-efficacy, and methods for behavioral change. Gaps identified included the need for additional dementia information and practical support in such matters as advanced directives and eligibility for VA benefits.

Conclusion

Our findings will inform future improvements to COE caregiver support services, such as an expansion of COE's caregiver educational content and capacity building of existing components such as resource referrals. These results also highlight opportunities for COE to interface with internal and external organizations to enhance existing caregiver services.

Introduction

Dementia affects approximately 14% of US adults aged 70 or older. Prevalence and related health care costs are expected to rise as the overall population ages (1–3), and recent estimates suggest that the annual cost of dementia care may double to $109 billion by 2040 (1). Informal caregivers play a critical role in the US health system, acting as supplemental, uncompensated support outside of clinical spheres for patients with dementia (4). Previous studies identified various consequences of extended caregiving, including psychological distress and poor physical health (5–7). These consequences are related to perceived caregiver burden (8). However, only about 25% of caregivers report use of support services, which could reduce this burden (5).

Research teams and government agencies have implemented, evaluated, and translated evidence-based interventions focused on the needs of dementia caregivers; some programs demonstrated success in reducing caregiver burden and improving caregiver well-being while remaining cost-effective (9–12). The Cognitive Disorders Specialty Care Education Center of Excellence (COE), an interprofessional collaborative practice at the Atlanta Veterans Affairs Health Care System (VAHCS), piloted a multicomponent intervention for primary caregivers of its dementia patients that includes services such as visits with staff social workers, resource referrals, and an evidence-based psychoeducational program, the Savvy Caregiver (13).

The primary objective of our formative evaluation was to examine the effectiveness of COE caregiver support services and referrals by using the Transactional Model of Stress and Coping (TMSC) as a framework (14). A secondary objective was to identify any gaps in these caregiver support services that, once addressed, would improve caregiver experiences as well as COE operations overall.

Methods

We conducted a qualitative, formative evaluation of COE caregiver support services from August 2016 through May 2017 in partnership with COE leadership, clinic staff members, and Emory University. The COE caregiver intervention components evaluated were the Savvy Caregiver Program, a 5-to-6-session psychoeducational training aimed at preparing dementia caregivers for the challenges of neurocognitive decline (13); the Tele-Savvy Program, a tablet- and internet-based remote adaptation of the Savvy Caregiver Program (15,16); caregiver visits and telephone calls with COE staff members (eg, nurse, social workers); and referrals to internal or external resources.

We used a purposive, nonprobability, convenience sample. The COE staff provided recommendations of eligible participants on the basis of the following criteria: 1) the caregiver was significantly involved in the outside support of a COE clinic patient diagnosed with dementia (ie, primary caregiver) and 2) the caregiver had participated in one or more COE caregiver support services. This evaluation was deemed nonresearch quality improvement by the Atlanta VAHCS Research Office and as such, did not require additional review by the Emory University institutional review board.

One researcher (S.B.) conducted 11 in-depth, semistructured interviews from November 2016 through February 2017 in private VAHCS offices, or by telephone when a caregiver was unable to travel. The participation rate was 65% (11 of 17). In general, nonparticipation was due to travel or caregiver time restrictions. With participant consent, the researcher used a VAHCS-approved device to audio-record all interviews and transcribed these interviews verbatim. Participants did not receive incentives for their time.

We used a standard interview guide developed in conjunction with COE leadership and Emory University faculty. Constructs from the TMSC (eg, primary and secondary appraisals, coping efforts) informed the development of interview questions. We categorized interview questions by the following domains of interest: demographics and other background information, previous caregiving experiences, present caregiving experiences, individual coping strategies, experiences with COE caregiver support services, and perceived gaps in these support services.

We completed transcript coding and analysis using MAXQDA 12 Base software (VERBI GmbH). We used a modified grounded theory approach in which the first collection of interviews informed later data collection and analysis strategies (17). One researcher (S.B.) coded an initial batch of transcripts and worked with the project team to develop and refine a codebook of 9 major themes. She then used the final codebook to code the remainder of the transcripts. A second coder (C.S.) coded 20% of the data to assess intercoder reliability and worked with S.B. to review and discuss all discrepancies between the coded transcripts until consensus was reached. S.B. applied any agreed-upon changes to the remaining transcripts. We synthesized and compared themes across all interviews to generate findings.

Results

All 11 caregivers were female spouses of veteran patients, with a mean age of 67 years (standard deviation [SD], 4.6 years; range, 57–72 years). Caregivers had been providing support to their spouse for a median of 6 years (range, 1.5–24.0 y) (Table 1).

Caregivers remarked on the VA COE caregiver support services (Table 2). Overall, opinions of COE caregiver support services were positive. Five major themes emerged as effective components of these services: information about dementia, social support, a focus on caregiver self-efficacy, application of behavioral strategies, and an emphasis on caregiver well-being.

Information about dementia. Most caregivers (n = 10) appreciated dementia information that COE services provided. Information about dementia reinforced the notion that caregivers had no control over disease progression, reducing feelings of guilt or responsibility. Caregivers who enrolled in the formal psychoeducational programs (ie, Savvy Caregiver and Tele-Savvy) were pleased with how the curriculum offered organized information on dementia, including what is normal and future prognosis. These caregivers noted how program information was used to tailor their routines to the unique symptoms and circumstances of various dementia stages. Program instruction seemed less constructive for caregivers managing late-stage dementia, for which care can be more taxing and complicated. Instead, one caregiver sought palliative care information from the internet and other avenues. In addition, 4 caregivers expressed difficulty in comprehending dementia symptoms, disease stages, and other information used to describe the veteran's illness.

Social support. Most caregivers who participated in the psychoeducational programs (n = 7) described the emotional benefits of interacting with other caregivers who were managing similar circumstances, noting a shared sense of empathy and encouragement. Caregivers were better able to "see what's coming" in terms of disease progression through sharing anecdotes, which better prepared them for their role. Caregivers also described using personal experiences to assist others, which facilitated community building (ie, being "in here together") and contrasted with instances when they repressed or shielded others from the difficulties of dementia caregiving. Additionally, caregivers discussed social support provided by COE clinic staff members who would purposefully reach out to caregivers to informally check in with them.

Caregiver self-efficacy. Seven caregivers noted increased self-efficacy, described as feeling more comfortable performing tasks typically ascribed to a caregiver, as a direct result of COE services. They recalled moments when they were better able to regulate their emotional responses to the veteran's behaviors after participation in the psychoeducational programs. With improved self-efficacy, caregivers felt less overwhelmed by their circumstances and better equipped to address challenges through such strategies as prioritizing tasks. Improved self-efficacy was more apparent among caregivers who participated in the psychoeducational programs than among those who did not.

Application of behavioral strategies. Six of the 11 caregivers described moments of consciously altering their behavior to reflect information gained from the COE staff and support services in an effort to respond more competently to the veteran's symptoms. These participants acknowledged using popular guidance from Savvy Caregiver materials, such as "Don't just do something; stand there." From this guidance, caregivers learned how to evaluate care recipient behavior and react supportively to each stage of the disease by using strategies such as meditation. Caregivers who had participated in the psychoeducational programs were more likely to be aware of appropriate behavioral strategies when caring for a patient with dementia and to adopt these practices into their routines.

Emphasis on caregiver well-being. Three caregivers noted difficulty in prioritizing personal needs because of the veteran's illness and deteriorating condition. Participants were, therefore, more likely to neglect their own health and well-being, citing in- stances of failing to schedule needed medical appointments, being unable to exercise, and experiencing chronic stress and disrupted sleep. Caregivers described how COE support services encour- aged continued self-care (ie, caring for the caregiver) and emphas- ized how caregivers may struggle to continue supporting the veter- an if they do not prioritize caring for themselves. In some cases, increased caregiver focus on their own well-being after COE program participation resulted in sustained behavior changes, such as better sleep management. An emphasis on caregiver well-being also prompted 2 caregivers to seek greater external support from loved ones, something they previously avoided.

Caregivers identified 4 gaps and recommended future COE services: 1) provide additional information on dementia, 2) provide additional support for individual caregiver challenges, 3) offer practical and logistical support (eg, navigating VA benefits, financial tasks), and 4) improve availability of formal caregiver programs.

Provide additional information on dementia. Although caregivers appreciated dementia information provided through COE services, 5 caregivers expressed a desire to acquire more detailed information about the disease and disease management. In particular, caregivers sought a clearer picture of the disease's expected pathology as a way to better manage their circumstances. Group interactions in COE programs also alerted caregivers to gaps in their dementia knowledge, and this prompted some to seek out additional dementia information and care that they may not have considered previously. Two caregivers were interested in information on end-of-life care, recognizing the importance of the topic but acknowledging that they felt overwhelmed about pursuing this discussion in detail.

Provide additional support for individual caregiver challenges. Seven caregivers emphasized a desire for support services that better addressed individual caregiver challenges. Three caregivers discussed alarming or frustrating behavior changes in the spouse that were likely manifesting because of dementia. One participant recalled her husband's obsessive behavior, explaining how she would have appreciated targeted support on how to manage this unique symptom. Caregivers emphasized that some concerns, such as increased sex drive or dementia-related infidelity, may be too personal to discuss with family and asked that COE services offer time to problem-solve specific dementia quirks with the staff or as a group, especially because other caregivers may have experienced similar difficulties.

Offer practical and logistical support. As a facet of navigating the VA health system, 6 caregivers indicated a need for increased practical and logistical support. Practical and logistical support encompassed external resource linkages, clarification on VA benefits and eligibility, and guidance on practical and legal matters such as advanced directives, financial management, and long-term care arrangements. Caregivers who were not familiar with the VA appeared to be at a particular disadvantage when navigating eligibility. Other caregivers wanted instruction on practical caregiving tasks, such as a do-not-resuscitate order for the spouse while he is still able to consent. Some caregivers noted that their husbands had handled household activities such as paying bills and overseeing investments and requested supplementary guidance on these tasks.

Improve Savvy Caregiver and Tele-Savvy course availability. Three caregivers would have liked the formal courses to be extended either through advanced modules or by increasing the number of sessions offered. Two caregivers requested an extension of the program over longer time intervals, and one caregiver described how it was difficult to keep up with weekly readings and assignments while acting as a caregiver. To accommodate caregivers who work full-time or have other commitments, one participant requested these programs be held at alternative times instead of weekday daytime hours.

Discussion

Our formative evaluation identified several components of COE caregiver services that were perceived as beneficial by participants. Caregivers responded positively to dementia information disseminated through COE services. This finding aligns with a previous meta-analysis of caregiver programs that found reductions in caregiver burden and emotional distress from interventions focused on increasing knowledge of the disease in an interactive format (18). To strengthen existing formal programs and resources that provide disease information, COE should consider expanding the current dementia curriculum for caregivers to provide supplementary details about the disease. With this updated curriculum, COE may address additional caregiver-requested content such as information that expands on introductory materials (eg, greater detail about disease stages), palliative care, and practical and logistical support. Some caregivers acknowledged challenges with comprehension of material on dementia topics. Research has shown that advanced health information may exacerbate caregiver distress if not presented in appropriate formats (19). COE should examine the health literacy levels of all dementia materials offered through caregiver services and refine materials as needed.

Consistent with previous research, caregivers attributed increased self-efficacy, behavior modification, and reduced feelings of caregiver burden to the Savvy Caregiver Program (13). Any expansion of COE services could consider methods to boost self-efficacy among caregivers of veterans beyond structured programs such as the Savvy Caregiver. Because self-efficacy is related to successfully completing tasks (20), caregiver self-efficacy may be improved through interactive mechanisms that encourage caregivers to share information about successfully managing their role. Additionally, novel alternatives such as home telehealth strategies would allow COE staff members to observe caregiving techniques used and offer constructive guidance (21).

Caregivers may neglect their needs or struggle to prioritize self-care while providing support to care recipients (22). Findings from our evaluation suggest that an emphasis on caregiver well-being functions as an impetus for behavior change, with caregivers citing moments when they chose to pursue self-care strategies after psychoeducational programs and COE staff guidance. COE may consider developing print and other materials on well-being practices for caregivers not already engaged in COE services to increase its reach to those who may struggle to prioritize their well-being.

Social support from interactions with other caregivers and COE clinic staff members was particularly well-received, echoing one meta-analysis that found caregiver support group participants demonstrated significant emotional gains (23). However, current COE caregiver support services are not structured to sustain long-term support groups because COE formal caregiver programs are time-limited. Although the COE is currently piloting remote delivery through the Tele-Savvy Program, its staff should continue to expand caregiver support to internet-based models. Asynchronous, informal online support groups may provide a feasible, cost-effective alternative to more traditional in-person formats, and recent work has demonstrated benefits from online support communities for dementia caregivers (24–26). Additionally, internet-based education and support interventions, as an alternative to in-person scheduled instruction, have also proven effective for dementia caregivers (27,28). Web-based delivery of information and support would address caregiver concerns about course availability, because they could access COE resources on their own schedule. COE may consider implementing any of these informal virtual strategies to enhance remote delivery of dementia information and to sustain social support.

Caregivers discussed a desire to engage with additional practical resources, similar to a previous study that found that only 19% of sampled caregivers were aware of how to access community services (29). COE could continue to offer and update a comprehensive resource list for caregivers that includes information on both health (eg, support groups) and practical resources (eg, legal counsel) to standardize and streamline referrals for external services in their local communities. In the future, COE may consider collaborating with other VA and external caregiver programs to expand services and to further address caregiver requests for more practical and logistical support.

Our study had several strengths. Because COE has documentation procedures for caregiver programs, such as rosters of psychoeducational program participants and clinical notes from caregiver interactions, we used well-maintained records to identify caregivers who had engaged in support services, which allowed us to capture multiple perspectives. Semistructured interviews provided caregivers with the appropriate conduit for more in-depth discussions of support services and the perceived effects these resources had on caregivers than quantitative surveys offer. In an attempt to reduce the likelihood of socially desirable responses, participants were informed that their feedback would not affect their benefits, and interviews were conducted by a third party not related to the provision of COE services.

Our formative evaluation also had some limitations. Because our analysis was qualitative and the sample size was small, findings are not generalizable to other caregiver populations or clinic environments outside the Atlanta VAHCS. However, the purpose of qualitative data is to provide insight, not generalizability, and the experiences of this sample aligned with published research on caregiver burden. Findings are also restricted to caregivers who engaged in caregiver support resources and who were interested in offering their perspectives on the program.

COE is in the process of collecting complementary survey data before and after program participation to assess how factors related to caregiver burden, such as stress and depression, are influenced by COE support services and to bolster these qualitative findings. Future work should seek to explore the perspectives of caregivers who are less engaged in these services to improve reach. Future efforts may also incorporate staff perspectives on caregiver support services, a useful vantage point when considering program feasibility and sustainability. Any expansion or translation of COE caregiver services should ultimately undergo a full program evaluation.

Caregiver support services piloted by COE are well-regarded among dementia caregivers who use these resources to better manage the challenging circumstances and responsibilities of their role. Although caregivers noted some important limitations of these services that should be considered in the future, COE support services were found to be beneficial to caregivers through such mechanisms as increased knowledge of dementia, greater social support, increased self-efficacy to care for the veteran, behavior modification, and an emphasis on caregiver well-being. Findings from our formative evaluation support the continuation and expansion of these COE programs and demonstrate the usefulness of providing caregiver services through VA facilities to improve the care and quality of life of veterans living with dementia and their caregivers.

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Tables

Table 1. Demgraphic Characteristics, Caregivers (N = 11) Participating in Caregiver Support Services, Atlanta Veterans Affairs Health Care System, Atlanta, Georgia, August 2016–May 2017[a]

Characteristic	Value
Age, mean (standard deviation) [range], y	67.3 (4.6) [57–72]
Length of time caregiving, median (range), y	6.0 (1.5–24.0)
Female sex	11
Relationship to veteran is spouse	11
Race	
White	7
Black	4
Education	
Some high school	1
High school graduate	3
Some college	4
College graduate	1
Advanced degree	2
Lives with veteran	
Yes	10
No	1

[a] Values are number unless otherwise indicated.

Table 2. Themes and Sample Remarks from Caregiver Participants (N = 11), Study of Effectiveness of Caregiver Support Services, Atlanta Veterans Affairs Health Care System, Atlanta, Georgia, August 2016–May 2017[a]

Theme	Remark (Participant Identifier)
Effectiveness of the Cognitive Disorders Specialty Care Education Center of Excellence caregiver services	
Information about dementia	It had a lot of good information in it. It made me aware of . . . what stage he was in, you know, and what we've already been through, and what's normal, what's not normal. And what to look for as we go on, you know. …….I think it really helped me. It gave a lot of good advice. Reading materials and all helped. (P03)
	So they [staff in the caregiver program] have kind of helped me to know that it's not my fault that this is happening. It's nothing I can do about it. It's nothing that I did wrong. It happens, and we have no control over the disease. (P06)
Social support	[T]hey [other caregivers] may have experienced something that I have not done yet. Or my experience may have, you know, if I had shared about it, maybe something they're not going through yet. And it just kind of gives you a, a heads up on what may or may not be coming. You know, what to look for. (P11)
Caregiver self-efficacy	Well, I don't feel as overwhelmed……..I don't get as anxious as I used to cause now what I try to do is, first do the things that I know that I can do. If it's something that I know that I can't do, then I don't get overwhelmed about it, you know. I try to find an easier way to get it done.…… I try to handle one stress at a time. (P09)
Application of behavioral strategies	I had never thought about the fact that, that keeping them engaged, that is better for them. It keeps 'em busy. And so I have really worked on, you know, trying to keep him engaged in what I'm doing. 'Cause he'll get up and he'll say, you know, what's the plan for the day? And I'll say, well I need you in the house and this is what I need. I start [laughs] I start off with one thing, I said now do this and when you get that done come back and I'll give you something else to do. (P06)
Emphasis on caregiver well-being	[J]ust trying to get the support system group going and, not being so prideful when I do need help, to ask for help, instead of . . . trying to do everything myself. (P03)
Gaps in the Cognitive Disorders Specialty Care Education Center of Excellence caregiver services	
Provide additional information on dementia	You know, because I want to call it what it is. I don't want to label something it's not. . . . And . . . the stages………and how you handle situation 'cause that, you answer this lady question over here about her husband violent, you might be answering a question for me when that time come. (P02)
	So, you know, tell me anything that I . . . well, when I get to this final stage, you can expect such and such, you know. And what to, what you can do to make it easier on yourself . . . how you can continue to get the self-care that you need in order to be able to withstand that last, that final stage. (P09)
Provide additional support for individual caregiver challenges	I'm still . . . I mean, I was hoping it would help me, the obsession he has over the video tapes. That was something I would get some more concrete advice but even the doctors now they don't . . . [laughs] I mean they don't even really have any concrete things. Just handling it and . . . one thing that I've gotten most out of is just don't take him where they have videos [laughs] so. But that's hard to do sometimes. (P03)
Offer practical and logistical support	[As] a caregiver, all of a sudden, especially on a woman, lot of the roles that you didn't play, your veteran usually would do a lot of the financial things, any kind of dealing in stocks, you know things like that. . . . If somebody . . . or even, legal stuff is a lot of things I wish they were call in, maybe, an elder attorney to help describe some of the ways that, things that you need to do to make it easier for you, especially if you need to have the patient's signature ahead of time. Before they get to a part where they can't sign things.…… Or even to tell benefits that the VA could help you get, like that aide and attendance, some of the different things for that. (P01)
Improve course availability	I don't get home until like 4 or 5 and then, by the time I get here, it wouldn't be, it would be like 6 or 6:30 because of the traffic coming through. So it would have to be evening. Well then, I can't do too much because he . . . his confusion comes in the evening. (P04)

[a] An in-depth, semistructured interview was conducted with each participant from November 2016 through February 2017 in private Veterans Affairs Health Care System offices or by telephone.

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ORIGINAL RESEARCH

Rural–Urban Differences in Baseline Dietary Intake and Physical Activity Levels of Adolescents

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PEER REVIEWED

Abstract

Introduction

Differences in dietary intake and physical activity may explain the higher prevalence of obesity among adolescents living in rural versus urban settings. The objective of this cross-sectional secondary analysis was to compare baseline dietary intake and physical activity of adolescents by rurality.

Methods

We analyzed data on 940 adolescents who participated in ACTION PAC (Adolescents Committed to Improvement of Nutrition and Physical Activity), an obesity prevention and management intervention trial conducted from 2014 through 2017 in 8 public high schools in the southwestern United States. Dietary intake was assessed with the Block Food Screener, and participants completed an exercise log and wore an accelerometer to provide data on physical activity. We compared data by rural–urban commuting area (RUCA) codes and log population density by using multilevel models, with students nested within zip code and repeated measures for accelerometer analysis.

Results

After adjusting for socioeconomic status and ethnicity, accelerometer data indicated that moderate-to-vigorous physical activity was 8.17 min/d ($P = .02$) higher and sedentary time was 20.42 min/d ($P = .02$) lower in moderately urban areas than in the urban reference area. Each 1-unit increase in log population density was associated with higher reported intake of whole grains (0.02 ounce equivalents, $P = .03$), potatoes (0.01 cup equivalents, $P = .02$), and added sugar (0.37 tsp, $P = .02$) after adjusting for socioeconomic status and ethnicity.

Conclusion

Differences in reported dietary intake and physical activity level by measures of rurality were small and inconsistent in direction to explain the disparities observed in rural versus urban areas.

Introduction

One in 5 US adolescents are obese, and nationally representative data indicate that adolescent obesity prevalence is increasing (1–3). Overweight and obese adolescents are at risk for continued obesity and for heart disease, diabetes, cancer, and osteoarthritis as adults, and greater weight gain in early adulthood is associated with greater risk (4,5).

Adolescent obesity is a complex issue. Identifying behavioral, social, and environmental causes is imperative for designing effective obesity prevention and treatment strategies. Rural residency, an environmental factor, is associated with increased prevalence of childhood obesity (5–7). A recent meta-analysis of 10 studies examining urban and rural differences in childhood obesity in the United States found that in a pooled population of more than 74,000 children aged 2 to 19 years, children in rural areas had a 26% greater risk of obesity compared with urban children (8). The 2 studies that reported on adolescents aged 10 to 17 years found a similar difference, with adolescents in nonmetropolitan areas having a 28% greater odds of obesity compared with adolescents in metropolitan areas (6,9). No studies of children or adolescents have examined which environmental factors in rural areas contribute to obesity disparities.

Differences in dietary intake and physical activity levels could potentially explain the higher prevalence of obesity in rural versus urban populations. However, a narrative review of 17 studies examining rural–urban differences in the nutrition and physical activity behaviors of children and adolescents noted inconsistent findings, with few studies examining dietary intake and measuring physical activity using accelerometers (10). In addition, there was substantial variation in the way rurality was defined across studies (10).

The aim of this study was to compare the baseline dietary intake and physical activity levels of 9th- and 10th-grade public school students in the Southwest who enrolled in the ACTION PAC (Adolescents Committed to Improvement of Nutrition and Physical Activity) intervention trial, by measures of rurality.

Methods

Study population

We conducted a cross-sectional secondary analysis of baseline data collected from a subset of participants of ACTION PAC, a cluster-randomized, longitudinal trial of an adolescent obesity prevention and management intervention in school-based health centers (ClinicalTrials.gov identifier NCT02502383). Participants with complete data for the variables of interest were included in the analysis.

Adolescents from 8 public high schools in the Southwest were recruited to participate in the ACTION PAC trial. All participating high schools had functioning school-based health centers and similar food and physical activity environments. All high schools had more than 700 students, of whom more than 40% identified as Hispanic. Participant inclusion criteria were being enrolled in 9th or 10th grade at a participating school and having written informed adolescent assent and parental consent to participate in the longitudinal study. Exclusion criteria were 1) having blood pressure in the range of stage 2 hypertension; 2) having diagnosed diabetes; 3) using corticosteroids, antipsychotics, or medications for the treatment of diabetes, hypertension, or hyperlipidemia; 4) being unable to perform moderate-to-vigorous physical activity (MVPA) or not ambulatory; 5) having a score of 20 or more on the Eating Attitudes Test (11); 6) having developmental disorders that affect weight or ability to understand the study procedures or counseling; and 7) being pregnant. The study protocol was approved by the University of New Mexico Health Sciences Center Human Research Protections Office.

Data collection

Data were collected at 2 baseline study visits that occurred 1 week apart. Height was measured by using a portable stadiometer (±0.1 cm; Seca Model 213), and weight was measured with a portable electronic scale (±0.1 kg; Seca Model 770). Weight status was determined according to body mass index percentile (12).

Adolescents reported their intake of foods during the past week via the Block Food Screener for Ages 2–17 (2007 version, NutritionQuest). The Block Food Screener estimates average daily intake of fruit and fruit juice (cup equivalents [CEs]); vegetables excluding potatoes and legumes (CEs); whole grains (ounce equivalents [OEs]); legumes (CEs); dairy (CEs); meat, poultry, and fish (OEs); potatoes (CEs); saturated fat (grams); and added sugar (tsp) (13). Reported dietary intake was compared with the 2015–2020 Dietary Guidelines for Americans Recommended Intakes for age (14–18 years) and sex (14).

Physical activity was measured by using the GENEActiv triaxial accelerometer (Activinsights Ltd) for 7 days and the 3-Day Physical Activity Report (3D PAR) (15). Both tools have been validated in children or adolescents, and participants received instructions before use. The accelerometer records movement in acceleration values by using units of gravity (mG, where 1 mG = 0.00981 m/s^2). An R package (GGIR version 1.5–18) (16–19) was used to reduce accelerometer data to minutes of sedentary and MVPA per day during the hours of 5:00 AM to 11:00 PM. Activity that met the valid wear score generated in GGIR was classified as being sedentary when acceleration was less than 50 mG on average for 60 seconds and as being MVPA when acceleration was above 150 mG. Activity thresholds were chosen on the basis of validation research for the GENEActiv accelerometer (20,21). The 3D PAR was completed for 3 days of the same week, including 1 weekend day and 2 weekdays. Adolescents selected items from 74 predetermined activities or wrote in other activities for every 30-minute block of time between 5:00 AM and midnight (38 total blocks). They also recorded the intensity of the selected activity (light, medium, hard, or very hard) for each block. The blocks were scored by using a standard scoring system (22) that produced total blocks per day spent in MVPA or sedentary activity and total daily metabolic equivalents.

Demographic data, including participant zip code, parental education level, and annual household income, were collected from a health history form completed by the adolescent and parent.

Measures of rurality

There is no universally recognized classification system or definition of rurality. Commonly used delineations include the Rural–Urban Continuum Codes (RUCCs) (23), Rural–Urban

Commuting Area (RUCA) codes (24), and Frontier and Remote Area (FAR) codes (25). This study used both zip code–level RUCA approximation codes developed by the University of Washington Rural Health Research Center (26) and 2010 US Census population density (number of people per square mile) data (25) as measures of rurality.

RUCA codes 1 through 3 are considered metropolitan (urban), codes 4 through 6 are micropolitan, codes 7 through 9 are small town, and code 10 is rural (24). The codes are based on population density, urbanization, and the size and direction of primary daily commuter flow between areas. They are further subdivided on the basis of secondary daily commuter flow size and direction. There is no standard definition or cutoff for population density.

Data analysis

R version 3.4.3 was used for analysis (19). Relationships with RUCA code and population density were tabulated separately, because each captured substantially unique variance. RUCA codes explain about 23% of the variation in log population density. Four RUCA codes were present in the data: 1.0 (metropolitan area core: primary commuting flow within an urbanized area), 2.0 (metropolitan area high commuting: primary flow of ≥30% to an urbanized area), 2.1 (metropolitan area high commuting: secondary flow of 30%–50% to a larger urbanized area), and 10.0 (rural areas: primary commuting flow to a tract outside an urbanized area or urban cluster). Because so few participants were represented in RUCA code 10.0 (n = 3), they were dropped from analysis. The cutoff for rural versus urban population density was set at fewer than 1,000 people per square mile for descriptive analyses (27); the continuous variable log population density was used in all models.

Because measures of rurality were determined at the zip code level, there were multiple respondents per zip code, and multilevel models in which participants were nested within zip code were used for all analyses. For the accelerometer data, 3-level repeated measures models were used (ie, day nested within participant nested within zip code). To account for nonwear of accelerometers, each day was weighted by the proportion of nonwear, and all available data were included in the analysis. To examine the overall relationship between RUCA code and reported dietary intake and physical activity, we conducted 2-degrees-of-freedom log-likelihood (LL) ratio tests, which examine whether the RUCA codes were associated together with each outcome. Two dummy variables represented RUCA codes at the 3 included levels (1.0, 2.0, 2.1), with 1.0 as the reference category. If we found an overall effect of RUCA code, differences in means between the reference category and RUCA codes 2.0 and 2.1 were interpreted. We controlled for socioeconomic status as measured by annual family income (reference group, ≥$20,000 per year) and parental education level (reference group, <high school graduation). A difference in LL ratio test was used to test whether RUCA code contributed to variation in reported dietary intake and physical activity beyond the socioeconomic variables. LL tests for fixed effects were conducted by using maximum likelihood estimation.

Each of the dietary and physical activity outcomes was separately regressed on log population density, alone and then including the socioeconomic variables. In these analyses the hypotheses were assessed directly by the regression parameter for log density and no LL ratio test was needed. Intra-class correlation coefficients were tabulated to describe the extent to which participants' reported dietary intake and physical activity differed within their zip codes or across zip codes. We did not tabulate results on participant weight status, because the design and recruitment methods of the longitudinal trial influenced the prevalence of overweight and obesity; approximately 40% of participants were overweight or obese at baseline by design.

Results

Participant characteristics

Most participants (80%) lived in RUCA code 1.0, identified as Hispanic (86%), and were female (55%) (Table 1). The proportion of Hispanic participants increased with less urban RUCA codes, and the proportion of female participants decreased with less urban RUCA codes. Participants from RUCA code 2.0 (moderately urban) had the highest proportion of annual family income less than $20,000 (54%) and the lowest proportion of parents who were college graduates (8%). Differences using the population density cutoff of 1,000 people per square mile were inconsistent with RUCA code observations; less densely populated areas (<1,000 people/mile^2) had a higher proportion of female participants, a lower proportion of families with income less than $20,000 per year, and a higher proportion of parents who were college graduates.

Overall reported diet quality was poor; 73% to 99% of adolescents reported that they consumed less than the 2015–2020 Dietary Guidelines for Americans sex- and age-specific recommended intake of fruits, vegetables, whole grains, dairy, and legumes. Less than 1% of participants met the recommended intake of legumes, and more participants met the recommendations for fruit than for all other food groups.

Differences in dietary intake and physical activity level by RUCA code

For most dietary intake variables and for blocks of MVPA and sedentary time on the 3D PAR, we found no significant relationship with RUCA code overall (Table 2). We found a significant overall relationship with RUCA code for whole grains (*P* = .02) and minutes per day of MVPA (*P* = .02) and of sedentary time (*P* = .02) as measured by accelerometer. The overall relationship with whole grains did not persist after controlling for family income, parent education level, and ethnicity. As measured by accelerometer, MVPA and sedentary time were 8.71 min/d (*P* = .02) higher and 20.42 min/d (*P* = .02) lower in RUCA code 2.0 than in RUCA code 1.0 after controlling for socioeconomic status and ethnicity. Minutes per day of MVPA and sedentary time for RUCA 2.1 fell in between and were not significantly different from the minutes per day for the other RUCA codes.

Differences in dietary intake and physical activity level by log population density

Each 1-unit increase in log population density was associated with increases in reported intake of whole grains (0.02 OE, *P* = .03), potatoes (0.01 CE, *P* = .02), and added sugar (0.37 tsp, *P* = .02), after adjustment for socioeconomic status and ethnicity (Table 3). We found no significant relationship between other dietary intake variables or any of the physical activity variables and log population density. Overall, intraclass correlation coefficients indicated that more than 98% of the variation in the sample with respect to reported dietary intake and physical activity occurred within zip codes as opposed to between zip codes.

Discussion

Overall, differences in reported dietary intake and physical activity level by RUCA code and log population density were small and not entirely consistent with the hypothesis that differences in dietary intake and physical activity have a prominent role in explaining observed rural versus urban obesity disparities in adolescents. The observed differences mostly persisted after controlling for socioeconomic status and ethnicity, indicating that perhaps other community level access factors were driving the differences. For example, the observed relationships between dietary intake and population density could reflect increased access to grocery stores (whole grains) and fast food restaurants (potatoes, added sugar) in more densely populated areas.

Our finding of a few significant differences in dietary intake by measures of rurality is consistent with a recent narrative review (10). We found little consistency in observed differences in food groups or nutrients by measures of rurality across 5 studies assessing dietary intake in US children or adolescents by measures of rurality (10). In the 3 studies that included adolescents, one found no significant differences in dietary intake between urban and rural adolescents (5). The second study noted a slightly smaller percentage of rural adolescents (12.2%) than urban adolescents (16.5%) who reported consuming 2 or more cups of fruit per day (27), and the third study found that nonmetropolitan and metropolitan black youth consumed fatty snack foods more often than did white metropolitan youth (28).

Our observation that physical activity level was higher with decreasing urbanization is also consistent with a recent narrative review, which found that urban youth were less active than rural youth in 9 of 16 studies examining physical activity levels in US children or adolescents by measures of rurality (10). The only 2 studies to use accelerometers, both conducted by Moore et al, had inconsistent findings, noting that MVPA was higher among urban middle school students than among rural middle school students in the southeastern United States (29) and that MVPA was higher in rural 4th- through 8th-grade girls compared with suburban and urban girls, but not boys, in North Carolina (30). Observed inconsistencies may reflect regional differences in physical activity infrastructure and employment and recreational opportunities for physical activity by measures of rurality or differences in how rurality is defined. In an examination of determinants of physical activity, both rural and urban families expressed the following as barriers: physical distance to activity areas, cost, electronic media, safety concerns, and the need for parental supervision (31). Some of the observed differences in our study could be related to access to electronic media and the internet. Internet connectivity is less reliable and less available in more rural settings and, conversely, ubiquitous in urban settings. This fact is supported by our finding that sedentary time was highest in youth from the most urban areas. We found inconsistent results for physical activity using RUCA codes versus log population density in our analysis.

Our study has several strengths, including a large sample size, the reporting of both dietary intake and physical activity data, and the objective measure of physical activity through the use of accelerometers. Our study also has limitations. First, the development patterns of the western US make it difficult to differentiate between subtle variations in rurality that may affect access to health care and nutrition services and the food and physical activity environment. Research staff members who observed the actual settings were surprised to find little variation in RUCA codes among participants in the study. Almost all of the communities involved were considered metropolitan/urban based on RUCA code, but the most urban community had many grocery stores and fast-food restaurants with easy access to the schools, compared with another community that had only 1 restaurant. Although zip code–level RUCA codes and population density were both used in this study, there are additional measures of rurality, and ours may not reflect differences within the zip code–level RUCA codes. For example, some of the communities involved in the study are health professional shortage areas, while others are not. Findings for RUCA code 2.1 should be interpreted cautiously, because this group included fewer than 50 participants. Dietary intake was assessed by using a food frequency screener, which allowed us to report on a limited set of variables. Use of a full food frequency questionnaire could have provided a more comprehensive, and potentially accurate, picture of dietary intake. Both the food frequency screener and the physical activity record have limitations related to social desirability bias, although we would not expect the magnitude of the bias to vary by measures of rurality. Finally, participants in this study were public school students who chose to participate in a longitudinal obesity prevention and management intervention trial, limiting the generalizability of the results.

Our findings have public health implications. The reported baseline dietary intake of all adolescents in the study was inadequate compared with the Dietary Guidelines for Americans, indicating an ongoing need for nutrition education and for policies that support access to nutritious foods in schools and communities. Given the inconsistent findings related to differences in dietary intake and physical activity in children and adolescents by measures of rurality, additional research is needed to understand the underlying causes of rural–urban obesity disparities. Future research should be conducted with representative rural and urban populations and include standardized, appropriate measures of rurality; comprehensive measures of dietary intake; objective measures of physical activity, such as accelerometers; and assessment of additional environmental and health system factors that could be causing obesity disparities among adolescents.

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Tables

Table 1. Characteristics of Participants, by Measures of Rurality[a], Study of Rural–Urban Differences in Baseline Dietary Intake and Physical Activity Levels Among Adolescents, ACTION PAC Cluster-Randomized Trial

Characteristic	Total (N = 940)	Zip Code–Level RUCA Code[b]			Population Density	
		1.0 (n = 749)	2.0 (n = 144)	2.1 (n = 47)	≥1,000 People/ mile^2 (n = 396)	<1,000 People/ mile^2 (n = 510)
Age, mean (SD), y	15.3 (0.7)	15.4 (0.7)	15.1 (0.7)	15.2 (0.7)	15.5 (0.7)	15.2 (0.7)
Female sex	519 (55)	419 (56)	75 (52)	25 (53)	210 (53)	291 (57)
Hispanic ethnicity	810 (86)	628 (84)	136 (94)	46 (98)	339 (86)	439 (86)
Race[c],						
White	119 (13)	111 (15)	7 (5)	1 (2)	45 (11)	70 (14)
Black	34 (4)	34 (5)	0	0	16 (4)	18 (4)
American Indian	26 (3)	25 (3)	1 (1)	0	18 (5)	7 (1)
Asian	6 (0)	5 (1)	1 (1)	0	5 (1)	1 (0)
Pacific Islander	1 (0)	1 (0)	0	0	1 (0)	0
Multiple	24 (2)	22 (3)	1 (1)	1 (2)	15 (4)	9 (2)
Annual household income[d], $						
<20,000	392 (42)	300 (40)	78 (54)	14 (30)	182 (46)	196 (38)
≥20,000	548 (58)	449 (60)	66 (46)	33 (70)	214 (54)	314 (62)
Parent/guardian education level[e]						
Less than high school graduate	291 (31)	219 (29)	53 (37)	19 (40)	135 (34)	150 (29)
High school graduate or some college	506 (54)	403 (54)	79 (55)	24 (51)	214 (54)	271 (53)
College graduate	143 (15)	127 (17)	12 (8)	4 (9)	47 (12)	89 (18)

Abbreviations: ACTION PAC, Adolescents Committed to Improvement of Nutrition and Physical Activity; RUCA, rural–urban commuting area; SD, standard deviation.

[a] Values are no. (%) unless otherwise indicated.

[b] 1.0 = Metropolitan area core: primary commuting flow within an urbanized area; 2.0 = Metropolitan area high commuting: primary flow 30% or more to an urbanized area; 2.1 = Metropolitan area high commuting: secondary flow 30% to 50% to a larger urbanized area.

[c] Seventy-eight percent of participants selected only an ethnicity.

[d] Four percent of participants had missing data for family income.

[e] One percent of participants had missing data for parent/guardian education level.

Table 2. Differences in Reported Dietary Intake and Physical Activity[a] by Zip Code–Level Rural–Urban Commuting Area (RUCA) Codes, Study of Rural–Urban Differences in Baseline Dietary Intake and Physical Activity Levels Among Adolescents, ACTION PAC Cluster-Randomized Trial

	Unadjusted Results				Adjusted Results							
		Zip Code–Level RUCA Code[b]				Zip Code–Level RUCA Code[b]			Parent Education			
Variable	Intercept (SE)	2.0 (SE)	2.1 (SE)	LL Test[c] (*P* Value)	Intercept (SE)	2.0 (SE)	2.1 (SE)	Annual Household Income <$20,000 (SE)	<High School (SE)	High School Graduate or Some College (SE)	Hispanic (SE)	LL Test[c] (*P* Value)
Dietary intake as estimated by Block Food Screener (N = 940)												
Fruit/fruit juice, CE	1.44 (0.04)	−0.21 (0.10)	−0.02 (0.16)	4.49 (.11)	1.49 (0.12)	−0.21 (0.10)	−0.02 (0.16)	0.07 (0.09)	−0.02 (0.13)	−0.04 (0.11)	−0.09 (0.05)	4.34 (.11)
Vegetables[d], CE	0.72 (0.02)	−0.07 (0.05)	0.08 (0.08)	3.40 (.18)	0.85 (0.06)	−0.05 (0.05)	0.10 (0.08)	−0.03 (0.05)	−0.06 (0.06)	−0.03 (0.06)	−0.09 (0.05)	3.17 (.21)
Legumes, CE	0.14 (0.01)	0.02 (0.02)	0.05 (0.03)	2.69 (.26)	0.11 (0.02)	0.02 (0.02)	0.04 (0.03)	0.01 (0.02)	0.02 (0.02)	0.02 (0.02)	0.04 (0.02)	1.98 (.37)
Whole grains, OE	0.52 (0.02)	−0.11 (0.04)	−0.09 (0.07)	7.47 (.02)	0.61 (0.05)	−0.10 (0.04)	−0.07 (0.07)	−0.05 (0.04)	−0.05 (0.05)	−0.04 (0.05)	−0.02 (0.05)	5.33 (.07)
Meat/poultry/fish, OE	2.73 (0.12)	−0.07 (0.32)	0.55 (0.43)	1.67 (.44)	3.01 (0.29)	−0.02 (0.34)	0.61 (0.45)	−0.02 (0.22)	−0.21 (0.31)	0.04 (0.28)	−0.28 (0.26)	1.87 (.39)
Dairy, CE	1.32 (0.04)	0.06 (0.09)	0.13 (0.15)	1.23 (.54)	1.42 (0.10)	0.08 (0.09)	0.15 (0.15)	−0.08 (0.08)	−0.03 (0.12)	−0.02 (0.10)	−0.03 (0.10)	1.62 (.45)
Potato, CE	0.31 (0.01)	−0.06 (0.03)	−0.04 (0.04)	4.37 (.11)	0.33 (0.03)	−0.05 (0.03)	−0.03 (0.04)	−0.02 (0.02)	0.08 (0.03)	0.07 (0.03)	−0.08 (0.03)	3.55 (.17)
Saturated fat, g	18.31 (0.49)	−0.65 (1.24)	2.24 (1.92)	1.76 (.41)	19.42 (1.34)	−0.47 (1.32)	2.44 (1.96)	−0.75 (1.04)	0.14 (1.48)	0.32 (1.31)	−1.01 (1.24)	1.79 (.41)
Added sugar, tsp	8.36 (0.26)	−1.04 (0.64)	1.03 (1.06)	3.71 (.16)	7.45 (0.75)	−1.17 (0.65)	0.88 (1.06)	0.04 (0.58)	1.45 (0.83)	0.79 (0.74)	0.03 (0.70)	4.34 (.11)
3-Day physical activity record (N = 795)												
Total activity, MET	75.24 (0.68)	2.31 (1.66)	6.00 (2.85)	5.30 (.07)	75.72 (1.49)	2.37 (1.87)	5.84 (2.94)	6.25 (2.87)	−0.62 (2.20)	0.26 (1.96)	6.25 (2.87)	5.50 (.06)
MVPA, 30-min block	5.56 (0.13)	0.26 (0.33)	0.41 (0.56)	1.03 (.60)	5.59 (0.38)	0.26 (0.33)	0.34 (0.60)	0.44 (0.57)	0.11 (0.43)	0.18 (0.39)	0.44 (0.57)	1.10 (.58)
Sedentary, 30-min block	29.41 (0.17)	−0.08 (0.43)	−0.25 (0.64)	0.62 (.92)	29.68 (0.42)	−.004 (0.49)	−0.04 (0.64	−0.24 (0.63)	−0.16 (0.48)	−0.23 (0.42)	−0.24 (0.63)	.15 (.93)
Accelerometer data (N = 891)												
MVPA, min/d	52.61 (1.14)	8.10 (2.85)	3.42 (4.92)	7.59 (.02)	53.71 (3.29)	8.17 (2.87)	3.78 (4.93)	4.65 (2.61)	−5.31 (3.71)	−1.94 (3.29)	−2.10 (.09)	7.71 (.02)
Sedentary, min/d	818.25 (2.79)	−22.13 (7.00)	−6.28 (11.95)	7.70 (.02)	830.46 (7.93)	−20.42 (6.91)	−5.29 (11.90)	−14.17 (6.30)	5.33 (8.95)	−2.52 (7.95)	−3.02 (7.46)	7.62 (.02)

Abbreviations: ACTION PAC, Adolescents Committed to Improvement of Nutrition and Physical Activity; CE, cup equivalent; LL, log-likelihood ratio; MET, metabolic equivalent of task, MVPA, moderate to vigorous physical activity; OE, ounce equivalent; RUCA, rural–urban commuting area; SE, standard error.

[a] Dietary intake was measured by using the Block Food Screener for ages 2–17 (2007 version, NutritionQuest) (13). Physical activity was measured by using the GENEActiv triaxial accelerometer (Activinsights Ltd) for 7 days and the 3-Day Physical Activity Report (3D PAR) (15).

[b] 1.0 = Metropolitan area core: primary commuting flow within an urbanized area (reference group); 2.0 = metropolitan area high commuting: primary flow 30% or more to an urbanized area; 2.1 = metropolitan area high commuting: secondary flow 30% to 50% to a larger urbanized area.

[c] Multilevel models in which participants were nested within zip code were used for all analyses. For the accelerometer data, 3-level repeated measures models with day nested within participant nested within zip code were used. To examine the overall relationship between RUCA code and reported dietary intake and physical activity, 2-degrees-of-freedom LL tests, which examine whether together the 3 RUCA codes predicted each outcome, were used.

[d] Vegetables not including potatoes or legumes.

Table 3. Differences in Reported Dietary Intake and Physical Activity,[a] by Log Population Density, Study of Rural-Urban Differences in Baseline Dietary Intake and Physical Activity Levels Among Adolescents, ACTION PAC Cluster-Randomized Trial

	Unadjusted Results				Adjusted Results						
								Parent Education			
Variable	Intercept (SE)	Log Population Density (SE)	*P* [b]	ICC	Intercept (SE)	Log Population Density (SE)	Family Income <$20K (SE)	<High School (SE)	High School Graduate or Some College (SE)	Hispanic (SE)	*P* [b]
Dietary intake as estimated by Block Food Screener (N = 906)											
Fruit/fruit juice, CE	1.19 (0.14)	0.03 (0.02)	.13	0	1.28 (0.18)	0.03 (0.02)	0.02 (0.09)	−0.01 (0.13)	−0.03 (0.12)	−0.10 (0.11)	.15
Vegetables,[c] CE	0.76 (0.08)	−0.01 (0.01)	.63	0.005	0.87 (0.09)	−0.003 (0.01)	−0.03 (0.05)	−0.07 (0.07)	−0.03 (0.06)	−0.08 (0.06)	.77
Legumes, CE	0.17 (0.03)	−0.01 (0.01)	.33	0.019	0.12 (0.04)	−0.01 (0.01)	0.01 (0.02)	0.02 (0.02)	0.02 (0.02)	0.04 (0.02)	.23
Whole grains, OE	0.38 (0.06)	0.02 (0.01)	.07	0.002	0.47 (0.08)	0.02 (0.01)	−0.06 (0.04)	−0.06 (0.06)	−0.05 (0.05)	−0.03 (0.05)	.03
Meat/ poultry/ fish, OE	2.53 (0.44)	0.04 (0.07)	.56	0.014	2.80 (0.52)	0.04 (0.07)	0.01 (0.23)	.029 (0.23)	−0.01 (0.28)	−0.24 (0.27)	.57
Dairy, CE	1.40 (0.13)	−0.01 (0.02)	.62	0	1.46 (0.16)	−0.01 (0.02)	−0.05 (0.08)	−0.05 (0.12)	−0.04 (0.11)	−0.01 (0.10)	.73
Potato, CE	0.21 (0.04)	0.02 (0.01)	.02	0.002	0.25 (0.05)	0.01 (0.01)	−0.03 (0.02)	.07 (0.03)	0.07 (0.03)	−0.08 (0.03)	.02
Saturated fat, g	16.95 (1.78)	0.23 (0.28)	.42	0.003	17.98 (2.21)	0.24 (0.29)	−0.57 (1.07)	−0.25 (1.05)	0.04 (1.35)	−0.82 (1.26)	.41
Added sugar, tsp	5.77 (0.93)	0.40 (0.15)	.01	0	4.99 (1.16)	0.37 (0.15)	−0.07 (0.60)	1.50 (0.85)	0.85 (0.76)	0.08 (0.71)	.02
3-Day physical activity record (N = 764)											
Total activity, MET	80.81 (2.80)	−0.79 (0.44)	.08	0.007	81.21 (3.34)	−0.83 (0.44)	1.65 (1.60)	−1.34 (2.27)	−0.53 (2.03)	−0.47 (1.92)	.07
MVPA, 30-min block	6.06 (0.56)	−0.07 (0.09)	.41	0.007	6.20 (0.66)	−0.09 (0.09)	0.28 (0.32)	−0.09 (0.45)	0.02 (0.40)	−0.27 (0.38)	.34
Sedentary, 30-min block	29.06 (0.64)	0.05 (0.10)	.60	0.010	29.15 (0.72)	0.07 (0.10)	−0.46 (0.35)	.04 (0.49)	−0.08 (0.44)	0.14 (0.41)	.45
Accelerometer data (N = 860)											
MVPA, min/d	59.78 (4.48)	−0.93 (0.70)	.19	—[d]	59.72 (5.28)	−1.07 (0.69)	4.99 (2.71)	−3.62 (3.83)	−0.33 (3.41)	−1.58 (3.16)	.13
Sedentary, min/d	805.87 (12.09)	1.41 (1.89)	.46	—[d]	817.68 (13.33)	1.91 (1.77)	−13.85 (6.54)	1.56 (9.23)	−6.42 (8.21)	−2.63 (7.61)	.29

Abbreviations: ACTION PAC, Adolescents Committed to Improvement of Nutrition and Physical Activity; CE, cup equivalents; ICC, intraclass correlation coefficient; MET, metabolic equivalent of task; MVPA, moderate to vigorous physical activity; OE, ounce equivalents; SE, standard error.

[a] Dietary intake was measured by using the Block Food Screener for ages 2–17 (2007 version, NutritionQuest) (13). Physical activity was measured by using the GENEActiv triaxial accelerometer (Activinsights Ltd) for 7 days and the 3-Day Physical Activity Report (3D PAR) (15).

[b] Multilevel models in which participants were nested within zip code were used for all analyses. For the accelerometer data, 3-level repeated measures models with day nested within participant nested within zip code were used. In these analyses, the hypotheses were assessed directly by the regression parameter for log density.

[c] Vegetables not including potatoes or legumes.

[d] Because there are multiple ICCs for analyses with 3 levels, we reported the variance components instead. The variance for zip code is 3.44 for MVPA, 749.97 for individual, and 1332.47 for time within individual; for sedentary behavior, the variances are 63.75, 4110.56, and 9298.99, respectively.

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GIS SNAPSHOTS

Diabetes Disparities In Illinois

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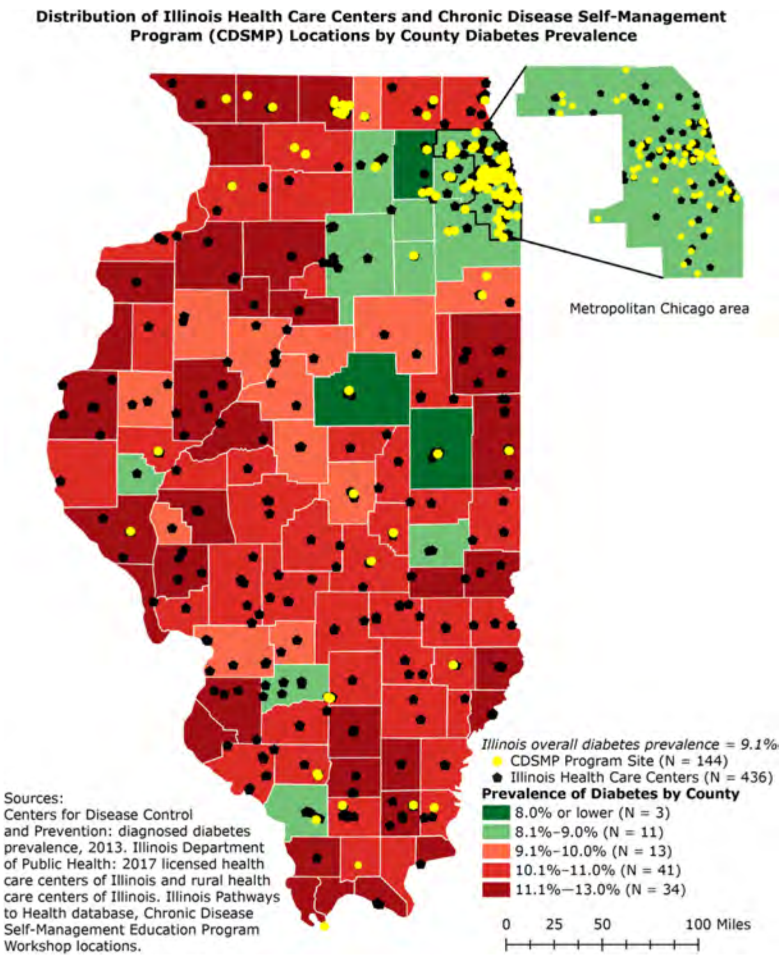

Sources: Centers for Disease Control and Prevention: diagnosed diabetes prevalence, 2013. Illinois Department of Public Health: 2017 licensed health care centers of Illinois and rural health care centers of Illinois. Illinois Pathways to Health database, Chronic Disease Self-Management Education Program Workshop locations.

The map depicts the availability of Chronic Disease Self-Management Program workshops and health care centers in Illinois in relation to diabetes prevalence in each county. County-level diabetes prevalence ranges from 7% to 13%, whereas Illinois diabetes prevalence is 9.1%. Green counties have prevalences below the state rate of 9.1%, and red counties have prevalences at 9.1% or higher. Darker colors represent the lowest and highest rates of diabetes prevalence in Illinois.

Background

Currently, 30.3 million people have diabetes in the United States (1). In 2015, the prevalence of diabetes in Illinois was approximately 9.1% (1). Access to health care centers and health promotion programs are essential in managing diabetes (2). Rural areas are often underserved because they have fewer health care centers (eg, general hospitals, critical access hospitals, rural health centers) (2). Consequently, rural communities have limited opportunities to participate in disease prevention and control programs (2). To address these health disparities, the Administration for Community Living has funded the Illinois Pathways to Health (3) initiative since 2015 to implement evidence-based Chronic Disease Self-Management Programs (CDSMPs) in geographically underserved areas in Illinois. CDSMPs are evidence-based programs recommended by the Centers for Disease Control and Prevention (CDC) to address various chronic diseases (eg, diabetes, heart disease, hypertension, arthritis) (1,2,4,5). Trained facilitators teach participants techniques to manage medicines, improve health literacy, and promote physical activity and nutrition (1,2,4,5). Participation in CDSMPs has been linked to better health outcomes among participants with chronic diseases (2,4,5). Yet, evaluations of program implementation revealed that CDSMPs are most often delivered in urban areas, failing to reach rural counties (2). This map shows geographic differences in diabetes prevalence across Illinois and the associations between diabetes needs and the avail- ability of health care centers and CDSMPs.

Data Sources and Map Logistics

We obtained data displayed in the map from 3 secondary databases and from Illinois Pathways to Health (3), a program coordinated by the research team. Geographic information for the 2017 licensed health care centers of Illinois and rural health care centers of Illinois was retrieved from the Illinois Department of Public Health data portal (6). These Excel (Microsoft Corp) files were combined and represented on the map as Illinois health care centers. Prevalence of diabetes was retrieved from the CDC's diagnosed diabetes prevalence county-level indicator (1), which represents estimates of type 1 and type 2 diabetes prevalence in Illinois per county from 2013. Gestational diabetes was not considered (1). Addresses of the CDSMP workshop sites were obtained from our Illinois Pathways to Health database (3). We geocoded health care centers and CDSMP site addresses in Google Earth Pro (Google), transformed into latitude and longitude points, and then plotted them in ArcMap 10.5.1 (Esri, Inc). The numbers of health care centers and CDSMP workshops in each county were calculated into counts in ArcMap by using a spatial attribute join. We used the counts to test the correlations between the number of health care centers and CDSMP workshops with the prevalence of diabetes per county.

Cook County, the metropolitan area of Chicago, was included in the map analysis, but excluded from the statistical testing because it was an outlier. After excluding Cook County, the Shapiro–Wilks test was used to test for normality in the distribution. The findings showed that none of our variables had a normal distribution (prevalence of diabetes $P = .03$, number of workshops $P < .001$, and number of health care centers $P < .001$). Therefore, the nonparametric Spearman ρ correlation test was used to examine the associations between diabetes prevalence with the number of health care centers and with the number of CDSMP workshops offered per county. All statistical tests were conducted using SPSS Statistics 24 (IBM, Inc).

Highlights

Although the average diabetes prevalence by county in Illinois is 9.1%, diabetes prevalence by county ranged from 7% to 13%. The map represents each county's diabetes prevalence in 5 intervals of above or below and equal to the state rate of 9.1%, (eg, 8.0% or lower, 8.1%–9.0%, 9.1%–10.0%, 10.1%–11.0%, and 11.1% or higher).

After excluding Cook County, the metropolitan area of Chicago, the number of health care centers per county ranged from 1 to 12 and the number of CDSMP workshops per county ranged from 0 to 10. Cook County had 66 health care centers and 80 CDSMP workshops. A significant negative correlation was found between diabetes prevalence and CDSMP workshops offered per county (r_s [98] = −0.242; $P = .02$). However, a significant association was not found between the number of health care centers per county and diabetes prevalence (r_s [98] = −0.001; $P = .99$). Therefore, our findings are that counties with high diabetes prevalence were more likely to have lower access to CDSMP workshops than other counties, while counties with low diabetes prevalence had higher access to CDSMP workshops than other counties.

By neglecting areas with high diabetes prevalence, the allocation of the CDSMP workshops may have spatially widened established health inequalities between rural and urban communities.

Action

This map highlights the need to provide areas that have high diabetes prevalence with access to health care services and chronic disease programs such as CDSMPs. Reaching underserved populations is a problem that needs to be addressed through intentional planning and collaboration among policy makers and communities (2). To facilitate growth of programs in underserved areas, efforts for diversifying community partners will be needed (2). Future efforts should aim to engage nonclinical health partners (eg, senior centers/Area Agencies on Aging, churches, schools, extension offices, recreation centers) in the implementation of CDSMPs (2). Spatial inequalities should be examined when allocating chronic disease programs to avoid increasing the diabetes disparities between well-served and underserved areas in Illinois.

Our study is limited to examining the availability and access of CDSMP workshops rather than inferring that the presence alone lessens the burden of diabetes. Another consideration is that some programs may be less diabetes-specific than others, and therefore, less likely to reduce the prevalence of diabetes. Although diabetes estimates in the study used data on both type 1 and type 2 diabetes diagnoses, type 2 diabetes accounts for about 90% to 95% of diagnosed diabetes cases in adults (1), and we believe this trend was translated in our sample.

This map can be used to inform Illinois policy makers where the needs are being met and where additional resources, like CDSMPs, would be beneficial.

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No copyrighted instruments, figures, surveys, tools, or data were used. Datasets from CDC and the Illinois Department of Public Health were publicly accessible and did not require permission to use.

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ORIGINAL RESEARCH

Assessing the Relationship Between a Composite Score of Urban Park Quality and Health

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Abstract

Introduction

Walkable access to parks, sufficient park acreage, and investments in park and recreation resources are 3 indicators of quality city park systems. Few studies, however, have examined the collective effects of these indicators on public health outcomes.

Methods

Combining 3 nationwide public data sets, this study modeled the relationships between a composite score of urban park system quality effects on physical activity and self-reported health while controlling for demographic and lifestyle variables. Data were obtained from the Centers for Disease Control and Prevention's 500 Cities Project, the Trust for Public Land's City Park Facts Report, and the US Census Bureau.

Results

Regression analyses indicated that the composite park quality score was significantly related to both physical activity levels and physical health across a sample of 59 cities. Higher scores were associated with fewer physically inactive residents but were not significantly associated with better physical health.

Conclusion

Assessing the collective contribution of park access, park acreage, and investment suggests that improvements to a city's composite score may correspond with greater physical activity, but more research is needed to establish the long-term relationships between park system quality and physical health.

Introduction

Use of public parks is associated with many health benefits, including increased physical activity levels, reduced stress, and better self-reported health (1–3). Prior research has established that walkable park access, park availability, and adequate park funding are particularly important contributors to health outcomes (4–6), but these have yet to be tested together empirically. For example, living within walkable access to parks is associated with significantly higher physical activity and park use (7) and better mental health (8). One study also found that psychological sense of community increased as residential distance from the park decreased (9). Therefore, having a park within walking distance can offer multiple health benefits. The amount of available park land and a city's physical park assets are also associated with better physical and mental health outcomes (10). A prior study found that more park acres per capita and higher park density were associated with lower levels of obesity and higher levels of exercise and physical activity (11). Finally, adequate funding is required to provide both this walkable proximity to parks and sufficient acreage, in addition to supporting the in-park amenities, programming, and maintenance that draw users. Financial expenditures on parks and recreation can lead to increases in physical activity and sports participation (12–13).

Because of potential linkages to health, we used the Trust for Public Land's composite measure of access, acreage, and investment, known as ParkScore (14), to test its relationship with physical activity and self-reported health across a sample of US cities. An earlier study (11) examined the individual impact of these indicators on urban health, but their collective impact on health could be even greater. We assessed ParkScore's relationship to city-level physical activity and health while controlling for a range of citywide demographic and lifestyle characteristics.

Methods

Using the 2014 City Park Facts Report (15) from the Trust for Public Land (16), the public health database from the Centers for Disease Control and Prevention (CDC) 500 Cities Project (17), and data from the US Census Bureau, we examined the relationships among walkable park access, spending on parks and recreation, park assets, and public health for 59 cities in the United States.

Data sources

Health outcomes and covariates. The 500 Cities Project (17) from CDC is a nationwide public health project that has produced several free, open-access databases. The data are from the Behavioral Risk Factor Surveillance System (BRFSS), an annual nationwide health survey, and the results have been grouped by city. BRFSS data are typically grouped by metropolitan statistical area (MSA); this project, however, partnered with the Robert Wood Johnson Foundation to aggregate data to the city-boundary level for the 500 largest cities in the United States. Using small area estimation, the individual-level data were aggregated to the city-level. The city-level database includes 27 measures of chronic disease, including obesity, physical health, and physical activity, which are modeled predictions based on samples of BRFSS respondents and weighted based on each city's demographic profile. Additional information on this project can be found online (17). Data for the 500 Cities Project were collected during the 2014 BRFSS. The two outcome variables from BRFSS chosen for this study were the number of days in the last month that residents felt physically unwell, as a measure of physical health (aggregated to proportion reporting >14 days) and proportion of the population getting no leisure-time physical activity. Health variables that served as controls because of their demonstrated relationships with self-reported health were prevalence of smoking and obesity in each city (18,19).

Walkable park access, park acreage, and park and recreation spending. The Trust for Public Land (TPL) releases an annual report on the economic conditions of city park and recreation systems across the country. The City Park Facts Reports are free and available to the public on the TPL website (16). More about how TPL determines city boundaries is also available on the website. We used the 2014 City Park Facts Report (15) to maintain consistency in year with the BRFSS data set. These yearly TPL reports contain many variables describing the assets and spending patterns of the country's 100 largest cities. The predictor variable in this study was ParkScore, a composite measure of park access, park spending, and park acreage created by TPL. TPL calculates a score for each of the 100 largest cities based on specific criteria; scores range from 0–100, with 100 being a perfect score. The ParkScore is the sum of 3 equally weighted scores in 1) access, 2) acreage, and 3) investments and amenities. Access is based on the percentage of the city population living within a 10-minute walk to a park. Acreage includes measures of median park size and parkland as a percentage of city land area. Investment and amenities include measures of spending on parks and recreation per resident and a per capita average of amenities such as basketball hoops, dog parks, playgrounds, and recreation centers. More information on how TPL calculates scores is available elsewhere (20). This composite score enabled us to test the effects of our 3 predictor variables at once, which was important for this sample.

Certain demographic characteristics of each city in the sample were obtained from the Census Bureau's American Community Survey (ACS) for 2014 (21). Race was represented as percentage of the adult population that is black or African American and ethnicity was represented by percentage of the adult population that is Hispanic or Latino. Although not a comprehensive measure of race and ethnicity, these 2 races/ethnicities are the largest minority groups in the United States, are often studied in regard to physical activity and park use (22,23), and experience significant health disparities compared with the white non-Hispanic population (24,25). Median income for the city was obtained from Data USA (26). Finally, education was represented as the percentage of the adult population with a college degree, according to the 2014 ACS. City-wide median income and education level were converted to Z scores and averaged together to create a socioeconomic status (SES) variable. Prevalence of smoking and obesity were expressed as percentage of the adult population in the city who smoke and meet criteria for obesity, respectively.

Analysis

First, descriptive statistics were calculated for sociodemographic characteristics, city population, smoking and obesity prevalence, ParkScore, physical health, and leisure-time physical inactivity (Table 1). Pearson correlations were run to examine the strength of the relationships between outcome and predictor variables. ParkScore as a predictor of physical inactivity and perceived health was then tested using 2 weighted least squares regression models, controlling for city-wide SES, race, ethnicity, smoking rates, and obesity levels. The health outcome variables are already adjusted for age, eliminating the need to control for age with an additional variable; information on age-adjustment procedures is also available (14). Analytic weights were applied to both models to account for variation in the precision of estimates (eg, larger cities construct estimates from larger samples than do smaller cities). Weights were calculated by using the inverse of the standard error of the confidence intervals for estimates of physical inactivity and physical health. All analyses were conducted by using the IBM Statistical Package for the Social Sciences version 24.

Results

Sample characteristics

Of the 500 cities from the CDC data set and 100 cities from the TPL data set, 98 overlapped, and of those, 59 had ParkScores, providing a sample of 59 cities. Those 59 cities represent 31 states and the District of Columbia. Mean ParkScore was 52 (standard deviation [SD] = 13.6). The mean physical inactivity score, representing percentage of the population that gets *no* leisure-time physical activity, was 25% (SD = 5.1%). And the mean physical health score, representing modeled predictions of the proportion of the population who reported feeling physically unwell >14 days over the last month, was 12.8% (SD = 2.4%). Table 1 shows full descriptive statistics.

Correlations were strong between predictor and outcome variables. ParkScore was significantly related to both physical inactivity ($r = -.55$, $P < .001$) and physical health ($r = -.49$, $P < .001$). The negative correlation indicated that higher ParkScores are associated with smaller proportions of the population having no physical activity and a smaller proportion of the population reporting they felt physically unwell >14 days in the last month. Regression models assessed the associations between ParkScore and physical inactivity and physical health. Smoking prevalence was removed from both models, because of problems with multicollinearity (variance inflation factor = 8.34 and 7.79 for physical inactivity and physical health, respectively). When controlling for SES, race, ethnicity, city population, and obesity prevalence, ParkScore significantly predicted physical inactivity ($\beta = -.06$, $t = -2.186$, $P = .033$, $R^2 = .76$) but did not significantly predict physical health ($\beta = -.018$, $t = -1.147$, $P = .257$, $R^2 = .71$) (Tables 2 and 3).

Discussion

Our results illustrate the potential contribution of a quality city park system to physical activity. We found that in cities with robust park systems (as determined by their ParkScores), residents were more engaged in physical activity. For example, residents from cities with higher ParkScores were less likely to be physically inactive, even while controlling for other lifestyle factors, such as SES, race, ethnicity, and obesity. These results are consistent with prior research that looked at park acreage and its impact on obesity and physical activity (11), and our study shows the additional impact of 2 other domains of park capacity, park access and investment, as part of the ParkScore (although the individual contributions of these factors were not assessed in this study).

These results have implications for city governments, park agencies, and park nonprofit organizations. According to our model, if a city increases its ParkScore by 10 points (out of a possible 100 points) while holding all else constant, the percentage of the population getting no leisure-time physical activity could decrease by 0.64%. At a population level, this effect could be quite noticeable. For example, if Atlanta — a city with a 2010 population of 420,003 — increased its 2014 ParkScore of 44 points to 54 points, 2,688 additional people could engage in leisure-time physical activity. Although this study was cross-sectional and therefore did not look at increases directly, it is possible that enhancements made to proximity, acreage, and funding could provide physical activity benefits across these cities.

Limitations

We acknowledge several study limitations. First, our results represent a snapshot in time; all data are from 2014, and therefore causality cannot be determined. Additionally, correlations indicate that 25% of physical health is associated with ParkScore, leaving about 75% of physical health associated with other factors not measured in this study, such as genetics, lifestyle, occupation, or diet. The way physical health was measured in this study may limit its usefulness. The criteria for determining physical health are restrictive, and the range in values within the sample was small compared with other variables in the models. A limited measure of proportion of population feeling unwell for >14 days in the last month may not be the best indicator of physical health in a city. Additionally, physical health may take longer to achieve and be more resistant to change than physical activity. A longitudinal study may be better able to capture the possible effects of park system quality and physical activity on physical health. Finally, a sample size of 59 cities is relatively small.

Despite these limitations, our findings have implications for future research that integrates park capacity data with health data. More effort could be devoted to connecting secondary parks, recreation, and health data, especially from this type of paired data set (27). Given that city-level health data are now available, fulfilling prior promises to connect physical activity and health at more precise levels (27), their use could be expanded. In addition to CDC's 500 Cities Project, more detailed measures of physical activity and health could be incorporated into park assessments and vice versa: park use and leisure-time physical activity items could be incorporated into public health measures. For researchers, the development of the CDC city-level data set is significant, because of its potential to be matched with city-level park excellence data, allowing for a more direct comparison between park metrics and health outcomes.

Future work in this area is encouraged and could become part of a wider research agenda. For instance, in addition to physically active use of parks, social indicators related to park use should not be forgotten in this research agenda. Nor should other chronic disease or public health outcomes be neglected. Additionally, more frequent tracking of public health related to park use at the city level is needed beyond cross-sectional data. For instance, longitudinal studies tracking ParkScore and health outcomes over time would be an interesting, and potentially compelling, examination of the impact of city park systems on chronic disease. Tracking of residents' health and physical activity over time could be paired with changes in their environment, access to parks and recreation resources, and changes in park investment to examine relationships over time.

Conclusion

Given the growth in city populations in recent decades, and projected increases in the future, the relative health of cities' built and natural environments can affect a large portion of the country's population. As such, the contribution of urban parks to sustaining and improving public health is important to demonstrate to park agencies, city officials, and lawmakers. Future research linking park access, acreage, and investment with the prevalence of chronic disease is needed to confirm the importance of each of these indicators (as well as other, more salutogenic, indicators) in relation to other health benefits for urban residents. As cities work to promote health for *all* of their residents, the health contribution of their park systems should not be overlooked.

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Tables

Table 1. Descriptive Statistics, 59 US Cities, 2014

Characteristic	Mean (SD)	Median	Range
Proportion Hispanic[a,b]	26.6 (19.8)	23.3	3.7–79.7
Proportion Black/African American[a]	21.3 (18.3)	16.0	1.2–80.9
Education: bachelor's degree or higher	31.5 (9.8)	29.7	11.8–57.9
Median income, $	53,136 (14,584)	50,721	25,980–105,355
Obesity prevalence[c]	29.9 (5.5)	30.4	15.6–45.2
2010 population	607,256 (929,885)	373,903	204,214–8,175,133
ParkScore[d]	52.2 (13.6)	51.0	26.0–82.0
Physical inactivity[e]	25.0 (5.1)	25.7	13.6–37.6
Physical health[f]	12.8 (2.4)	13.0	7.9–18.4

[a] Percentage of population from 2014 American Community Survey (21) estimates.
[b] Median used for Hispanic population because of its negatively skewed distribution, to avoid extreme values influencing the mean.
[c] Age-adjusted prevalence of obesity in adult population.
[d] Scores range from 0 to 100.
[e] Operationalized as modeled prediction of proportion of the population getting no leisure-time physical activity.
[f] Operationalized as modeled prediction of proportion of the population who reported >14 days physically unwell in the last month.

Table 2. Multiple Regression of ParkScore Predicting Physical Inactivity[a,b], 59 US Cities, 2014

Independent Variable	β (SE)	Standardized β	*P* value
Proportion Hispanic[c]	.08 (.02)	.32	.001
Proportion Black/African American[c]	.08 (.03)	.32	.01
Socioeconomic status[d]	−.95 (.68)	−.18	.17
Obesity prevalence[c]	.34 (.12)	.40	.01
2010 population[e]	.00000062 (.00000026)	.16	.02
ParkScore[f]	−.06 (.03)	−.19	.03

[a] Model summary: $R^2 = .76$, $F(6, 51) = 31.62$, $P < .001$.
[b] Operationalized as modeled prediction of the proportion of the population getting no leisure-time physical activity.
[c] Values range from 0 to 100, representing percentage of the city population.
[d] Average of Z scores for median income and percentage of the city population with a college degree.
[e] Population from 2010 Census.
[f] Scores range from 0 to 100.

Table 3. Multiple Regression of ParkScore Predicting Physical Health[a–c], 59 US Cities, 2014

Independent Variable	β (SE)	Standardized β	*P* value
Proportion Hispanic[d]	.04 (.01)	.29	.01
Proportion Black/African American[d]	.06 (.02)	.49	<.001
Socioeconomic status[e]	−1.55 (.36)	−.60	<.001
Obesity prevalence[d]	−.03 (.05)	−.08	.60
2010 population[f]	.000000147 (.00000015)	.07	.33
ParkScore[c]	−.02 (.02)	−.11	.26

[a] Model summary: $R^2 = .71$, $F(6, 51) = 23.76$, $P < .001$.
[b] Operationalized as modeled prediction of the citywide proportion of the population who reported being physically unwell >14 days in the last month.
[c] Scores range from 0 to 100.
[d] Values range from 0 to 100, representing percentage of the city population.
[e] Average of Z scores for median income and percentage of the city population with a college degree.
[f] Population from 2010 Census.

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ORIGINAL RESEARCH

Perceived Social and Built Environment Correlates of Transportation and Recreation-Only Bicycling Among Adults

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PEER REVIEWED

Abstract

Introduction

Research on perceptions of environmental factors in relation to transportation and recreation bicycling is limited in the United States. We explored the association between perceived social and built environment factors with total, transportation, and recreation bicycling in a sample of adult bicyclists in Austin, Texas, and Birmingham, Alabama. The objective of this study was to examine the relationship between perceived social and built environment factors and domain-specific bicycling in a sample of adult bicyclists.

Methods

Adults aged 18 to 65 who rode a bicycle at least once in the past year completed an internet-based survey that was developed for this study to specifically assess correlates of bicycling; the study was conducted from October 2016 through January 2017. Perceived environmental factors assessed were residential density, traffic safety, destination, connectivity, safety from crime, aesthetics, and bicycle infrastructure. Multivariable logistic regression models were used to estimate the association of each perceived environmental factor (tertile 1, lowest; tertile 3, highest) with recreation-only and transportation bicycling. Effect modification of the relation between environmental factors and bicycling outcomes by sex was also examined.

Results

The final analytic sample size was 801 participants. All environmental factors examined, including residential density, traffic safety, destinations, connectivity, aesthetics, bicycle infrastructure, and safety from crime showed significantly direct associations with transportation bicycling. Traffic safety, destinations, aesthetics, and bicycle infrastructure showed significant direct and inverse associations with recreation-only bicycling. Effect modification by sex was identified with residential density; a significant direct association with recreation-only bicycling was seen among women.

Conclusion

These findings illustrate that bicycling for transportation is associated with different perceived environmental factors than is recreation-only bicycling, with some significant modification by sex. Comprehensive tools that assess the perceived environment for bikeability in the United States are warranted.

Introduction

Bicycling is a physical activity behavior with known benefits to health and well-being (1,2). Bicyclists have a reduced risk of illness and death and improved cardiorespiratory fitness compared with both active and inactive nonbicyclists (2). Most of the US population is insufficiently active (3), but evidence suggests that bicycling is a way for people to meet physical activity guidelines for aerobic activity (4).

Evidence from around the world suggests that factors from multiple levels of the ecologic model (5) are associated with physical activity (6). Relative to the breadth of studies on physical activity in general, few studies have explored ecologic factors associated with bicycling, and those have shown mixed results (7–10). For example, perceived environmental correlates of bicycling in Belgium, where bicycling is common and supporting infrastructure is ubiquitous, differ from those in the United States (11), where the behavior and supporting infrastructure are much rarer (12). These findings suggest that local context plays an important role in these associations.

Additionally, often these studies have relied on assessment tools designed to identify perceived environmental factors related to walking (9,11,13–15). Given the unique nature of these two behaviors, walking and bicycling, it is likely that the factors influencing them vary (11). Evidence from the International Physical Activity and Environment Network project suggests that highly walkable environments may not support transportation bicycling (16).

Another limitation of past research is the lack of bicycling domain specificity — recreation and transportation. Limited research on recreation and transportation bicyclists has shown that different environmental factors are associated with bicycling by domain (17–19). Furthermore, sex has been identified as a potential effect modifier in the association between environmental factors and bicycling behavior by domain (20). The objective of this study was to explore the association between perceived social and built environment factors and domain-specific bicycling in a sample of adult bicyclists.

Methods

Study design

A cross-sectional study was conducted to assess ecological factors and their association with domain-specific bicycling among adults living in Travis County, Texas, and Jefferson County, Alabama. These sites were chosen to attain a wide range of perceived social and built environmental variability. Austin, Texas, located in Travis County, was awarded “gold status” for bicycling-friendliness in 2015 by the League of American Bicyclists (21). In contrast, Birmingham, Alabama, located in Jefferson County, has been identified as one of the worst US cities for bicycling (22).

An internet-based questionnaire was designed specifically for our study. A comprehensive review of the literature was conducted to identify existing instruments that have been used by others for examining correlates of bicycling behavior among adults. Furthermore, focus groups were conducted in Austin, Texas, and Birmingham, Alabama, to determine what factors bicyclists perceive as important for both adopting and maintaining bicycling behaviors. Focus groups were conducted for both transportation and recreation bicyclists, balanced in terms of length of riding, race/ethnicity, age, and sex. Information gleaned from the literature review and focus groups was used to create an initial questionnaire. This questionnaire was pretested in a small convenience sample of cyclists residing in the study areas, and a final version was developed by incorporating necessary revisions based on feedback.

Adult participants were recruited from October 2016 through January 2017 via the internet (Facebook, Reddit, Nextdoor), advertisements and by word of mouth. Recruitment was managed so that there was an equal number (±5%) of participants from the two study sites. People were eligible to participate if they reported living in the study area, were aged 18 to 65, and had ridden a bicycle at least once in the past year.

Data were collected and managed using Research Electronic Data Capture electronic data capture tools (REDCap) (23). REDCap is a secure, web-based application designed to support data capture for research studies. As incentive, participants were put into a drawing to win a $20 gift card. The University of Texas Health Institutional Review Board deemed this pilot study exempt from review.

Study measures

Participants were identified as bicycling for transportation via the question: “In the past year, have you ridden a bicycle specifically for transportation (for example, to get to work, school, or other places)?” Those who answered yes were then asked: “Do you typically ride a bicycle for transportation at least once a month?” Similarly, participants were identified as bicycling for recreation via the question: “In the past year, have you ridden a bicycle specifically for recreation (for example, simply for fun, exercise, or competition)?” Those who answered yes were then asked: “Do you typically ride a bicycle for recreation at least once a month?” For the purposes of this analysis, participants were categorized into 1 of 3 groups (1). People who reported that they typically rode a bicycle for transportation at least once a month were categorized as transportation bicycling (2). Participants who reported they typically rode a bicycle for recreation at least once a month, and not identified as transportation bicycling, were categorized as recreation-only bicycling (3). Participants who reported that they did not typically ride a bicycle for recreation at least once a month, and not identified as transportation bicycling, were categorized as a nonbicycling. The sample size was not sufficient for a fourth category of transportation-only bicycling.

Perceived social and built environmental factors were assessed by using adapted questions from the Abbreviated Neighborhood Environment Walkability Scale (24), which included scales of residential density, destination, connectivity, safety from crime, and aesthetics (Appendix). For the purposes of this study, questions related to connectivity and aesthetics were modified to consider the routes the respondents took while riding a bicycle. Perceived social and built environment were further explored via a composite score of bicycle infrastructure by Handy and colleagues (25), which includes questions about bicycle lanes and street width. Finally, traffic safety was assessed via a composite score of perceived driver behavior based on an index by Handy and colleagues (25) that asked how drivers interact with bicyclists where respondents live.

Demographic variables used to describe the sample and as covariates were age (calculated from date of birth to date of questionnaire completion), sex, race/ethnicity, education, employment status, and household income; these were chosen a priori based on previous literature (10,11).

Statistical analysis

Descriptive statistics were median and interquartile range (IQR) for continuous variables and proportion for categorical and nominal variables. We examined missing data patterns using Little's χ^2 test for missing completely at random. We used multinomial logistic regression models to estimate the association of the perceived environmental variables with transportation and recreation-only bicycling. Nonbicycling was used as the referent for all models. Because of a lack of normality, we categorized perceived environmental variables into tertiles. We calculated the intracluster correlation coefficient (ICC) to assess clustering by study site; a significant ICC ($P < .05$) indicated the need to account for clustering (26).

For all models, we first examined each perceived environmental variable in independent bivariate multinomial logistic regression models. Perceived environmental variables that were significantly associated ($P < .05$) with one of the outcomes were then examined in a multivariable multinomial logistic regression model, adjusting for demographic covariates. Next, we conducted Wald tests for interactions between each perceived environmental variable and sex; a P value of <.15 indicated a significant interaction (26). If a significant interaction was identified, we examined results as a linear combination of coefficients by sex. We assessed collinearity via variance inflation factors (VIF); a VIF less than 10 indicated variable collinearity (27). Final regression estimates are reported as adjusted odds ratios (AOR) with 95% confidence intervals (CIs). Analyses were conducted using STATA version 13.1 (STATA Corporation).

Results

A total of 998 people completed the survey. Missing data were missing completely at random ($P > .05$); thus, a complete case analysis was conducted. The final analytic sample was 801 (80.2%) participants. Fifty-three percent of the participants were from Travis County, Texas, and 47% were from Jefferson County, Alabama. The ICC was significant, so clustering by study site was accounted for in all models.

Overall, participants' median age was 35.5 years; they were primarily male (55.4%), white (83.4%), college educated (highest level undergraduate or graduate, 77.7%), and employed (85.0%) (Table 1). Forty-eight percent reported a household income of $75,000 and above. Fourteen percent were categorized as nonbicycling, 34.0% were categorized as recreation-only bicycling, and 52% were categorized as transportation bicycling. Among those that rode a bicycle for transportation in the past year, 93% reported bicycling for recreation in the past year.

In the bivariate multinomial logistic regression (Table 2), as compared with nonbicycling, at least one level of destination and safety from crime was significantly associated with both recreation-only and transportation bicycling. Traffic safety, residential density, connectivity, and infrastructure were significantly associated with transportation bicycling. Aesthetics was significantly associated with recreation-only bicycling.

The multivariable multinomial logistic regression models, adjusted for demographic variables, for recreation-only and transportation bicycling are reported (Table 3). The VIF indicated that collinearity could be discarded as a concern. The second tertile of perceived traffic safety was significantly associated with recreation-only (AOR = 1.12; 95% CI, 1.05–1.21) and transportation bicycling (AOR = 1.44; 95% CI, 1.37–1.50), but not the third tertile. Higher access to destinations by bicycle was significantly associated with both recreation-only and transportation bicycling; tertile 2 was associated with lower odds (AOR=0.73;95% CI 0.66–0.81) and tertile 3 was associated with higher odds of recreation-only bicycling (AOR = 1.42; 95% CI, 1.07–1.89), whereas both tertiles were associated with higher odds of transportation bicycling (tertile 2, AOR = 2.31; 95% CI, 1.92–2.78; tertile 3, AOR = 6.80; 95% CI, 3.18–14.53). The highest level of connectivity was significantly associated with transportation bicycling (AOR = 2.11; 95% CI, 1.84–2.41). The highest level of aesthetically pleasing routes was significantly associated with both recreation-only (AOR = 1.57; 95% CI, 1.41–1.74) and transportation bicycling (AOR = 1.48; 95% CI, 1.10–1.82). Bicycle infrastructure was associated with recreation-only bicycling at tertile 2 (AOR = 1.03; 95% CI, 1.03–1.04), but not at tertile 3 (AOR = 1.15; 95% CI, 0.67–1.98). The highest level of bicycle infrastructure was significantly associated with transportation bicycling (AOR = 3.45; 95% CI, 1.43–4.18). A higher perceived safety from crime was significantly associated with a higher odds of transportation bicycling (tertile 2, AOR = 2.38; 95% CI, 1.34–4.23), but not at the highest level.

The effects of residential density on the studied bicycling behavior outcomes were modified by sex. As residential density increased, men had significantly higher odds of transportation bicycling (tertile 2, AOR = 4.20; 95% CI, 1.85–9.51; tertile 3, AOR = 2.48; 95% CI, 1.04–5.95). For women, as residential density increased, there were significant higher odds of transportation bicycling (tertile 2, AOR = 3.62; 95% CI, 3.21–4.07; tertile 3, AOR = 3.14; 95% CI, 2.16–4.56); furthermore, the highest tier of residential density was associated with recreation-only bicycling (AOR = 1.06; 95% CI, 1.00–1.12).

Discussion

Our study examined perceived social and built environment factors and their association with recreation-only and transportation bicycling among a sample of bicyclists residing in Jefferson County, Alabama, and Travis County, Texas. The perceived environmental factors found to be significantly associated with bicycling differed by domain. These associations were further examined by sex; significant interactions between sex and perceived environmental variables were identified. The patterns of interaction differed by bicycling domain.

Overall, the perceived environment appeared to be associated more with transportation bicycling, both in terms of strength of the associations and in the number of perceived environment factors significantly associated with the behavior. These findings illustrate that the perceived environment correlates of transportation and recreation-only bicycling differ. Our findings stress that bicycling is not a homogeneous behavior. It is important to consider recreation and transportation bicycling as independent activities, motivated and influenced by different factors.

Differences by bicycling domain were also observed with respect to residential density when examining the potential effect modification of sex on the association between perceived environment variables and bicycling. In our study, residential density was measured as type of housing (ie, single family, apartments) in the participant's neighborhood. Residential density was significantly associated with transportation bicycling for both men and women. In addition, the highest level of residential density had a significant association with recreation-only bicycling among women. Previous research has reported that men are generally more physically active than women and are more likely to be bicyclists (15). The explanations of these differing physical activity behaviors by sex are surely complex and due to multiple factors, but the perceived environment appears to be influential (20). Future research should continue to explore these concepts and how they might differentially affect bicycling among men and women.

Perceived bicycling infrastructure was associated with both recreation-only and transportation bicycling. This builds upon previous evidence of an association between perceived bicycling infrastructure and bicycling in the United States (28). Furthermore, a moderate level of traffic safety was identified as being important for both recreation-only and transportation bicycling, but not at the highest level. Similarly, transportation bicycling was associated with safety from crime at the mid level, but not at the highest level. How these different perceptions of the social and built environment interact and influence bicycling warrants further study.

One of the few other studies to examine the association between environmental perceptions and recreation-only and transportation bicycling was conducted by Heesch, Giles-Corti, and Turrell (10) in a sample of adults aged 40 to 65 residing in Brisbane, Australia (10). The methods used in our study were in part modeled after that study, and the findings seen in our study are largely comparable to what was observed in their sample, in that the perceived environment seemed overall more significantly associated with transportation bicycling than with recreation-only bicycling. However, the patterns of association by domain differed by study. There were notable differences between the ages of the participants and operationalization of the perceived environmental concepts. Despite these differences, findings indicate that country, and even region within a country, is an important consideration for any inquiry into how perceptions of the environment influence physical activity.

Taken together, many of the Neighborhood Environment Walkability Scale (NEWS) variables were associated with bicycling, but the patterns of association were more complex than previously reported. Sallis and colleagues (15) used NEWS to measure associations between perceived environment variables and bicycling frequency in 2 US cities — Baltimore, Maryland, and Seattle, Washington. They found that only one of the NEWS variables, destination, was significantly associated with bicycling frequency (15). One important difference between our work and their study is that theirs did not examine bicycling domains. A large, multicountry study by Kerr and colleagues (16) used NEWS to assess the association between perceived environmental variables and transportation bicycling. That study reported that many perceived built environment factors were significantly associated with engaging in any bicycling over the past week, but that only traffic safety and crime safety were associated with minutes per week of transportation bicycling (16). In comparison, many NEWS-related variables were associated with transportation bicycling in our study.

A notable difference between these previous studies and our current work is that we adapted NEWS to be specifically applicable to bicycling rather than to the more general walkability measures used by Kerr and Sallis (15,16). This may partly explain the differing findings. In all, the results from these studies suggest that measures designed to capture walkability (eg, NEWS) may not be the best suited for understanding the influences of the perceived built environment on bicycling. Future research should focus on developing better measures to capture the construct of bikeability in neighborhoods and routes, considering bicycling domains.

This study had many strengths. We collected bicycling behavior and perceived environment data from a sample of adults from 2 environmentally diverse counties in the United States, thus maximizing the variability of our exposure of interest. Both neighborhood- and route-based measures of the perceived social and built environment were used. This represents an innovation for exploring the potential drivers of bicycling, independent of walking, active travel, or other physical activity. The purposeful identification of both transportation and recreation bicycling behaviors, and the analysis of each independently is also a strength, especially considering the dearth of work examining the factors influencing different bicycling domains.

This study also had limitations. The convenience sample precludes generalizability of findings; caution is necessary in interpreting results. Although using a random sample would have been ideal, there were several challenges associated with this. The lack of a census of adults that had bicycled at least once in the past year in Travis and Jefferson counties made random sampling expensive and logistically complicated. Alternatively, if we had used a random sample of adults regardless of whether they had bicycled or not over the past year, we would be challenged by the low prevalence of transportation bicycling in the United States (approximately 8%) (12), thus requiring an excessively large sample size. Although the sample size overall was robust, small cell sizes influenced the stability of some estimates. The use of self-report supposes inherent risks of information bias (29). Not all items used to measure the perceived environment have been validated for bicycling. Finally, because of the cross-sectional design of the study, causality could not be determined.

Our findings have several implications for practice. First, it is imperative that practitioners target their interventions to a particular domain, while at the same time considering how a particular change may inadvertently affect other bicycling populations outside of their intended target. In addition, it is important to recognize that perceptions of the built environment may differ from what is objectively measured (28). Interventions that strive to increase bicycling behavior should consider not only aspects of the environment that influence bicycling, such as bike lanes, but also how they are perceived by the population. Furthermore, the influence of sex on these perceptions is worth consideration when exploring potential built environment changes.

Among our sample of adult bicyclists, it was evident that perceptions of the social and built environment differed by bicycling domain, recreation and transportation. For some perceived environmental factors, these perceptions further differed for men and women. Future research should consider domain when investigating potential correlates of bicycling, as well as how these factors differentially influence men and women. Future research should aim to have more diverse and representative samples, including representation from racial/ethnic minorities and low-income populations. New, better measures of the perceived environment as it relates to domain-specific bicycling are warranted. For a community to be truly "activity promoting," urban and transportation planning should aim to accommodate both walking and bicycling as well as other physical activities.

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Tables

Table 1. Characteristics of Adult Bicyclists in Travis County, Texas, and Jefferson County, Alabama, October 2016–January 2017

Variable[a]	Total Sample, N = 801	Nonbicycling, n = 113	Recreation-Only Bicycling, n = 271	Transportation Bicycling, n = 417
Demographic Variables				
Age in years, median (interquartile range)	35.5 (16.9)	34.4 (15.2)	41.5 (17.6)	32.9 (14.6)
Sex				
Male	444 (55.4)	30 (26.5)	142 (52.4)	272 (65.2)
Female	357 (44.6)	83 (73.5)	129 (47.6)	145 (34.8)
Race/ethnicity				
White	668 (83.4)	93 (82.3)	231 (85.2)	344 (82.5)
Black	31 (3.9)	6 (5.3)	18 (6.6)	7 (1.7)
Hispanic	46 (5.7)	6 (5.3)	12 (4.4)	28 (6.7)
Other	56 (7.0)	8 (7.1)	10 (3.7)	38 (9.1)
Education				
Less than high school/ high school graduate or equivalent	41 (5.1)	9 (8.0)	13 (4.8)	19 (4.6)
Some college/associates degree	138 (17.2)	17 (15.0)	42 (15.5)	79 (18.9)
Undergraduate degree	353 (44.1)	47 (41.6)	121 (44.7)	185 (44.4)
Graduate degree	269 (33.6)	40 (35.4)	95 (35.1)	134 (32.1)
Employed part-time or full-time				
Yes	681 (85.0)	93 (82.3)	237 (87.4)	351 (84.2)
No	120 (15.0)	20 (17.7)	34 (12.6)	66 (15.8)
Annual household income, $				
< 30,000	132 (16.5)	16 (14.2)	20 (7.4)	96 (23.0)
30,000 to <75,000	282 (35.2)	37 (32.7)	87 (32.1)	158 (37.9)
≥75,000	387 (48.3)	60 (53.1)	164 (60.5)	163 (39.1)
Perceived Environment Variables				
Residential density				
Tertile 1	330 (41.2)	65 (57.5)	148 (54.6)	117 (28.1)
Tertile 2	204 (25.5)	19 (16.8)	60 (22.1)	125 (30.0)
Tertile 3	267 (33.3)	29 (25.7)	63 (23.3)	175 (42.0)
Destination				
Tertile 1	298 (37.2)	55 (48.7)	142 (52.4)	101 (24.2)
Tertile 2	361 (45.1)	49 (43.4)	94 (34.7)	218 (52.3)
Tertile 3	142 (17.7)	9 (8.0)	35 (13.0)	98 (23.5)
Connectivity				
Tertile 1	299 (37.3)	48 (42.5)	116 (42.8)	135 (32.4)
Tertile 2	280 (35.0)	42 (37.2)	101 (37.3)	137 (32.9)
Tertile 3	222 (27.7)	23 (20.4)	54 (19.9)	145 (34.8)

[a] Values are n (%) unless otherwise noted.

(continued on next page)

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Table 1. Characteristics of Adult Bicyclists in Travis County, Texas, and Jefferson County, Alabama, October 2016–January 2017

Variable[a]	Total Sample, N = 801	Nonbicycling, n = 113	Recreation-Only Bicycling, n = 271	Transportation Bicycling, n = 417
Safety from crime				
Tertile 1	233 (29.1)	45 (39.8)	72 (26.6)	116 (27.8)
Tertile 2	221 (27.6)	22 (19.5)	60 (22.1)	139 (33.3)
Tertile 3	347 (43.3)	46 (40.7)	139 (51.3)	162 (38.9)
Aesthetics				
Tertile 1	453 (56.6)	74 (65.5)	145 (53.5)	234 (56.1)
Tertile 2	103 (12.9)	11 (9.7)	36 (13.3)	56 (13.4)
Tertile 3	245 (30.6)	28 (24.8)	90 (33.2)	127 (30.5)
Bicycle infrastructure				
Tertile 1	300 (37.5)	52 (46.0)	122 (45.0)	126 (30.2)
Tertile 2	241 (30.1)	32 (28.3)	75 (27.7)	134 (32.1)
Tertile 3	260 (32.5)	29 (25.7)	74 (27.3)	157 (37.7)
Traffic safety				
Tertile 1	277 (34.6)	42 (37.2)	104 (38.4)	131 (31.4)
Tertile 2	348 (43.5)	43 (38.1)	116 (42.8)	189 (45.3)
Tertile 3	176 (22.0)	28 (24.8)	51 (18.8)	97 (23.3)

[a] Values are n (%) unless otherwise noted.

Table 2. Bivariate Multinomial Logistic Regression Models, Adult Bicyclists (N = 801) in Travis County, Texas, and Jefferson County, Alabama, October 2016–January 2017

Perceived Environment Variable[a]	Recreation-Only Bicycling[b], OR (95% CI)	Transportation Bicycling[b], OR (95% CI)
Residential density		
Tertile 2	1.39 (0.81–2.38)	3.65 (2.33–5.73)[c]
Tertile 3	0.95 (0.69–1.31)	3.35 (1.96–5.73)[c]
Traffic safety		
Tertile 2	1.09 (0.85–1.39)	1.41 (1.25–1.58)[c]
Tertile 3	0.74 (0.42–1.29)	1.11 (0.44–2.83)
Destination		
Tertile 2	0.74 (0.62–0.89)[c]	2.42 (2.31–2.54)[c]
Tertile 3	1.51 (1.11–2.04)[c]	5.93 (2.76–12.76)[c]
Connectivity		
Tertile 2	1.00 (0.90–1.10)	1.16 (1.06–1.27)[c]
Tertile 3	0.97 (0.89–1.06)	2.24 (2.10–2.39)[c]
Aesthetics		
Tertile 2	1.67 (0.70–3.96)	1.61 (0.52–5.01)
Tertile 3	1.64 (1.33–2.02)[c]	1.43 (0.85–2.41)
Infrastructure		
Tertile 2	1.00 (0.93–1.08)	1.73 (0.93–1.08)
Tertile 3	1.09 (0.64–1.84)	2.23 (1.29–3.88)[c]
Safety from crime		
Tertile 2	1.70 (0.72–4.05)	2.45 (1.70–3.53)[c]
Tertile 3	1.89 (1.22–2.92)[c]	1.37 (0.53–3.49)

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

[a] Referent is tertile 1 for all models. Tertile 1 represents the lowest scores for that perceived environmental variable, and tertile 3 represents the highest scores for that variable.

[b] As compared to nonbicycling.

[c] *P* < .05.

Table 3. Multivariable Multinomial Logistic Regression Models, Adult Bicyclists (N = 801) in Travis County, Texas, and Jefferson County, Alabama, October 2016–January 2017

Perceived Environment Variable[a]	Recreation-Only Bicycling[b], AOR (95% CI)	Transportation Bicycling[b], AOR (95% CI)
Residential density[c]		
Men		
Tertile 2	2.13 (0.81–5.60)	4.20 (1.85–9.51)[d]
Tertile 3	1.11 (0.43–2.89)	2.48 (1.04–5.95)[d]
Women		
Tertile 2	1.06 (0.66–1.72)	3.62 (3.21–4.07)[d]
Tertile 3	1.06 (1.00–1.12)[d]	3.14 (2.16–4.56)[d]
Traffic safety		
Tertile 2	1.12 (1.05–1.21)[d]	1.44 (1.37–1.50)[d]
Tertile 3	0.73 (0.45–1.19)	1.10 (0.45–2.70)
Destination		
Tertile 2	0.73 (0.66–0.81)[d]	2.31 (1.92–2.78)[d]
Tertile 3	1.42 (1.07–1.89)[d]	6.80 (3.18–14.53)[d]
Connectivity		
Tertile 2	1.02 (0.81–1.28)	1.05 (0.85–1.29)
Tertile 3	1.07 (0.90–1.27)	2.11 (1.84–2.41)[d]
Aesthetics		
Tertile 2	1.48 (0.48–4.58)	1.54 (0.43–5.57)
Tertile 3	1.57 (1.41–1.74)[d]	1.48 (1.20–1.82)[d]
Infrastructure		
Tertile 2	1.03 (1.03–1.04)[d]	1.61 (0.84–3.10)
Tertile 3	1.15 (0.67–1.98)	3.45 (1.43–4.18)[d]
Safety from crime		
Tertile 2	1.47 (0.56–3.86)	2.38 (1.34–4.23)[d]
Tertile 3	1.52 (0.85–2.71)	1.38 (0.55–3.50)

Abbreviations: AOR, adjusted odds ratio; CI, confidence interval.

[a] Models were adjusted for age, education, income, employment, and race, controlling either for sex or presented as a linear combination by sex. Referent is tertile 1 for all models. Tertile 1 represents the lowest scores for that perceived environmental variable, and tertile 3 represents the highest scores for that variable.

[b] As compared to nonbicycling.

[c] A significant interaction between this perceived built environment variable and sex was observed (Wald test $P < 0.15$). The association of this perceived built environment variable with recreation bicycling are presented as a linear combination of coefficients by sex.

[d] $P < .05$.

Appendix. Questionnaire Items Assessing the Social and Built Environment, Titled by the Variable They Are Measuring, With Information on Scoring

Traffic Safety[a]

What are drivers like where you ride?	Strongly disagree (1)	Some-what disagree (2)	Some-what agree (3)	Strongly agree (4)
TS1. Most drivers seem oblivious to bicyclists (reverse scored)				
TS2. Most drivers yield to bicyclists				
TS3. Most drivers watch for bicyclists at intersections				
TS4. Most people do not drive faster than the speed limit				

[a] Traffic safety scoring: TS = (TS1 + TS2 +TS3 + TS4)/4.

Residential Density

How common are the following housing types in the neighborhood where you live?[a]	None (1)	A few (2)	Some (3)	Most (4)	All (5)
A1. Detached single-family residences					
A2. Townhouses or row houses					
A3. Apartment or condos 1-3 stories					
A4. Apartments or condos 4-6 stories					

[a] Residential scoring: A = A1 + (12 × A2) + (10 × A3) + (25 × A4).

Destination[a]

These questions are about where you can go in the neighborhood where you live. Think of biking distance as within a 10-15 minute bike ride from your home.	Strongly disagree (1)	Somewhat disagree (2)	Somewhat agree (3)	Strongly agree (4)
C1. Stores are within easy biking distance of my home				
C2. There are many places to go within easy biking distance of my home				
C3. It is easy to bike to a transit stop (bus, train) from my home				
C4. Parking my car is difficult in local shopping areas (reverse scored)				

[a] Destination scoring: C = (C1 + C2 + C3 + C4)/4.

Connectivity[a]

Please indicate the answer that best applies to the roads that you ride on.	Strongly disagree (1)	Somewhat disagree (2)	Somewhat agree (3)	Strongly agree (4)
D1. The distance between intersections in my neighborhood is usually short (100 yards or less; the length of a football field or less)				
D2. There are many alternative routes for getting from place to place (I don't have to go the same way every time)				
D3. The streets where I ride do not have many cul-de-sacs (dead-end streets)				
D4. There are major barriers to biking in my local area that make it hard to get from place to place (for example, freeways, railway lines, rivers) (reverse scored)				

[a] Connectivity scoring: D = (D1 + D2 + D3 + D4)/4.

(continued)

Safety From Crime[a]

These questions are about crime in the neighborhood where you live.	Strongly disagree (1)	Somewhat disagree (2)	Somewhat agree (3)	Strongly agree (4)
E1. There is a high crime rate in my neighborhood (reverse scored)				
E2. The crime rate in my neighborhood makes it unsafe to go on bike rides during the day (reverse scored)				
E3. The crime rate in my neighborhood makes it unsafe to go on bike rides at night (reverse scored)				

[a] Safety from crime scoring: E = (E1 + E2 + E3)/3.

Aesthetics[a]

The following questions are about how your regular bike routes look.	Strongly disagree (1)	Somewhat disagree (2)	Somewhat agree (3)	Strongly agree (4)
F1. There are trees along the streets on my bike routes				
F2. There are many interesting things to look at on my bike routes				
F3. There are many attractive natural sights on my bike route (such as landscaping, views)				
F4. There are attractive buildings/homes on my bike route				

[a] Aesthetics scoring: F = (F1 + F2 + F3 + F4) / 4.

Bicycle Infrastructure[a]

These next questions are about how your city is designed for biking.	Strongly disagree (1)	Somewhat disagree (2)	Somewhat agree (3)	Strongly agree (4)
I1. Major streets have bike lanes				
I2. Streets without bike lanes are generally wide enough to bike on				
I3. Store and other destinations have bike racks				
I4. Streets and bike paths are well lighted				
I5. The city has a network of off-street bike paths				
I6. Bike lanes are free of obstacles				
I7. The bike route network has big gaps (reverse scored)				
I8. The area is too hilly for easy biking (reverse scored)				

[a] Bicycle infrastructure scoring: I = (I1 + I2 + I3 +I4 + I5 +I6 + I7 + I8)/8.

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ORIGINAL RESEARCH

Psychosocial and Behavioral Risk Profiles of Cigarette Smokers and E-Cigarette Users Among Adolescents in Minnesota: The 2016 Minnesota Student Survey

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PEER REVIEWED

Abstract

Introduction

Understanding differences in predictors of adolescent cigarette smoking and e-cigarette use can inform public health strategies for preventing and reducing tobacco use among this population. The objective of this study was to examine the association of socioeconomic, psychosocial, and behavioral factors with cigarette smoking and e-cigarette use among adolescents in Minnesota.

Methods

Records (n = 126,868) were used from the 2016 Minnesota Student Survey for prevalence of and factors associated with cigarette smoking and e-cigarette use among students in grades 8, 9, and 11. Logistic regression models were used to estimate risk for smoking cigarettes, using e-cigarettes, or concurrent use of both for key independent variables.

Results

American Indian students were 3.6 times as likely to report smoking cigarettes (OR = 3.57; 95% CI, 3.04–4.19), and 1.7 times as likely to report using e-cigarettes (OR = 1.72; 95% CI, 1.47–2.01) as non-Hispanic white students. Bisexual students were 4 times as likely (adjusted odds ratio [AOR] = 4.40; 95% confidence interval [CI], 4.01–4.82) as heterosexual students to smoke cigarettes and twice as likely (AOR = 2.24; 95% CI, 2.06–2.43) to use e-cigarettes. Students receiving free/reduced lunch were nearly twice as likely (AOR = 1.92; 95% CI, 1.80–2.05) to smoke cigarettes and 1.3 times as likely (AOR = 1.33; 95% CI, 1.27–1.39) to use e-cigarettes. Increasing alcohol use and decreasing academic performance were associated with increasing likelihood of cigarette smoking and e-cigarette use, more so with cigarette smoking.

Conclusion

Results expand on existing research that show differences in psychosocial and behavioral risk factors between adolescent cigarette smokers and adolescent e-cigarette users.

Introduction

E-cigarettes are a type of noncombustible tobacco product designed to allow inhalation of nicotine via vaporization of a nicotine-containing solution (1). Although the health risks of cigarette smoking are well established (2), those of e-cigarettes are largely unknown because e-cigarettes have emerged as a commercially available product in the United States only since 2007 (3). However, both the Centers for Disease Control and Prevention and the Minnesota Department of Health assert that e-cigarette use among adolescents is a health concern (4,5). Rates of cigarette smoking among high school students have trended downward nationally from 15.8% in 2011 to 8.0% in 2016 (6) and in the state of Minnesota among students in grade 9 from 19.6% in 2001 to 4.3% in 2016 (5). However, the rates of e-cigarette use among high school students overall have trended upward nationally, from 1.5% in 2011 to 11.3% in 2016, and as of 2016 was at 17.1% among 11th-grade students in Minnesota (5,6).

A study in 2017 showed that prediction-model factors associated with cigarette smoking differed significantly from factors associated with e-cigarette use among adolescents in the United States (3). Regression models of key psychosocial factors that predicted the risk of adolescents becoming cigarette smokers approximately 75% of the time predicted adolescents becoming e-cigarette smokers only approximately 25% of the time.

Further understanding of potential differences in behavioral factors and other predictors of cigarette smoking and e-cigarette use among adolescents is critical to informing comprehensive pub- lic health strategies targeting prevention and reduction of tobacco use among this population. The objective of this study was to describe the association of key socioeconomic, psychosocial, and behavioral factors with cigarette smoking and e-cigarette use among adolescents in Minnesota.

Methods

Data for this study were sourced entirely from the 2016 Minnesota Student Survey (MSS) data set. The MSS is an anonymous, school-based, cross-sectional survey developed by 4 state agencies: the Department of Education, the Department of Health, the Department of Human Services, and the Department of Public Safety. The survey is administered every 3 years by local school districts (7). Data for the 2016 MSS were provided by public school students in Minnesota via local public school districts, and the data set is managed by the Minnesota Student Survey Interagency Team 2016 (8). The 2016 MSS data set contains 287 variables generated from approximately 112 questions on substance use, sexuality, academic performance, and other health and lifestyle behaviors and factors. The 2016 MSS is representative of 85% of Minnesota school districts (282 of 330) and comprises completed surveys of 168,733 Minnesota public school students across grades 5, 8, 9, and 11 (9). Some questions on the 2016 MSS, including those relating to the use of alcohol, drugs, and tobacco are asked only of students in grades 8, 9, and 11. Inquiry into sexual identity is asked only of students in grades 9 and 11. Because this study focused on cigarette smoking and e-cigarette use, data were analyzed for students in grades 8, 9, and 11 only. Records with missing values for demographic characteristics, targeted psychosocial and behavioral-related questions, or questions on use of cigarettes, e-cigarettes, other tobacco products, or marijuana were excluded from analyses of those topics. After excluding data for students in grade 5, the total number of records analyzed for this study was 126,868. The average age of respondents was 14.8 years (standard deviation, 1.3 y; range, 12 to 19–20 y [categories were whole numbers 12–18, then age 19–20]). Approval for use of the 2016 MSS data set was provided by the Minnesota Student Interagency Team (8) after institutional review board approval from the George Washington University Committee on Human Research.

Variables

For this study, 3 dependent outcome variables were created: current cigarette smokers, current e-cigarette users, and concurrent cigarette smokers and e-cigarette users. Students were categorized as current cigarette smokers if they indicated they had smoked cigarettes at least 1 day in the past 30 days by making any selection other than “0 days” to the question “During the last 30 days, on how many days did you smoke a cigarette?” Students were categorized as current e-cigarette users if they indicated they had used e-cigarettes at least 1 day in the past 30 days by making any selection other than “0 days” to the question “During the last 30 days, on how many days did you use an electronic cigarette (e-cigarette, e-hookah, vaping pen)?” Students were categorized as concurrent cigarette smokers and e-cigarette users if they indicated they had both smoked cigarettes and used e-cigarettes at least 1 day in the past 30 days by making any selection other than “0 days” to both questions on cigarette smoking and e-cigarette use.

Grade level (8, 9, or 11), sex (male or female), and race/ethnicity were assessed for baseline association with cigarette smoking and e-cigarette use outcomes. For race/ethnicity, students were asked 3 questions: “Are you Hispanic or Latino(a)?,” “Are you Somali?,” and “Are you Hmong?” Respondents were allowed to respond yes or no or leave blank (categorized as no response). Additionally, students were asked, “What is your race?” and were allowed to choose 1 or more of the following (or leave blank): American Indian or Alaskan Native, Asian, black, African, or African American, Native Hawaiian or other Pacific Islander, or white. The MSS Interagency Team then compiled these responses into the combined variable of race/ethnicity with the following categories: American Indian non-Hispanic, Asian non-Hispanic, black non-Hispanic, Pacific Islander non-Hispanic, white non-Hispanic, multiple races non-Hispanic, Hispanic, and race/ethnicity missing. Grade, sex, and race/ethnicity were then adjusted for in subsequent analysis of other independent variables because of the potential of these 3 variables as confounders that might be associated with differing cigarette and e-cigarette usage patterns, familiarity, and/or cultural norms. Only the race/ethnicity variable was used in controlling for race/ethnicity in subsequent analysis. Because of large numbers of missing responses to the questions on Hmong and Somali ethnicity, these 2 variables were excluded from the regression analysis.

The following independent socioeconomic, psychosocial, and behavioral indicator variables were analyzed for association with cigarette smoking and e-cigarette use outcomes: sexual identity (heterosexual, bisexual, gay/lesbian, not sure, or questioning), economic hardship (whether students receive free or reduced-price lunch and whether students skipped meals in the past 30 days because their family did not have enough money for food) , alcohol use in the past 30 days (0 days, 1 or 2 days, 3–5 days, 6–9 days, 10–19 days, 20–29 days, all 30 days), and academic performance (mostly As, mostly Bs, mostly Cs, mostly Ds, mostly Fs, mostly incompletes, or none of these letter grades).

Statistical analysis

Frequency analysis was conducted on the dependent variables of current cigarette smoking, e-cigarette use, and concurrent use of both as well as demographic categorical independent variables. To assess for significant association at a .05 level between each dichotomous dependent variable and the demographic, socioeconomic, psychosocial, and behavioral categorical independent variables, χ^2 and Fisher exact test bivariate analyses were conducted.

Frequency and bivariate analyses were conducted by using IBM SPSS Statistics for Macintosh, version 24.0 (IBM Corporation); SAS software (SAS Institute Inc) surveylogistic method was used to conduct multivariate logistical regression analysis for generating odds ratios for risk of smoking cigarettes, e-cigarette use, and concurrent use of both. All independent variables included were demonstrated to be significant at a .05 level in bivariate analyses for association with smoking cigarettes, e-cigarette use, and concurrent use of both. Regression models that included grade, sex, and race/ethnicity only were used to generate baseline odds ratios for cigarette smoking, e-cigarette use, and concurrent use of both. Separate regression models for sexual identity, socioeconomic indicators, academic performance, and alcohol use, each controlling for grade, sex, and race/ethnicity were then used to generate adjusted odds ratios for cigarette smoking, e-cigarette use, and concurrent use of both. Final determination of independent variables used in regression analysis was guided by forward selection as described previously (10) in conjunction with my own interests in factors for investigation.

Small amounts of data were missing from analysis, where no answer was provided by the respondent for one or more control variables of grade, sex, and race/ethnicity, independent variables, and outcome variables. All observations for grade level contained a response. Missing data was less than 1% for sex (n = 373) and race/ethnicity (n = 1,047), 1.2% (n = 1,521) for the question on free or reduced-price lunch, 2.9% (n = 3,714) for the question on skipped meals, 1.6% (n = 1,267) for the question on sexual identity, 4.9% (n = 6,213) for the question on Somali race/ethnicity, 4.6% (n =6,170) for the question on Hmong race/ethnicity, 6.9% (n = 8,763) for the question on alcohol use, 6.9% (n = 8,760) for the question on e-cigarette use, and the 7.0% (n = 8,850) for question on cigarette smoking.

Results

The distribution of female adolescents and male adolescents was similar across grades; of 126,868 students, 49.5% were female, and 50.5% were male (Table 1). Representation of students in grade 8 (35.5%) and grade 9 (35.7%) was similar, whereas 28.8% of students were in grade 11. Across all 3 grades, 1.2% of respondents were American Indian non-Hispanic, 6.0% Asian non-Hispanic, 6.3% black non-Hispanic, 7.4% multiracial, 0.2% Pacific Islander non-Hispanic, and 68.6% white non-Hispanic; 9.5% of respondents were Hispanic, 1.9% Somali, and 2.9% Hmong.

Of 126,868 students, 13,902 (11.0%) reported smoking cigarettes or using e-cigarettes in the past 30 days: 5,816 students (4.6%) reported smoking cigarettes on at least 1 day, 12,101 students (9.5%) reported using e-cigarettes on at least 1 day, 1,801 students (1.4%) reported smoking cigarettes only, 8,086 (6.4%) reported using e-cigarettes only, and 4,015 (3.2%) reported both smoking cigarettes and using e-cigarettes in the past 30 days.

Logistic regression analysis of grade, sex, and race/ethnicity in relation to cigarette smoking, e-cigarette use, and concurrent use of cigarettes and e-cigarettes demonstrated significant association for grade and most races/ethnicities but not for sex (Table 2). Students in grade 11 were 3.5 times as likely to report using e-cigarettes (OR = 3.50; 95% confidence interval [CI], 3.33–3.68) and 3.3 times as likely to report smoking cigarettes (OR = 3.34; 95% CI, 3.11–3.58) in the past 30 days as students in grade 8. American Indian students were 3.6 times as likely to report smoking cigarettes (OR = 3.57; 95% CI, 3.04–4.19), and 1.7 times as likely to report using e-cigarettes (OR = 1.72; 95% CI, 1.47–2.01) as non-Hispanic white students. Asian students were 0.33 times as likely to report smoking cigarettes (OR = 0.33; 95% CI, 0.26–0.41), and 0.47 times as likely to report using e-cigarettes (OR = 0.47; 95% CI, 0.41–0.54) as non-Hispanic white students.

Logistic regression analysis of sexual identity in relation to cigarette smoking, e-cigarette use, and concurrent use of both overall demonstrated significant association, except for gay/lesbian respondents and e-cigarette use (Table 3). Bisexual students were more than 4 times as likely (adjusted OR [AOR] = 4.40; 95% CI, 4.01–4.82) as heterosexual students to smoke cigarettes but only twice as likely (AOR = 2.24; 95% CI, 2.06–2.43) to use e-cigarettes.

Logistic regression analysis of students who reported receiving free or reduced-price lunch at school or skipping meals because of economic hardship was significantly associated with increased likelihood of cigarette smoking, e-cigarette use, and concurrent use of both (Table 3). Students receiving free or reduced-price lunch were nearly twice as likely (AOR = 1.92; 95% CI, 1.80–2.05) to smoke cigarettes but only 1.33 times as likely (AOR = 1.33; 95% CI, 1.27–1.39) to use e-cigarettes as students not receiving such lunch. Students reporting skipping meals were more than 3.5 times as likely (AOR = 3.63; 95% CI, 3.33–3.95) to smoke cigarettes but only 2.79 times as likely (AOR = 2.79; 95% CI, 2.59–2.99) to use e-cigarettes as students not skipping meals.

Logistic regression analysis demonstrated significant association between academic performance and cigarette smoking, e-cigarette use, and concurrent use of both (Table 3). Students reporting mostly Bs were more than twice as likely (AOR = 2.47; 95% CI, 2.25–2.7) to have smoked cigarettes in the past 30 days and nearly twice as likely (AOR = 1.91; 95% CI, 1.80–2.01) to have used e-cigarettes in the past 30 days as students reporting that they receive mostly As. Students reporting mostly Fs were 8 times as likely (AOR = 8.08; 95% CI, 6.81–9.59) to smoke cigarettes but only 3.64 times as likely (AOR = 3.64; 95% CI, 3.16–4.19) to use e-cigarettes as students reporting mostly As.

Logistic regression analysis yielded significant association levels of alcohol use and cigarette smoking, e-cigarette use and concurrent use of both, demonstrating the highest odds ratios, compared with any variable analyzed for this study, for each category of alcohol use, even at the lowest level of 1 or 2 days (Table 3). The odds ratios for concurrent cigarette and e-cigarette use were larger across all categories of alcohol use than for cigarette smoking and e-cigarette use alone. Odds ratios for 1 or 2 days of drinking were similar for cigarettes (AOR = 9.79; 95% CI, 9.08–10.56) and e-cigarettes (AOR = 9.25; CI 95% 8.78, 9.75) but higher for concurrent cigarette and e-cigarette use (AOR = 11.3; 95% CI 10.3–12.4). Odds ratios increased more steeply at higher levels of alcohol use for cigarette smoking than for e-cigarette use.

Discussion

Although the potential health harms of e-cigarettes are under study and yet largely unknown (3), investigation into patterns of e-cigarette use among adolescents, particularly when patterns diverge from those of cigarette smoking among adolescents, is an important priority for public health agencies. The Centers for Disease Control and Prevention and other public health agencies consider e-cigarette use among adolescents a public health concern (5,6), and one goal of Healthy People 2020 is the reduction of tobacco use among adolescents (11). Additionally, although e-cigarettes contain no tobacco, they are regulated by the US Food and Drug Administration as tobacco products because of their nicotine content (12).

This study adds to research (3) highlighting significant differences in psychosocial and behavioral risk factors predicting cigarette smoking and e-cigarette use among adolescents. This analysis showed significant associations between independent variables (sexual identity, socioeconomic indicators, alcohol use, and academic performance) and the outcomes of cigarette smoking and e-cigarette use. It also suggests that differences exist in the magnitude of risk for cigarette smoking or e-cigarette use for some categories of sexual identity, economic status, school performance, and alcohol use. For example, bisexual students, students reporting mostly Fs, and students reporting alcohol use 10 or more days in the past 30 days were at least twice as likely to smoke cigarettes as e-cigarettes. Further analysis should test these differences. Also of interest was that although in this sample of adolescents in Minnesota the prevalence of cigarette smoking (4.6%) was approximately half that of e-cigarette use (9.5%), the odds ratios for cigarette smoking were greater than for e-cigarette use across all categories of the independent variables analyzed. Ideally, further research will shed more light on the various risk factors for cigarette smoking and e-cigarette use among adolescents as well as on the health risks of e-cigarette use among this population. Such research would allow public health practitioners to more effectively target tobacco-reduction interventions by differentiating between cigarette smokers and e-cigarette users and determining which group may be at higher risk for harmful health outcomes.

This study has numerous limitations and opportunities for further analysis. One limitation was the extent of missing data. Missing data for demographic, independent, and outcome variables ranged from less than 1% for the question on sex (n = 373) to 6.9% (n = 8,760) for using e-cigarettes and 7.0% (n = 8,850) for cigarette smoking. For a sample size of 126,868, these are relatively small amounts. However, when comparing these numbers to the numbers of students who reported smoking (n = 5,816 or 4.6%) or using e-cigarettes (n = 12,101 or 9.5%), the extent of missing data is more relevant. Additionally, given that Minnesota is home to an estimated 40,000 people of Somali origin (13), 70,000 people of Hmong ethnicity (13), and 288,000 people of Hispanic or Latino ethnicity (13), having further insight into patterns of tobacco use among adolescents in these populations would be valuable to public health practitioners. If time had permitted, I would have conducted a more in-depth and systematic investigation into the reasons for missing data and how to account for them.

Another limitation of this study is use of a single cross-sectional survey. Given further time and a more robust study design, it would be worth conducting regression analyses separately across multiple years of the MSS. One opportunity for a more robust analysis of the MSS data set would be an investigation into the increased prevalence of cigarette smoking and e-cigarette use with each successive grade level. This investigation would include running separate regression analyses by grade rather than controlling for grade as well as developing an all-inclusive regression model for all variables.

One strength of this study is having used the MSS. Although studies of data from the National Youth Tobacco Survey (14) and the Minnesota Youth Tobacco Survey (15) provide a more robust inquiry into the home, environment, and exposure characteristics of adolescent smokers, both surveys have smaller sample sizes (20,675 in 2016 and 4,243 in 2014, respectively) that limit utility of extracting data on racial/ethnic and geographic characteristics (16,17). The larger sample size of the MSS potentially allows for a more robust analysis of racial/ethnic and geographic characteristics and an inquiry into a broader range of socioeconomic and behaviors.

This study adds to research indicating that socioeconomic and behavioral risk factors differ between students who smoke cigarettes and students who use e-cigarettes, further suggesting that public health outreach programs to reduce tobacco use among adolescents may need to differ in methods and messages, with program choices depending on the risk factors of the target audience and whether the goal is to reduce cigarette smoking or reduce e-cigarette use.

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Tables

Table 1. Prevalence of Cigarette Smoking and E-Cigarette Use in the Past 30 Days, by Selected Demographic, Socioeconomic and Behavioral Characteristics Among Adolescents in Minnesota (N = 126,868), Minnesota Student Survey, 2016[a]

Variable	Total, No. (%) (N = 126,868)	Cigarettes, No. (%) (n = 5,816)	E-Cigarettes, No. (%) (n = 12,101)	Both Cigarettes and E-Cigarettes, No. (%) (n =4,015)
Grade level				
Grade 8	44,983 (35.5)	1,176 (20.2)	2,412 (19.9)	776 (19.3)
Grade 9	45,309 (35.7)	1,787 (30.7)	3,891 (32.2)	1,236 (30.8)
Grade 11	35,576 (28.8)	2,853 (49.1)	5,798 (47.9)	2,003 (49.9)
Sex				
Male	63,818 (50.5)	2,738 (47.1)	6,328 (52.3)	1,976 (49.2)
Female	62,677 (49.5)	3,064 (52.7)	5,747 (47.5)	2,030 (50.6)
Race/ethnicity[b]				
American Indian	1,516 (1.2)	188 (3.2)	203 (1.7)	104 (2.6)
Asian	7,551 (6.0)	128 (2.2)	361 (3.0)	89 (2.2)
Black	8,052 (6.3)	213 (3.7)	488 (4.0)	149 (3.7)
Hispanic	12,040 (9.5)	652 (11.2)	1,402 (11.6)	451 (11.2)
Multiple races	9,372 (7.4)	640 (11.0)	1,196 (9.9)	439 (10.9)
Pacific Islander	207 (0.2)	14 (0.2)	25 (0.2)	11 (0.3)
White	87,083 (68.6)	3,949 (67.9)	8,351 (69.0)	2,747 (68.4)
Somali[c]	2,406 (1.9)	88 (1.5)	137 (1.1)	71 (1.8)
Hmong[c]	3,631 (2.9)	92 (1.6)	213 (1.8)	65 (1.6)
Sexual identity[d]				
Heterosexual	72,305 (89.7)	3,506 (76.3)	8,256 (85.9)	2,462 (76.7)
Bisexual	4,014 (5.0)	727 (15.8)	860 (9.0)	502 (15.6)
Gay or lesbian	1,027 (1.3)	128 (2.8)	167 (1.7)	85 (2.7)
Not sure or questioning	3,272 (4.1)	233 (5.1)	324 (3.4)	160 (5.0)
Economic status				
Receives free or reduced-price lunch	35,663 (28.5)	2,344 (40.5)	3906 (32.4)	1564 (39.2)
In past 30 days, skipped meals because family did not have enough money to buy food	5,700 (4.6)	866 (15.0)	1,269 (10.5)	620 (15.6)
Grades reported[e]				
Mostly As	54914 (43.8)	763 (13.3)	2,515 (21.1)	484 (12.2)
Mostly Bs	43,702 (34.9)	1,910 (33.3)	4,576 (38.3)	1,307 (33.0)
Mostly Cs	19,125 (15.3)	1,865 (32.5)	3,245 (27.2)	1,330 (33.5)

[a] Numbers do not total expected value because of missing data. Percentages are based on n's in column head.
[b] All categories are non-Hispanic, except Hispanic.
[c] Somali and Hmong race/ethnicity asked about as a yes-or-no question separately from the question on race.
[d] Sexual identity inquired of grades 9 and 11 only.
[e] Numbers may not total expected value because of a small number of responses of "mostly incompletes" or "none of these letter grades."

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Table 1. Prevalence of Cigarette Smoking and E-Cigarette Use in the Past 30 Days, by Selected Demographic, Socioeconomic and Behavioral Characteristics Among Adolescents in Minnesota (N = 126,868), Minnesota Student Survey, 2016[a]

Variable	Total, No. (%) (N = 126,868)	Cigarettes, No. (%) (n = 5,816)	E-Cigarettes, No. (%) (n = 12,101)	Both Cigarettes and E-Cigarettes, No. (%) (n =4,015)
Mostly Ds	4,483 (3.6)	682 (11.9)	982 (8.2)	486 (12.3)
Mostly Fs	1,716 (1.4)	354 (6.2)	420 (3.52)	238 (6.0)
No. of days of alcohol use in past 30 days				
0	101,737 (86.1)	1,777 (30.8)	4,946 (41.2)	1,010 (25.4)
1 or 2	9,931 (8.4)	1,612 (28.0)	3,416 (28.5)	1,096 (27.5)
3–5	3,519 (3.0)	1,062 (18.4)	1,838 (15.3)	824 (20.7)
6–9	1,613 (1.4)	663 (11.5)	1,002 (8.4)	522 (13.1)
10–19	811 (0.7)	441 (7.7)	537 (4.5)	357 (9.0)
20–29	205 (0.2)	111 (1.9)	129 (1.1)	90 (2.3)
All 30	289 (0.2)	102 (1.8)	130 (1.1)	83 (2.1)

[a] Numbers do not total expected value because of missing data. Percentages are based on n's in column head.
[b] All categories are non-Hispanic, except Hispanic.
[c] Somali and Hmong race/ethnicity asked about as a yes-or-no question separately from the question on race.
[d] Sexual identity inquired of grades 9 and 11 only.
[e] Numbers may not total expected value because of a small number of responses of "mostly incompletes" or "none of these letter grades."

Table 2. Crude Odds Ratios for Cigarette Smoking and E-Cigarette Use in the Past 30 Days, by Selected Demographic Characteristics Among Adolescents in Minnesota (N = 126,868), Minnesota Student Survey, 2016

Demographic Characteristic	Cigarettes		E-cigarettes		Both Cigarettes and E-Cigarettes	
	Crude OR[a] (95% CI)	*P* Value[b]	Crude OR[a] (95% CI)	*P* Value[b]	Crude OR[a] (95% CI)	*P* Value[b]
Grade level						
Grade 8	1.0 [Reference]	NA	1.0 [Reference]	NA	1.0 [Reference]	NA
Grade 9	1.58 (1.46–1.70)	<.001	1.71 (1.62–1.80)	<.001	1.64 (1.50–1.80)	<.001
Grade 11	3.34 (3.11–3.58)	<.001	3.50 (3.33–3.68)	<.001	3.47 (3.19–3.77)	<.001
Sex[c]						
Male	1.0 [Reference]	NA	1.0 [Reference]	NA	1.0 [Reference]	NA
Female	1.11 (1.01–1.17)	.80	0.88 (0.84–0.91)	.42	1.01 (0.95–1.08)	.97
Race/ethnicity[d]						
American Indian	3.57 (3.04–4.19)	<.001	1.72 (1.47–2.01)	<.001	2.65 (2.15–3.26)	<.001
Asian	0.33 (0.26–0.41)	<.001	0.47 (0.41–0.54)	<.001	0.33 (0.25–0.43)	<.001
Black	0.67 (0.57–0.72)	<.001	0.81 (0.73–0.91)	<.001	0.64 (0.52–0.78)	<.001
Hispanic	1.37 (1.25–1.49)	.001	1.45 (1.37–1.55)	<.001	1.36 (1.23–1.51)	.003
Multiple races	1.74 (1.60–1.90)	<.001	1.59 (1.49–1.70)	<.001	1.70 (1.53–1.89)	<.001
Pacific Islander	1.72 (0.98–3.01)	.09	1.47 (0.94–2.30)	.15	1.94 (1.03–3.63)	.05
White	1.0 [Reference]	NA	1.0 [Reference]	NA	1.0 [Reference]	NA
Somali[e]	1.40 (1.07–1.83)	.007	0.93 (0.76–1.15)	.43	1.68 (1.24–2.28)	<.001
Hmong[e]	1.43 (1.07–1.90)	.09	1.15 (0.95–1.40	.14	1.47 (1.05–2.05)	.14

Abbreviations: CI, confidence interval; NA, not applicable; OR, odds ratio.

[a] Crude ORs calculated by using a logistic regression model for grade, sex, and race/ethnicity.

[b] Significant at *P* = .05.

[c] Numbers do not total expected value because of a small portion of responses of “no answer” to the question, “what is your biological sex?”

[d] All categories are non-Hispanic, except Hispanic. Percentages for racial or ethnic categories of American Indian, Asian, black, Hispanic, multiple races, Pacific Islander, and white do not total 100 because of a small portion of responses of “no answer.”

[e] Somali and Hmong race/ethnicity asked about as a yes-or-no question separately from the question on race; reference group for each is “no response.”

Table 3. Adjusted Odds Ratios for Cigarette Smoking and E-Cigarette Use in the Past 30 Days, by Selected Socioeconomic and Behavioral Characteristics Among Adolescents in Minnesota (N = 126,868), Minnesota Student Survey, 2016

Risk Factor	Cigarettes		E-Cigarettes		Both Cigarettes and E-Cigarettes	
	Adjusted OR[a] (95% CI)	*P* Value[b]	Adjusted OR[a] (95% CI)	*P* Value[b]	Adjusted OR[a] (95% CI)	*P* Value[b]
Sexual identity[c]						
Heterosexual (straight)	1.0 [Reference]	NA	1.0 [Reference]	NA	1.0 [Reference]	NA
Bisexual	4.40 (4.01–4.82)	<.001	2.24 (2.06–2.43)	<.001	4.22 (3.79–4.69)	<.001
Gay/lesbian	2.75 (2.27–3.34)	.001	1.48 (1.24–1.76)	.19	2.52 (2.00–3.17)	.03
Economic status[d]						
Receives free or reduced-price lunch	1.92 (1.80–2.05)	<.001	1.33 (1.27–1.39)	<.001	1.77 (1.64–1.91)	<.001
In last 30 days, skipped meals because family did not have enough money to buy food	3.63 (3.33–3.95)	<.001	2.79 (2.59–2.99)	<.001	3.70 (3.35–4.08)	<.001
Grades reported						
Mostly As	1.0 [Reference]	NA	1.0 [Reference]	NA	1.0 [Reference]	NA
Mostly Bs	2.47 (2.25–2.70)	<.001	1.91 (1.80–2.01)	<.001	2.63 (2.35–2.94)	<.001
Mostly Cs	4.58 (4.14–5.07)	<.001	2.75 (2.58–2.94)	<.001	4.93 (4.36–5.58)	<.001
Mostly Ds	5.89 (5.16–6.72)	<.001	3.10 (2.81–3.41)	<.001	6.11 (5.24–7.14)	<.001
Mostly Fs	8.08 (6.81–9.59)	<.001	3.64 (3.16–4.19)	<.001	7.42 (6.08–9.06)	<.001
No. of days of alcohol use in past 30 days						
0	1.0 [Reference]	NA	1.0 [Reference]	NA	1.0 [Reference]	NA
1 or 2	9.79 (9.08–10.6)	<.001	9.25 (8.78–9.75)	<.001	11.3 (10.3–12.4)	<.001
3–5	21.5 (19.6–23.5)	.01	18.7 (17.3–20.1)	<.001	27.4 (24.7–30.5)	<.001
6–9	34.5 (30.7–38.7)	<.001	27.5 (24.7–30.7)	<.001	42.5 (37.3–48.3)	<.001
10–19	61.6 (52.9–71.7)	<.001	34.4 (29.5–40.2)	<.001	72.0 (61.4–84.3)	<.001
20–29	68.4 (50.8–92.0)	<.001	34.3 (25.2–46.8)	<.001	78.7 (58.5–106.0)	<.001
All 30	31.2 (24.0–40.6)	<.001	15.2 (11.8–19.7)	.33	40.0 (30.3–52.7)	<.001

Abbreviations: CI, confidence interval; NA, not applicable; OR, odds ratio.

[a] Adjusted ORs calculated by using a logistic regression model adjusted for grade, sex, and race/ethnicity.

[b] Significant at *P* = .05.

[c] Sexual identity inquired of grades 9 and 11 only.

[d] Reference group is students who responded no.

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ORIGINAL RESEARCH

Self-Efficacy and Adherence Behaviors in Rheumatoid Arthritis Patients

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PEER REVIEWED

Abstract

Introduction

Rheumatoid arthritis (RA) is a common disease that requires patient self-management with chronic medications. Adherence rates for RA medications are suboptimal. This study explores medication adherence and self-efficacy behaviors among RA patients.

Methods

We conducted a qualitative study comprising focus groups and individual interviews. Nineteen participants were recruited and screened to participate in three 90-minute focus groups (n = 13) and six 60-minute individual interviews. We created and maintained a codebook to analyze data. Interviews were analyzed by using NViVo qualitative analysis software.

Results

Key points in participant interviews were 1) self-efficacy as influenced by the ability to establish routines, and having an understanding relationship with their healthcare provider; 2) self-efficacy to adjust medications depended on having permission from providers to adjust medications, perceptions of the effectiveness of medications, and confidence in self-knowledge to make appropriate adjustments; and 3) changes in self-efficacy over time were influenced by initial denial and later acceptance of the diagnosis. Participant interviews revealed that medication adherence is a spectrum that ranges from adherent to nonadherent.

Conclusion

Participants' experience with RA medications revealed varied underlying reasons for adherence behaviors. Recognizing adherence as a dynamic behavior has important implications for how adherence interventions are designed. For example, participants reported adjusting medications in response to the unpredictable nature of RA. Interventions could collect information about RA symptoms and be tailored to provide adherence support at times when patients need it most. The importance of self-efficacy in influencing participants' adherence behaviors is an area for continuing research among patients and providers.

Introduction

Rheumatoid arthritis (RA) patients rely on fast-acting NSAIDs (nonsteroidal anti-inflammatory drugs) to reduce inflammation and slow-acting DMARDs (disease-modifying antirheumatic drugs) to delay disease progression (1). Although overall adherence to chronic disease medications is approximately 50% (2), RA studies report adherence rates ranging from 30% to 80% (3).

Medication adherence is the extent to which patients start and persist with prescribed regimens (2,4). Deviations from this protocol constitute nonadherence (5,6). No standardized guide exists for management of RA pain, which varies between patients (3). In response, some patients adjust dosages of prescribed medications to control pain and flare-ups. Characterization of this behavior is absent from the existing literature (3,7).

Barriers to realizing proper adherence can readily mount and decrease an individual's perception of their ability to adhere (2,8). Self-efficacy is the individual's belief in their ability to complete specific tasks. Self-efficacy is associated with health-promoting behaviors, such as improving communication with providers (9), engaging in recommended health behaviors (10–12), and adjusting to illness and treatments (13,14). This article operationalizes self-efficacy as an individual's belief in their ability to follow prescribed medication regimens to achieve improved health outcomes (15).

Although several RA studies have evaluated the relationship between self-efficacy and various social factors (1,8,16–18), few have considered how self-efficacy affects medication adherence (1,19). The primary objective of this study was to examine the association between self-efficacy and medication-taking behaviors in RA patients. The secondary objective included investigating RA patients' experience with taking medications, a rare perspective in existing studies.

Methods

A research company recruited participants who self-identified as RA patients and resided in Durham, North Carolina. Focus group participants received a $75 gift card. Flyers were posted in Durham RA clinics to recruit for individual interviews. Interviewees received a $35 gift card.

Participants were included if aged between 18 and 75 years, diagnosed with RA for at least 6 months, currently taking RA medications, and had seen a medical doctor for RA in the past 18 months. Female participants were excluded if pregnant, breastfeeding, or planning to become pregnant within 1 year. Participants were selected to ensure representation by age, gender, ethnicity, length of RA diagnosis, and self-perceived level of adherence. Focus groups presented opportunities for discussion about adherence and medication-taking behavior. Individual interviews were conducted to probe participants' responses without group dynamic influence.

Two 90-minute focus groups were held in November and December of 2017, respectively. Later, a third focus group (January 2018) and six 60-minute individual interviews (January and February 2018) were conducted. Focus groups and individual interviews were conducted by using a guide (Table 1) shaped by the Health Belief Model (HBM) (20) and developed by multidisciplinary experts in the fields of marketing, psychology, and health services research.

A codebook was developed a priori based on research themes. Research analysts sequentially coded the transcripts through a rotational system of primary, secondary, and tertiary reviewers by using NViVo 10 (QSR International Pty Ltd, Version 10). Duke University Institutional Review Board approved this study (IRB # 2018–0156).

Results

Three focus groups (n = 13) and 6 individual interviews were conducted between November 2017 and February 2018, for a study total of 19 participants. Participants were aged from 18 to 70 years (average age 45 years [SD = 14.8]). Six participants (30%) were male. The average self-reported impact of RA was 4.25 (SD = 1.25) on a scale of 1 to 7 with 1 = no impact and 7 = extreme impact. Most participants (65%) held or were pursuing a bachelor's degree or higher and most (75%) received health insurance through their employer. Participants' self-reported adherence levels were measured on a scale of 1 to 5, with the average reported adherence level at 4.35 (SD = 0.72). Table 2 further details participant characteristics. Table 3 lists medications participants were prescribed, but does not represent all medications available to RA patients.

Participant responses presented self-efficacy as an outcome influenced by participants' beliefs in the necessity of medication and in the patient–provider relationship. Two types of self-efficacy were most evident in affecting participants' adherence: confidence in their ability to manage medication and confidence to make adjustments to medication dosages.

Medication management

Most participants reported having high self-efficacy to manage RA medication. They expressed feeling competent about the func- tion and dosage of their medications. They described developing routines, such as using weekly pill organizers, leaving pills in familiar places in homes, and always taking medications at regular intervals, which allowed them to integrate medication-taking into their daily lives.

> I try to take mine at the same time every day. It's not a big deal. I just get up in the middle of the night, take it, go back to sleep. (Focus Group [FG] 1, Participant 1)

Some participants reported scheduling reminders through devices and having support from close family members who reminded them to take their medications. These participants reported that, over time, the act of taking their medications became natural, often without the need of explicit reminders to take medications.

> I just take the medication in the morning, first thing. I don't get out of bed. I don't go to the bathroom. I just take it. (Individual Interview [IDI] #5)

Some participants expressed that having supportive healthcare providers who thoroughly explained their RA medications made them feel more capable to take their medications appropriately.

> I felt comfortable with her [rheumatologist] because she was very knowledgeable about the different medication types, and I said I would prefer to start on something that has been out there longer with fewer adverse side effects and so that's how we got on Humira. (IDI #3)

Participants discussed having dealt with insensitive healthcare providers who did not provide necessary guidance. Participants who expressed lower self-efficacy were unsure of the necessity of their medications. They revealed abruptly discontinuing their medications. They were unclear about side effects and unmotivated to continue taking their medications.

> She [rheumatologist] would suggest other medications, and I could never get a real clear answer why she thought I should do that instead, and that was just kind of frustrating for me, and consequently I usually didn't do that [take the medications]. (FG1, Participant 4)

> I've had other rheumatologists that have said, "That's not that bad" about my pain. My [current] doctor wants to treat it and figure out if there's something else that works. I wish I had her [rheumatologist] from the beginning. I wouldn't have had some of the deformities that I do. (FG2, Participant 2)

A participant's perception of a positive relationship with their healthcare provider made them feel more comfortable with following the directions and advice of their providers. Most participants expressed currently having positive, communicative relationships with their healthcare providers, which contributed to their comfort with taking their medications.

Medication adjustment

About half of participants reported intermittently adjusting their medications. They expressed high self-efficacy to make these adjustments. Interviews revealed that participants often received clearance from physicians to adjust fast-acting steroids and NSAIDs, such as prednisone (Table 3), to manage pain and flare-ups. This clearance from providers made participants more confident to adjust medications as needed during episodes of pain and flare-ups.

> 'Cause I've been taking it so long, I'm really close to my doctor, he told me to do that if anything happens I can go up [on medication dosage]. (FG1, Participant 1)

> It was supposed to be two tablets a day, but he [rheumatologist] said that if I see I'm doing okay, I can go down to a pill and a half. Whereas if I see that I'm starting to ache or feel pain, then go back up. (IDI #6)

Other participants adjusted their medications because they were confident in their ability to self-medicate. They expressed knowing their body and pain tolerance better than their providers, thus making them the decision maker on how to adjust medications during flare-ups.

> I know my body well enough that I could say that I need 10 mg of prednisone today or for a couple of days. (FG2, Participant 2)

The remaining individuals adjusted medications that were not working appropriately to control regular pain and inflammation. Perceived failure of their medications contributed to their belief of having leeway to make adjustments. Others expressed confidently making adjustments after consulting external sources (eg, relatives, internet). These participants detailed adjustment to DMARDs and Biologics (Table 3), often without consulting their provider beforehand.

> I was taking the prescription the way I was supposed to take it, and I wasn't getting any relief. I just took one extra one, and then the pain did go away. (FG2, Participant 2)

> I've been trying to space it [Humira] out as much as I can in-between injections, and I do that at my own discretion. My rheumatologists have gotten on me. They're like, "You should take it more often." Because I'll have a flare-up, and then I'll try to push through. (IDI #3)

All participants who adjusted their medications stated that they informed their providers either before or immediately after adjusting their medications.

> They initially told me it was fine if I skipped a week, because there was still medication in my system, so I did inform her [rheumatologist] whenever that was going to happen . . . (IDI #2)

Some participants who expressed low self-efficacy to make adjustments to their medication regimen were those who did not receive permission from their providers to adjust their medications. These individuals were strongly against adjusting medications. They believed that doing so without provider supervision placed them at risk for possible side effects.

> You don't know what's going to happen when you change the doses and if you change the doses you change the medication side-effects too. (FG1, Participant 1)

Participants with comorbid conditions in addition to RA often reported that they did not adjust their medications for fear of possible complications. In addition, other participants had regimens titrated to treat the severity of their RA and did not adjust their medications because of the sensitive nature of their regimens.

> I can't take a lot of different medications. Normally the medicines that the doctor prescribes, that's what I take, because my liver is in stage 4 cirrhosis. (FG2, Participant 5)

Change in self-efficacy over time

A few participants said that their belief in their ability to manage RA increased as they understood the cause of their symptoms and the purpose of their medications better. They described once having uncertainties in their ability to manage RA because they initially disagreed with their RA diagnosis. These individuals often delayed initiating medications or would abruptly discontinue treatment. The painful and debilitating nature of RA prompted them eventually to adhere to their medication regimen.

One participant expressed what is characterized as a low perceived susceptibility to RA (ie, denial) when initially diagnosed, and her denial influenced her decision initially not to adhere to her medications. She expressed that her denial was attached to her negative perceptions of being prescribed intense and aggressive medications and in her disappointment at her body's loss of ability.

> You're stubborn at the beginning like, "I'm not sick, leave me alone." But then the more you have the disease and the more you're getting damaged, you'll take the medication. (FG2, Participant 4)

Most other participants reported almost no changes in their self-efficacy over the course of their disease. These individuals have always felt confident in their ability to manage their medication regimens. Many attributed this to supportive health providers, minor impact of RA, uncomplicated medication regimens, and discipline in adhering to medications.

Adherence as a spectrum

Most participants reported exhibiting both adherent and nonadherent behaviors. They described having major periods of adherent behaviors with occasional intervals of nonadherent events in between that comprised infrequently forgetting, discontinuing, delaying, or being negligent with their medications.

> I just forget it. I don't have any pain, so until that evening, I'm like, "Wait a minute, did I take my pill?" At that point, I just wait till the next morning. (FG3, Participant 1)

Participants' reports referred to either past or present nonadherent behaviors. The Figure depicts the emergent factors that determined the position of a participant on the spectrum of adherence. Discontinuing, delaying, or being negligent was typically connected to fear of side effects, a poor patient–physician relationship, and low severity of RA.

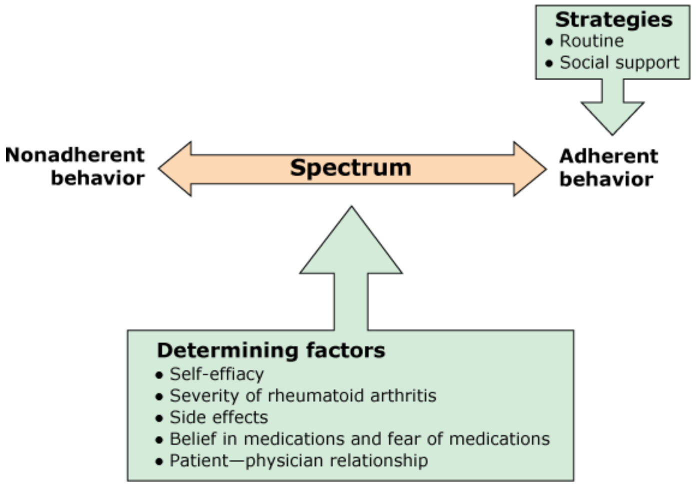

Figure. Adherence as a Spectrum of Behaviors. This figure presents the phenomenon of adherence behavior as it relates to medication-taking behavior among rheumatoid arthritis (RA) patients.

> I take meloxicam every single day, but a certain point into it, when I start feeling dizzy, I said, 'No, I'm not taking that anymore.' (FG2, Participant 5)

These accounts of intermittent nonadherence were often accompanied by expressions of guilt and frustration. They voiced their discomfort with the possible long-term effects of RA medications, and most expressed feeling inconvenienced by taking long-term medications. Nevertheless, most realized the necessity of their medications as pain relievers and mechanisms to stop the progression of RA.

> I can definitely say the long-term effects concern me, but right now the benefits outweigh the risks. (FG3, Participant 3)

Discussion

This study revealed the importance of high self-efficacy in participants' ability to manage and make adjustments to RA medications. These results are consistent with the few existing studies on the impact of self-efficacy on medication adherence among RA patients (1,19). Most participants reported positive relationships with their providers, and participants who expressed having positive communication with their providers expressed feeling more capable of taking medications appropriately. Self-efficacy was positively influenced by good patient–provider communication, and this implies that the patient–provider relationship could be used as a mechanism to positively influence the self-efficacy of RA patients.

Participants provided perspectives about the role of self-efficacy in enabling them to adjust medications. Individuals with low self-efficacy to adjust medications feared possible side effects and preferred to follow providers' instructions strictly. Participants with high self-efficacy to adjust medications either did so because of the ineffectiveness of their medications or because they believed they knew their bodies enough to make these adjustments. Accounts of some high self-efficacy participants revealed that some were given leeway from providers to adjust fast-acting medications at their own discretion to manage symptoms.

Patients adjusting prescribed medications is typically classified as nonadherent behavior because this practice does not fit existing definitions of adherence, which consider adherence as a commitment and abidance to the treatment protocol established by the provider (6). But patients with high self-efficacy to adjust medications may better control unpredictable flare-ups and inflammation. This broad classification of adherent versus nonadherent behaviors may complicate the exploration of adherence behaviors in RA patients because the difficulty of managing unpredictable inflammation and flare-ups may be better treated with an adaptable medication regimen. Some rheumatologists employ this circumstantial approach to alleviate pain and flare-ups in patients. This implies that participants who self-adjusted RA medications with permission of their healthcare provider may actually be exhibiting adherent behaviors, as these adjustments are made under the supervision of a healthcare provider.

Participants who stretched time between doses or who increased dosages without alerting their healthcare provider beforehand should be considered nonadherent, as these changes are made without the approval of the provider. But current literature does not differentiate between the aforementioned circumstances of adjusting medications (1–3,19). Thus the classification of all forms of making adjustments to medications as nonadherence might be a misconception of what is actually appropriate medication use by patients who adjust treatments as needed with prior permission from their healthcare provider.

RA adherence research could benefit from adopting the perspective that circumstantial adjustment to medications may be appropriate in cases where immediate access to a healthcare provider is not possible. There is scarce information available about the safe parameters within which adjustments to RA medications can be made (3). Thus, future research should investigate the treatment patterns of rheumatologists in regard to managing variable pain and flare-ups in RA patients, to develop universal pain management protocols to treat RA patients.

The interviews also provided insight into the changes in self-efficacy that participants experienced over time. Some participants disclosed having severe denial of RA when initially diagnosed, and because of this some decided not to adhere to their medication regimen. Most participants who did not experience changes in self-efficacy expressed making efforts to develop and maintain discipline in taking medications. Subsequent research should explore the factors that engender denial of RA. Interventions such as Adherence-Coping Education (ACE) therapy are cost-effective methods of targeting denial (21,22).

Participants depicted adherence to medications as existing on a spectrum of adherent to nonadherent. Many participants revealed moving along the spectrum at any given time as a result of several determining factors and successful implementation of various strategies to facilitate adherent behaviors. Existing literature explores and measures adherence levels as a single outcome; consequently, the examination and perception of adherence as a variable behavior is lacking (2,4). Therefore, these accounts of participants' adherence behavior as dynamic and variable have significant implications in shifting how patients are viewed in clinical settings. Instead of viewing adherence as dichotomous, adherence should be viewed as variable — patients have the potential to oscillate back and forth between adherent and nonadherent behaviors over time. These findings are supported by some existing literature endeavoring to shift understanding of adherence. For instance, the ABC taxonomy represents adherence as a process comprising 3 phases: initiation, persistence, and discontinuation (4,5).

This study has limitations. It cannot predict the impact of self-efficacy on medication adherence. Participants are from 1 region in North Carolina. To mitigate potential bias during data analysis, research analysts employed an iterative process of analyzing the data independently of one another and reconciling conflicting interpretations of the data through a mediator.

This study adds valuable context about the adherence behavior of RA patients. The importance of self-efficacy in the ability to manage and adjust medications emerged as a key finding. This finding implies that interventions should be developed and implemented for RA patients with low self-efficacy.

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Tables

Table 1. Excerpt of Focus Group and Interview Discussion Guide, RA Patients, Durham, North Carolina, November 2017 – January 2018

Relationship with	Example Questions
… disease	*How has RA impacted your life?* *Tell me about your last bad day?* *Tell me about your last good day?* *What is the most frustrating aspect of having RA?*
… others/social support	*What impact does RA have on your family life? Social life?* *How much do you share your condition with family or others?* *Do you interact with anyone else with RA?*
…Physician/Rheumatologist	*How much time do you typically spend during a visit with your doctor?* *What is your relationship with your doctor like?* *How much choice do you feel your doctor gives you in terms of treatment?* *How often do you go to your doctor with ideas/information about treatment adjustments?*
…medication	*What is it like to have to take medication every day?* *How confident are you that you are taking all your medication correctly?* *How satisfied are you with your medication?* *If your RA were a person — what would they be like?*
Conclusion	*Are there any areas about your experience with RA that we did not cover that you'd like to share?*

Abbreviation: RA, rheumatoid arthritis.

Table 2. Interview Participants Sociodemographic and Disease-Related Characteristics (N = 19), RA Patients, Durham, North Carolina, November 2017 – January 2018

Characteristic	Percent[a]	SD (Min, Max)
Age, mean, y	45.0	14.8 (18.0, 70.0)
Sex		
Male	30.0	–
Female	70.0	–
Race		
White	65.0	–
Black	17.5	–
Hispanic	17.5	–
Education		
High school diploma	15.0	–
Currently in college or Bachelors' degree	65.0	–
Graduate degree	20.0	–
Insurance type		
Self-purchased	20.0	–
Employer provided	75.0	–
Medicare Part D/Medicaid	5.0	–
Impact of RA, mean[b]	4.25	1.25 (2.00, 6.00)
Self-reported adherence level, mean[c]	4.35	0.72 (3.00, 5.00)
Average diagnosis, mean, y	11.13	6.67 (2.50, 27.00)

Abbreviation: RA, rheumatoid arthritis.

[a] Data are percentages, unless otherwise noted.

[b] Self-reported Impact of RA: 1=no impact; 7=extreme impact.

[c] Self-reported Adherence level: 1=never; 2=not often; 3=sometimes; 4=most of the time; 5=always.

Table 3. Frequently Prescribed RA Medications

Category	Medications
DMARDs	Plaquenil Azulfidine Arava Methotrexate
Biologics	Orencia Humira Actrema Enbrel Simponi
NSAIDs	Aspirin Celebrex Cambia Naproxen
Steroids	Prednisone Decadron

Abbreviations: Biologics, biologic response modifiers; DMARDs, Disease-modifying anti-rheumatic drugs; NSAIDs, non-steroidal anti-inflammatory drugs; RA, rheumatoid arthritis; Steroids, anti-inflammatory drugs.

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ORIGINAL RESEARCH

Geographic Association Between Income Inequality and Obesity Among Adults in New York State

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PEER REVIEWED

Abstract

Introduction

In addition to economic factors and geographic area poverty, area income inequality — the extent to which income is distributed in an uneven manner across a population — has been found to influence health outcomes and obesity. We used a spatial-based approach to describe interactions between neighboring areas with the objective of generating new insights into the relationships between county-level income inequality, poverty, and obesity prevalence across New York State (NYS).

Methods

We used data from the 2015 American Community Survey and 2013 obesity estimates from the Centers for Disease Control and Prevention for NYS to examine correlations between county-level economic factors and obesity. Spatial mapping and analysis were conducted with ArcMap. Ordinary least squares modeling with adjusting variables was used to examine associations between county-level obesity percentages and county-level income inequality (Gini index). Univariate spatial analysis was conducted between obesity and Gini index, and globally weighted regression and Hot Spot Analysis were used to view spatial clustering.

Results

Although higher income inequality was associated with lower obesity rates, a higher percentage of poverty was associated with higher obesity rates. A higher percentage of Hispanic population was associated with lower obesity rates. When tested spatially, higher income inequality was associated with a greater decrease in obesity in southern and eastern NYS counties than in the northern and western counties, with some differences by sex present in this association.

Conclusion

Increased income inequality and lower poverty percentage were significantly linked to lower obesity rates across NYS counties for men. Income inequality influence differed by geographic location. These findings indicate that in areas with high income inequality, currently unknown aspects of the environment may benefit low-income residents. Future studies should also include environmental factors possibly linked to obesity.

Introduction

Economic factors have been linked to numerous health outcomes, including obesity (1). However, research on area income inequality — the extent to which income is distributed unevenly across a population — and obesity rates is limited and inconsistent, because income inequality is a contextual variable specific to geographic scale and is differentially associated with social conditions. The relationship between income inequality and obesity changes by geographic area and is not fully understood.

In the United States, obesity is related to poverty, low individual income, and food-insecurity (1). A study that used data from the 2003–2008 National Health and Nutrition Examination Survey showed that at the tract and county levels, high degrees of income inequality was correlated with low obesity rates (2), suggesting that community affluence has a positive effect on residents' lifestyles. Similarly, city-level and tract-level income inequality was negatively associated with body weight in Los Angeles county in 2000–2001 (3). A study using the Behavioral Risk Factor Surveillance System (BRFSS) found that a high prevalence of income inequality was associated with reduced odds of obesity among non-Hispanic white women (4). To our knowledge, previous studies have not used spatial regression methods to examine the relationship between area income inequality and obesity rates. To address this research gap, we used spatial analysis to examine associations between small-area income inequality and obesity among adults in

New York State (NYS). We hypothesized that income inequality would have an inverse relationship with obesity rates and that a geographic difference exists between the two.

Methods

Data sources

Our study used a cross-sectional design of publicly available data sources to create estimates related to NYS residents. Data from the American Community Survey (ACS) (https://www.census.gov/programs-surveys/acs) were used for all independent variables, including area poverty prevalence and area income inequality. ACS is an annual survey conducted by the US Census Bureau throughout the United States and provides annual estimates of a series of monthly samples of people living in housing units, such as houses or apartments, and in institutional and noninstitutional group quarters, such as correctional facilities, mental hospitals, college dormitories, military barracks, and shelters. The Census Bureau uses several data collection methods (internet, mailed paper questionnaire, telephone, personal visit) to ensure representation of the US population. The ACS survey is mandatory by law, resulting in an extremely high response rate. Participants were excluded for refusal to participate based on legal or other reasons, insufficient data, inability to locate participants, temporary absences from their place of residence, and language barriers. ACS is conducted in English, meaning that results cannot be retrieved if interpreters are unavailable. Our study used ACS 5-year estimates (2011–2015), representing 790,051 observations. Even at a 99.5% confidence interval, the necessary sample size to ensure correct estimates for the NYS population was 38,341, less than the number of participants in the ACS survey.

County-level income inequality was measured by the Gini coefficient, or Gini index, which represents income dispersion across an area, assigning values from 0 to 1: the higher the number, the greater an area's income inequality. The numerator of the coefficient is the area between the Lorenz curve of the distribution and the uniform distribution line; the denominator is the area under the uniform distribution line. We converted this ratio into an index by multiplying each value by 100. Gini index was the only variable not separated by sex. In the ACS data set, racial groups were recorded as counts and were converted to percentages by dividing the counts for each racial group by the total estimated number of people in each county. We used the Gini index in this study because it is the most commonly used measure of income inequality; however, we acknowledge the existence of other measures, such as Atkinson's measures, Theil's T, and Theil's L, and that our results may not necessarily have held if these other measures were used instead of the Gini index (5,6).

The dependent variable, obesity prevalence, was drawn from the Centers for Disease Control and Prevention (CDC) statistical estimates (7,8). These were based on the Census Bureau's Population Estimates Program and the 2013 BRFSS (9), which was conducted via telephone interview. However, these estimates also include statistical adjustments designed to reduce the random sampling's inherent randomness (7). Obesity was defined as a body mass index (BMI, kg/m^2) of 30 or greater and was measured by physical examinations at the county level.

Statistical methods

We examined the association between county-level independent variables and obesity prevalence with ArcMap (Esri) by using ordinary least squares (OLS). OLS is a variation of linear regression, a statistical method that examines associations between multiple independent variables and a single dependent variable; once the assumptions are satisfied, the regression output indicates the strength of the association between the dependent variable and each of the independent variables. These assumptions, include linear parameters, random sampling, no multicollinearity, no autocorrelation, a conditional mean of zero, and normally distributed error terms; all of them were satisfied, meaning that our OLS models are efficient and represent a linear unbiased estimator of variable coefficients.

Final models included county-level Gini index, poverty percentage (defined as having an income below the Federal Poverty Level), adjusted for median age, percentage African-American, percentage Hispanic, percentage married, and percentage with at least a high school education. Statistical significance was set at $P < .05$. Interactions between the sex ratio with each of the other independent variables were tested. Because we found significant interactions between sex and the Gini index, analyses were conducted separately by sex. After these analyses, we found that coefficients and *P* values did not differ by sex; therefore we performed the analysis with both sexes combined.

Two spatial tests, geographically weighted regression (GWR) and Getis-Ord GI* Hot Spot Analysis (Esri), were used to add a different dimension to our analysis. GWR created a separate ordinary least squares (OLS) model for every county while considering spatial factors, such as the distances and OLS models of neighboring counties. GWR measured relationships that vary across space, whereas OLS linear regression assumes these relationships apply equally over an entire geographic area (9). We performed univariate GWR with Gini index as our independent variable, with both Gini index and obesity prevalence first matched to counties in a NYS ArcMap shapefile.

Hot Spot Analysis was conducted on the GWR regression results; this test determines whether the different coefficients of the Gini index variable for each county that GWR returned are randomly dispersed, or whether unusually high or unusually low values are clustered together. Hot Spot Analysis tests for clusters of similar values in a set of spatial data, indicating when similar values are close to one another. The method is specific, enabling us to detect possible local spatial associations whereas other methods, such as Moran's I, does not (10).

Although standard OLS regression makes one model for the entire state, giving an overall sense of a variable's effect on obesity rates, GWR combined with Hot Spot Analysis provides information about the degree of effect a variable has in different areas. This allowed for observation of differences in the effect of income inequality on obesity prevalence across NYS.

Results

The median age in our data set of the NYS population was 38.1 years; 48.5% were men, 15.6% were black, 18.4% were Hispanic, 44.5% were married, and 85.6% were high school graduates. During the time that these data were collected, the response rate varied by county; however, for NYS, the overall response rate of housing units was 93.3%, and the overall response rate of group quarters was 95.2%.

The OLS regression showed that among all adults, a higher county-level Gini index (or higher inequality) (β, −0.37; *P* = .01) and a higher percentage of Hispanic population (β, −0.22; *P* = .009) was significantly associated with a lower obesity rate. In contrast, a higher percentage of county-level poverty (β, 0.42; *P* = .004) and higher percentage of being married (β, 0.22; *P* = .03) was associated with a higher obesity rate (Table 1). Then in separate analyses, the same significant associations were observed among men and women with the exception of marital status, which was significant among men (Table 2) but not among women (Table 3). We used Hot Spot Analysis to test for spatial autocorrelation, and none was found. Variance inflation factor values of all variables were measured, with none exceeding 5, a benchmark for moderate multicollinearity.

The GWR analysis showed that a 1% increase in income inequality was associated with a greater decrease in obesity prevalence in southern NYS than in the western state for both sexes. The effect of the Gini index on obesity prevalence was highest in southern and eastern NYS, but showed a downward trend toward the north and west. These associations were stronger among men (Figure 1) than among women (Figure 2), just as the OLS models predicted.

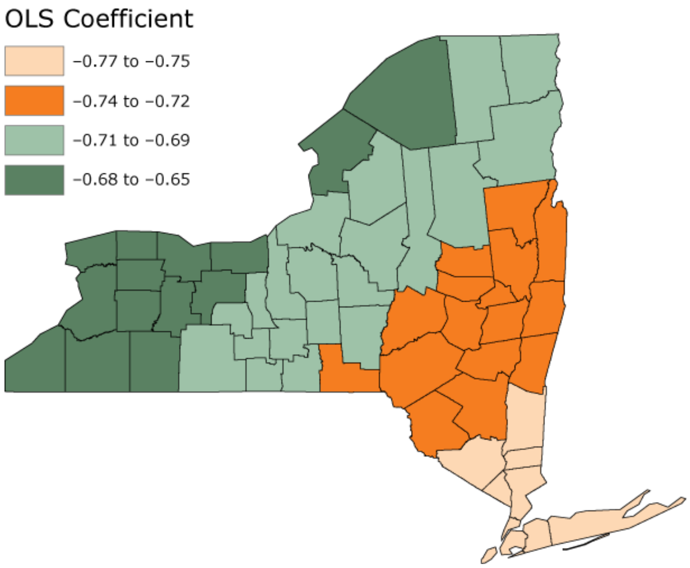

Figure 1. Results of geographically weighted regression (GWR) tests for men, mapping the individual ordinary least squares (OLS) coefficient constructed by GWR to each county in New York State. Data are from the American Community Survey and from CDC County Data Indicators estimates (11).

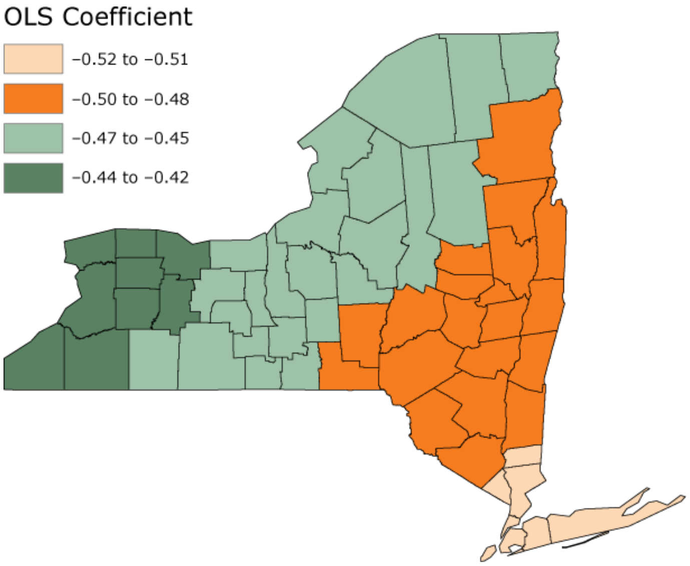

Figure 2. Results of geographically weighted regression (GWR) tests for women, mapping the individual ordinary least squares coefficient constructed by GWR to each county in New York State. Data are from the American Community Survey and from CDC County Data Indicators (11).

Hot Spot Analysis tests confirmed GWR results: a large area exists in the southeast where the effect of the Gini index is unusually high compared with its surrounding areas, and a large area in the west where this effect is unusually low compared with neighboring areas. From the results of the GWR and Hotspot tests, we observed a connection between the differing effects of income inequality (Gini index) and its relation to geographical direction in NYS. Moving east the absolute effect of income inequality on obesity increased, whereas moving west it, decreased, which the Hot Spot test confirmed.

Discussion

Our study examined associations between obesity prevalence and county-level income inequality and poverty percentage among adults in NYS. As we hypothesized, income inequality was inversely associated with obesity prevalence, and a difference in the geographical effect on income inequality and obesity was observed. Our findings using spatial analyses can help public health officials and lawmakers to tailor health initiatives to different geographical areas, thereby improving the sustainability of these initiatives on the well-being of the population.

The negative correlation of income inequality with obesity is not unilateral; a study of 21 developed countries showed that income inequality was positively correlated with obesity prevalence in men and women (12). Social inequalities were found to have a greater effect on obesity in women in a study of 11 member countries of the Organization for Economic Cooperation and Development (OECD), which include the United States (13). Our study found that income inequality had a greater effect on obesity among men than among women. These conflicting findings may be due to the use of different types of measurements, the inclusion of different countries in the studies, and the geographic area studied, such as NYS. The area level studied was shown to have differing effects of income inequality on other health outcomes (14).

Country-level studies examining national data suggested a detrimental effect of high income inequality to mean BMI and prevalence of obesity (15). A study of 68 countries noted that obesity prevalence was greater among women than among men in countries with a high Gini index (16). Another study using national data from the Behavioral Risk Factor Surveillance System found little to no association between income inequality and obesity in race–sex stratified groups in metropolitan areas (4). Similarly, using national data from Spain’s 2001 National Health Survey, a study found no association between income inequality and BMI (17). A multinational study associated high income inequality at the national level with increases in obesity prevalence; this association disappeared when the United States and Mexico were excluded from their model (18). In contrast, a study using county and tract data found an association between income inequality and BMI similar to our findings, leading us to think that differences in the overall geographical area measured may contribute to differences in the associations between income inequality and obesity.

When considering poverty, our study agrees with similar studies conducted among populations of adult men and women in various countries. A study of Canadian men and women found that rich men and poor women were more likely to be obese (19). Although that study did not measure individual income, poverty percentage was positively associated with obesity among women. Low area socioeconomic status, low-cost food stores, low education attainment, and individual income have been associated with high obesity rates in adults living in Seattle, Washington, and Paris, France (20). In England, a study of adults aged 18 to 75 showed that social and economic gradients existed for obesity in both sexes, with lower socioeconomic status associated with higher rates of obesity, and that this trend had not changed significantly in more than a decade (21).

A study that examined Gini index in adults at the US county and tract levels showed that the addition of potential confounders changed the degree of the association between income inequality and obesity, because area level factors such as neighborhood environment (eg, availability of parks and recreation, healthy food), and local policies may have an effect on residents’ weight status (2). One study of US counties showed that geographical differences in obesity rates can be explained through physical activity and food environments, along with settlement patterns and transportation habits (22). However, this may be due to other factors; income inequality has been associated with low rates of physical activity, which may contribute in part to our findings (23). Future studies may test these correlations by including potential factors as mediators, especially in an area-based study that takes into account context factors, such as distance from parks or other neighborhood services or conditions (23).

County-level poverty was positively associated with obesity in our study. A study of 1,150 children that used data from the National Institute of Child Health and Human Development Study of Early Child Care and Youth Development found that poverty in very early life was associated with obesity in adolescence (24). Some studies differentiated socioeconomic differences by sex, such as one that used data from the 2001–2009 Korea National Health and Nutrition Examination Survey to study Korean adults (25). That study found that lower education was associated with higher obesity rates in women, and higher income was related to higher obesity rates in men. Another study that looked at several US counties found a positive relationship between poverty and obesity (1), suggesting that the positive relationship could have been due to lower physical activity rates of people living in poor counties, which introduces another possible variable in the relationship between county-level poverty and obesity rates.

Studies looking at the relationship between poverty and obesity, have used the term "poverty-obesity paradox" to indicate the positive relationship often found between poverty and obesity. Similar results were observed among the elderly by using data from the Survey of Health, Ageing, and Retirement and from the English Longitudinal Study of Ageing (26). Another study indicated a relationship between food insecurity and obesity through resource scarcity, suggesting that obesity is a response to a threatened food supply (27).

Our study has numerous strengths, including the use of OLS regression and the relatively high number of counties that NYS has compared with other states. The data used were CDC estimates derived from statistical estimates that sought to minimize error, and from ACS data, which is a conglomerate of half a decade of data collected from a high number of interviews. Another strength of our study is the use of GWR and Hot Spot Analysis to determine obesity prevalence geographically, a combined approach that has not often been tried in the literature, allowing for spatial analysis. These results are also highly generalizable. This study was conducted with large data sets, improving the generalizability of the findings. A similar approach can be conducted for the entire United States as needed.

Our study also had limitations. The study's cross-sectional design limited our ability to infer causality. Also, some of the variables in the BRFSS dataset are self-reported and may be subject to desirability or recall bias (28).

In conclusion, we found that income inequality was inversely associated with obesity prevalence in NYS counties, although this effect differed by sex. Also, the effect of income inequality differed geographically; income inequality was weaker in western NYS and stronger in the east. This trend did not differ by sex. Poverty percentage, however, was positively associated with obesity. Future studies can use spatial-based multiple regression models by introducing potential area-level factors that may contribute to the differing geographical effects of income inequality on obesity. The findings can help design effective programs that will be tailored to address the unique needs of the geographic locations, thus improving the sustainability of health outcomes.

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Tables

Table 1. Effects of Income Inequality[a], Poverty Percentage, and Sociodemographic Variables on Obesity at the County Level Among Adults in New York State[b]

Variable	β Coefficient	Standard Error	*P* Value[c]
Intercept[d]	16.91	21.06	.43
Gini index	−.37	.14	.01
Poverty[e], %	.42	.14	.004
Median age	.09	.10	.36
African-American, %	.14	.10	.14
Hispanic, %	−.22	.09	.009
Married, %	.22	.10	.03
High school graduate, %	.08	.16	.64

[a] Calculated by Gini index drawn from 5-year estimates of the American Community Survey for 2015.

[b] Based on an ordinary least squares multivariable linear regression model. Poverty percentage and sociodemographic variables were drawn from 5-year estimates of the American Community Survey for 2015. The dependent variable, obesity percentage, is based on 2013 CDC County Data Indicators (https://www.cdc.gov/diabetes/data/countydata/countydataindicators.html) estimates based on the BRFSS (Behavioral Risk Factor Surveillance System) survey (9).

[c] *P* values were calculated by using the ordinary least squares statistical test. Significance was set at $P < .05$.

[d] The intercept of the OLS regression model. Defined, in this case, as the expected value of obesity prevalence if all independent variables used in the equation are set to 0.

[e] Defined as percentage of population with annual incomes below the Federal Poverty Level.

Table 2. Effects of Income Inequality[a], Poverty Percentage, and Sociodemographic Variables on Obesity at the County Level Among Adult Men in New York State[b]

Variable	β Coefficient	Standard Error	*P* Value[c]
Intercept[d]	35.68	15.89	.03
Gini index	−.41	.13	.004
Poverty[e], %	.31	.14	.03
Median age	.04	.10	.68
African-American, %	.07	.09	.48
Hispanic, %	−.26	.08	<.001
Married, %	.21	.08	.01
High school graduate, %	−.04	.13	.76

[a] Calculated by Gini index drawn from 5-year estimates of the American Community Survey for 2015.

[b] Based on an ordinary least squares multivariable linear regression model. Poverty percentage and sociodemographic variables were drawn from 5-year estimates of the American Community Survey for 2015. The dependent variable, obesity percentage, is based on 2013 CDC estimates based on the BRFSS (Behavioral Risk Factor Surveillance System) survey (9).

[c] *P* values were calculated by using the ordinary least squares statistical test. Significance was set at $P < .05$.

[d] The intercept of the OLS regression model. Defined, in this case, as the expected value of obesity prevalence if all independent variables used in the equation are set to 0.

[e] Defined as percentage of population with annual incomes below the Federal Poverty Level.

Table 3. Effects of Income Inequality[a], Poverty Percentage, and Sociodemographic Variables on Obesity at the County Level Among Adult Women in New York State[b]

Variable	β Coefficient	Standard Error	*P* Value[c]
Intercept[d]	19.82	22.92	.39
Gini index	−.34	.15	.03
Poverty, %[e]	.38	.13	.004
Median age	.08	.10	.40
African-American, %	.18	.10	.07
Hispanic, %	−.20	.09	.03
Married, %	.15	.10	.14
High school graduate, %	.05	.18	.80

[a] Calculated by Gini index drawn from 5-year estimates of the American Community Survey for 2015.

[b] Based on an ordinary least squares multivariable linear regression model. Poverty percentage and sociodemographic variables were drawn from 5-year estimates of the American Community Survey for 2015. The dependent variable, obesity percentage, is based on 2013 CDC estimates based on the BRFSS (Behavioral Risk Factor Surveillance System) survey (9).

[c] *P* values were calculated by using the ordinary least squares statistical test. Significance was set at $P < .05$.

[d] The intercept of the OLS regression model. Defined, in this case, as the expected value of obesity prevalence if all independent variables used in the equation are set to 0.

[e] Defined as percentage of population with annual incomes below the Federal Poverty Level.

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ORIGINAL RESEARCH

Factors Affecting Obesity and Waist Circumference Among US Adults

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PEER REVIEWED

Abstract

Introduction

Physical activity, sedentary activity, and food intake affect waist circumference and obesity among adults; however, the relationship is unclear. The objective of our study was to explore how these factors affect waist circumference and obesity prevalence among adults.

Methods

We used cross-sectional data from the National Health and Nutrition Examination Survey 2013–2014 on 4,118 adults, 49% men and 51% women, aged 20 to 64 (mean age, 42). Weighted logistic regression models were fitted for abdominal obesity or obesity status and adjusted for variables of demographic characteristics, food intake, types of physical and sedentary activity, television and video viewing, and computer use. Analyses were stratified by sex.

Results

Of the 4,118 people studied, 39% were obese (body mass index ≥30) and 55% had a high-risk waist circumference (hereinafter, abdominal obesity: men, ≥120 cm; women, ≥88 cm). People who watched television or videos 2 hours or more per day had increased odds of being abdominally obese (men, odds ratio [OR], 1.96; 95% confidence interval [CI], 1.29%–2.98%; women, OR, 1.66; 95% CI, 1.06%–2.59%) or obese (men, OR, 2.17; 95% CI, 1.18%–4.02%; women, OR, 1.66; 95% CI, 1.12%–2.48%). After adjusting for types of physical activity, associations remained significant only among men. Moderate recreational physical activity for 150 minutes or more a week versus 149 minutes or less was associated with reduced odds of abdominal obesity for both men (OR, 0.44; 95% CI. 0.22%–0.89%) and women (OR, 0.98; 95% CI, 0.23%–0.67%). Consuming meals prepared away from home was associated with high odds of obesity among women (OR, 1.67; 95% CI, 1.08%–2.58%).

Conclusion

Watching television and videos was positively associated with prevalence of abdominal obesity and obesity among men and women. Prevalence remained significant only among men with inclusion of physical activity. Further study is needed of the differences between the sexes in how physical and sedentary activity and food consumption are associated with obesity.

Introduction

Poor diet, low levels of physical activity, and high levels of sedentary activities are risk factors for obesity. Because diet and activity are modifiable factors, addressing this risk requires an understanding of their contribution to obesity. A meta-study of National Health and Nutrition Examination Survey (NHANES) data sets showed leisure-time physical activity to be inversely associated with obesity (1). In the Coronary Artery Risk Development in Young Adults study, transportation-related physical activity was shown to lessen or reverse effects of weight gain (2). Multiple studies have shown an association between sedentary activity and increased rates of obesity, independent of physical activity (3,4,5).

Abdominal obesity (waist circumference ≥102 cm for men and ≥88 cm for women), independent of body mass index (BMI) (calculated as weight in kilograms divided by height in meters squared), has been associated with major chronic diseases and all-cause mortality (6). Abdominal fat, rather than total body fat, was found to be the cause of the systemic inflammation that contributes to chronic disease (7). Intervention and population studies have indicated that being sedentary or having a low fitness level is also associated with visceral fat accumulation (7,8,9). Various sedentary activities are differentially associated with cardiometabolic factors, including abdominal obesity (10). Associations between sedentary activity and obesity differ between the sexes. A large population study of employed Canadian adults found occupation-related sedentary activity to be associated with BMI and waist circumference among men irrespective of leisure-time physical activity (11).

Little research has been conducted on specific types of physical activity and their relationship to obesity, and few studies have examined how waist circumference (hereinafter, abdominal obesity) is related to physical activity, sedentary activity, and diet. To address this information gap, we examined how adult obesity and abdominal obesity is associated with physical activity, sedentary activity, and consumption of meals prepared outside the home (ie, from conventional or fast-food restaurants, food stands or trucks, grocery stores, or vending machines). We hypothesized that all types of physical activity have an inverse relationship with obesity and abdominal obesity, and frequent sedentary activity and consumption of meals prepared outside the home increase the risk of both conditions. Such information can guide public health policies and interventions.

Methods

We examined associations between obesity and abdominal obesity and types of physical activity, sedentary activity, and diet among US adults aged 20 to 64 who participated in the National Health and Nutrition Examination Survey (NHANES) 2013–2014. NHANES collects survey-based data annually to assess variables related to health and nutrition among the noninstitutionalized, civilian population of the United States (12).

Demographic variables were age, race/ethnicity, education, employment (employed, unemployed), and marital status (married, unmarried); all variables were self-reported. To ensure representation of minority groups, NHANES oversamples certain populations, such as Hispanic, black, and Asian populations; low-income populations; and the elderly (13). NHANES uses the following stages in sample selection: 1) counties or small groups of counties (primary sampling units), 2) segments within sampling units, 3) households within segments, and 4) individuals within households (12). Of the 10,175 individuals in the NHANES 2013–2014 data set, we excluded children aged 0 to 19 years, adults 65 years of age or older, pregnant women, underweight adults (BMI <18.5), morbidly obese adults (BMI >60), and parti- cipants with missing, “don’t know,” or null responses, for a sample size of 4,118 for our analysis. The Institutional Review Board for the Ethics Review Board of the National Center for Health Statistics approved NHANES data collection and allowed data files to be posted on their website for public use (14). Written informed consent was obtained from participants before collection.

Dependent variables

We examined prevalence of obesity and abdominal obesity as outcome variables in independent analyses. Height and weight were collected in a mobile examination center by using standardized protocols. From those measurements, we calculated BMI and rounded it to the nearest tenth. Obesity was defined as BMI at or above 30. Waist circumference was measured with a tape measure at the uppermost lateral border of the hip crest (15). Waist circumferences of 120 cm or more for men and 88 cm or more for women were considered high risk and termed abdominal obesity.

Independent variables

Measurements of physical activity arising from work, recreation, and transportation were used to assess the effect of each on total obesity and abdominal obesity. Physical activity was based on the Centers for Disease Control and Prevention’s (CDC’s) physical activity guidelines for adults (16). According to CDC’s guidelines, to achieve substantial health benefits, adults should engage in at least 150 minutes a week of moderate physical activity or 75 minutes a week of vigorous physical activity. Vigorous activity was defined as activity that caused large heart rate or breathing increases, and moderate activity was defined as activity that caused small increases. Thus, we dichotomized work-related and recreational physical activity variables to vigorous (<75 vs ≥75 min/wk) or moderate (<150 vs ≥150 min/wk). Transportation was defined as walking or bicycling to get to and from places. Transportation-related physical activity was dichotomized to less than 75 minutes per week versus 75 minutes or more per week.

Overall sedentary activity was assessed by asking participants to enter the total minutes each day they spent sitting in various settings: school, at home, getting to and from places, or with friends, including time spent sitting at a desk, traveling in a car or bus, reading, playing cards, watching television, or using a computer. Responses ranged from 0 to 1,200 minutes per day. Three categories of daily sedentary activity were created (0 to 360 minutes, 360 to 540 minutes, or 540 minutes or more) on the basis of categories used in a previous study of leisure time among US adults (17) and median statistics on time spent in sedentary activity in the United States (18).

Television viewing (including watching videos) and computer use were separately examined as sedentary activities. Participants were asked to report the average hours per day in the past 30 days they spent sitting and watching television or using a computer; 6 response categories ranged from less than 1 hour to 5 hours or more.

Responses for television watching or computer use variables were dichotomized to less than 2 hours a day versus 2 hours or more per day, because less than 2 hours per day of television watching is associated with gains in life expectancy (19).

Two variables related to types of meals consumed in the past 30 days were included in the model: food prepared outside the home and frozen meals or pizza consumed in the home. Participants were asked to report the number of meals they consumed in the past 7 days that were prepared outside the home. Responses ranged from none to more than 21. Participants were also asked to report how often they ate frozen meals or pizza at home during the past 30 days. Responses ranged from never to 180 times. Responses were dichotomized to 0 to 2 versus 3 or more times per week on the basis of the Eat Among Teens survey, which measured fast food's influence on families when consumed 3 times per week or more (20).

Statistical analysis

Statistical analyses were performed by using sample weights and stratum as designed and collected by the National Center for Health Statistics for complex sampling to provide nationally representative estimates and to address oversampling, nonresponse, and noncoverage. We used weighted analysis of variance for continuous variables and χ^2 test for categorical variables to perform univariate analysis to evaluate independent associations between population characteristics and obesity, abdominal obesity, and sex. Weighted logistic regression models were fitted for obesity status (obese, yes/no) or abdominal obesity risk status (high or low) as the dependent variables. Models were developed for each type of physical activity, because small sample sizes precluded simultaneous inclusion of all physical activity variables. For logistic regression, physical activity, sedentary activity, and television watching or computer use variables were transformed into categorical variables according to CDC research guidelines or our defined high-risk and low-risk groups. All logistic regression analyses were stratified by sex.

Six models were created for each outcome (obesity and abdominal obesity). The base model included all the demographic variables, 2 food intake variables, general sedentary activity, and television and computer use variables. Each of the other models included the base model adjusted for each type of physical activity (ie, moderate, vigorous, transportation) as an independent variable. These models were constructed by adding the additional independent variable to our base model. Odds ratios (ORs) and their 95% confidence intervals (CIs) were estimated and tested for significance on the basis of logistic regression. Two-way interactions between physical activities and other characteristics (eg, interaction between physical activity and obesity status for abdominal obesity model) were evaluated in the weighted logistic regressions; however, because of sparsely distributed physical activity data, no valid model-fitting could be achieved with the inclusion of the interactions (ie, convergence or maximum likelihood estimates could not be obtained). Therefore, all interactions were excluded from final models. Calculations and model creations were performed by using SAS version 9.4 (SAS Institute, Inc).

Results

Of the 4,118 participants included in the study, 69% were white, 55% were married, and 51% were women; the mean age of participants was 42 (Table 1). More women (42%) than men (35%) were obese, and more women (66%) than men (44%) had abdominal obesity. More men engaged in transportation physical activity than women (57% men vs 47% women). A higher percentage of men (70%) than women (65%) watched television more than 2 hours a day. Also, more men (60%) than women (45%) consumed meals prepared outside the home 3 times or more a week.

In the base model, adults who watched television 2 hours or more per day had higher odds of abdominal obesity (men, OR, 1.96; 95% CI, 1.29–2.98; women, OR, 1.66; 95% CI, 1.06–2.59) and obesity (men, OR, 2.17; 95% CI, 1.18–4.02; women, OR, 1.66; 95% CI, 1.12–2.48) than those who watched 2 hours or less (Table 2). In the model that adjusted for moderate work-related physical activity, only men who watched television more than 2 hours a day had higher odds of abdominal obesity (OR, 2.68; 95% CI, 1.30–5.53) than men who watched less than 2 hours daily. In the model that adjusted for transportation physical activity, only men who watched television 2 hours or more per day had higher odds of abdominal obesity (OR, 3.24; 95% CI, 1.28–8.20) or obesity (OR, 3.28; 95% CI, 1.20–8.96) than men who watched less than 2 hours (Table 3). In the model that adjusted for vigorous recreational physical activity, watching television 2 hours or more per day was also associated with higher odds (OR, 3.87; 95% CI, 1.53–9.78) of obesity among men only. In the model that adjusted for transportation activity, men who engaged in sedentary activity for 540 minutes or more per day had higher odds of abdominal obesity after adjusting for transportation physical activity (OR, 2.84; 95% CI, 0.93–8.64) than men who engaged in sedentary activities 359 minutes or less per day.

Engaging in moderate recreational physical activity for 150 minutes or more per week versus 149 minutes or less was associated with reduced odds of abdominal obesity for both men (OR, 0.44; 95% CI, 0.22–0.89) and women (OR, 0.38; 95% CI, 0.23–0.67) (Table 3) and with lower odds of obesity among women only (OR, 0.48; 95% CI, 0.27–0.84). Engaging in vigorous work-related or vigorous recreational activity was protective against abdominal obesity for men only (work-related, OR, 0.25; 95% CI, 0.08–0.77 [Table 2]; recreational, OR, 0.31; 95% CI, 0.11–0.88 [Table 3]). In the model that adjusted for transportation-related physical activity, an inverse association between overall sedentary activity and abdominal obesity was found among women only (OR, 0.13, 95% CI, 0.3–0.54).

Among women, eating meals prepared away from home 3 days a week or more versus less than 3 days was associated with higher odds of obesity (OR, 1.67; 95% CI, 1.08–2.58) in the base model and after adjusting for moderate work-related physical activity (OR, 2.37; 95% CI, 1.09–5.13) (Table 2). Eating frozen meals or pizza 3 or more times a week versus less than 3 days was associated with increased odds of abdominal obesity among women (OR, 3.56; 95% CI, 2.18–5.81) (Table 3) after adjustment for vigorous recreational physical activity. We found no association among men between eating meals prepared away from home and obesity or abdominal obesity.

Discussion

Although many types of physical activity were associated with reduced risk of obesity and abdominal obesity as our hypothesis predicted, work-based physical activity was not. Sedentary activity in general was not linked to increased risk, in opposition to our hypothesis; only excess television watching was linked to the risk of obesity and abdominal obesity. Unhealthy meals did not increase obesity risk, in complete contrast to what we initially hypothesized. When considering public health implications, our models show that public health initiatives must focus on increasing recreational physical activity and decreasing television-based sedentary activity.

Other studies measured associations between types of physical activity and obesity, but connections between specific types of activity in relationship to work and recreational physical activity have rarely been studied. One study used accelerometer data to evaluate NHANES 2003–2006 and found strong associations between moderate and vigorous physical activity and obesity (21), although our study did not. This accelerometer-based study used a different method and a different time period than we did, although these differences may not be strong enough to account for the difference in results.

The consistent link between excess television viewing and risk for abdominal obesity and obesity among both sexes and the persistent link among men after incorporating types of physical activity indicates that efforts to prevent or reduce weight gain should focus on reducing television watching independent of increasing physical activity. Our findings agree with other studies showing the consistent associations between obesity risk and sedentary activity, physical activity, and waist circumference. A longitudinal study found a synergistic effect of reduced moderate-to-vigorous physical activity and increased television viewing on increases in waist circumference among a large sample of adults (22). In the Nurse's Health Study, women with high levels of sedentary activity, especially television watching, had a significantly elevated risk of obesity, independent of physical activity levels; even small increases in moderate activity substantially lowered their obesity risk (23).

Our findings showed strengthening of the associations between television watching and measures of obesity (waist circumference and BMI) after adjusting for various types of physical activity, especially for men. A large longitudinal Canadian study found a strong association among men between occupational sedentary behaviors and obesity indicators after adjusting for vigorous physical activity (11). Little research exists about computer use among adults because most studies focus on youth and adolescents. Our study agrees somewhat with a study of 2,650 adults in Adelaide, Australia, that demonstrated that participants with high internet and other computer use were much more likely to be obese than those without. That study did not examine the effects of television watching, although it considered leisure-time sedentary activity (24).

Our finding of a persistent association among men between sedentary activity and measures of obesity after adjusting for various types of physical activity warrants further investigation. A systematic review suggested that snacking or other dietary intake during television viewing may mediate this association (25). Because the prevalence of excess television viewing was similar among men and women in our study, related behaviors (eg, consumption of alcohol or nutrient-dense snacks) need to be explored to more accurately establish the differences between the sexes in the association between television viewing and obesity and abdominal obesity (11). Furthermore, obesity prevention programs should explore creative ways to replace some television viewing time for men with other less sedentary activities. One study showed that replacing time spent in sedentary behavior with the same time in light or moderate-to-vigorous physical activity resulted in a decrease in waist circumference and cardiovascular biomarkers (26).

A surprising finding in our study was the inverse association among women between engaging in overall sedentary activities and abdominal obesity after adjusting for transportation physical activity. A similar result was found in a study by Nicholas and colleagues, indicating an inverse association between sedentary time and waist-to-hip ratio (11).

In our study, consuming meals prepared away from home was linked to increased abdominal obesity and obesity among women, irrespective of types of physical activity. This finding indicates that dietary intake may differentially influence weight gain for women compared with men. Furthermore, the separately significant associations between higher consumption of meals prepared outside the home, overall sedentary activity, and higher frequency of television watching (in our base model) with obesity prevalence substantially increases women's risk for obesity-related chronic diseases. However, our models that adjusted for various types of physical activity attenuated these associations, indicating benefits of even moderate physical activity for women. A meta-analysis that focused on long-term walking patterns in adults concluded that walking can prevent or reduce common weight gains (2).

A strength of our study is its large sample size, which provided the statistical power to explore sex-specific associations. Using the NHANES data set — which represents a cross-section of the entire US population, including ethnic and underserved populations — enhances the generalizability of our findings. Another strength of our study is the inclusion of different types of physical activity, which we explored along with sedentary activity, dietary practices, and sociodemographic characteristics.

A limitation of our study is its cross-sectional design, which precludes a causal inference of our findings. Our study also suggests that the associations of physical activity, sedentary activity, and obesity outcomes might be bidirectional. As previously indicated, testing for interactions between physical activity and other variables was not possible. Social desirability bias may have lead respondents to underestimate their sedentary activity or overestimate their physical activity, causing further inaccuracies. Such inaccuracies are unavoidable in a study based on the NHANES data set.

Our findings suggest that television watching is positively associated with prevalence of abdominal obesity and obesity among both men and women. These associations persisted even after adjusting for various types and levels of physical activity, especially among men, suggesting the concurrence of other obesogenic behaviors, such as snacking or alcohol consumption while watching television. Future studies should explore these potential confounders. Our findings also show that consuming meals prepared away from home or frozen prepared meals was associated with risk of abdominal obesity and obesity among women only. This finding indicates that dietary intake may differentially influence weight gain in women compared with men. Although most of our findings are in agreement with other studies, little research exists that explores differences between the sexes in the associations between various types of sedentary and physical activity behaviors and obesity measures, adjusting for underlying factors such as food intake, that are linked to these activity behaviors.

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Tables

Table 1. Sociodemographic and Physical Characteristics by Factors Affecting Obesity and Waist Circumference (Abdominal Obesity) Among US Adults Aged 20 to 64 (N = 4,118), NHANES 2013–2014[a]

Characteristic	Total	Men	Women	*P* Value[b]
Respondents, no. (%)	4,118 (100)	2,014 (49)	2,104 (51)	NA
Age, mean, y	42	42	42	.12
Race/ethnicity				
White	1,634 (69)	810 (69)	824 (69)	.76
Black	859 (13)	421 (12)	438 (14)	.007
Hispanic	988 (18)	474 (19)	514 (18)	.35
Education				
Less than high school diploma	814 (14)	432 (15)	382 (13)	.11
High school graduate	2,244 (55)	1,061 (53)	1,183 (57)	
Some college	1,059 (31)	521 (31)	538 (30)	
Married	2,125 (55)	1,081 (57)	1,044 (53)	.001
Employed	2,825 (72)	1,517 (80)	1,308 (65)	<.001
Physical characteristics				
Overweight or obese	2,894 (71)	1,447 (75)	1,447 (66)	<.001
Obese (body mass index[c] ≥30)	1,599 (39)	686 (35)	913 (42)	.004
Abdominally obese[d]	2,159 (55)	798 (44)	1,361 (66)	<.001
Work-related physical activity, min/wk				
Vigorous (75–149)	758 (88)	533 (90)	225 (84)	.05
Moderate (150–299)	1,146 (79)	632 (80)	514 (78)	.57
Recreational physical activity, min/wk				
Vigorous (75–149)	927 (86)	552 (86)	375 (86)	.92
Moderate (150–299)	808 (46)	404 (47)	404 (46)	.68
Transportation physical activity ≥75 min/wk	601 (53)	349 (57)	252 (47)	.02
Total sedentary activity, min/d				
0–359	1,504 (35)	724 (34)	780 (36)	.44
360–539	1,474 (35)	736 (36)	738 (34)	
≥540	1,135 (30)	552 (30)	583 (30)	
Television viewing ≥2 hr/d	2,763 (67)	1,391 (70)	1,372 (65)	.007
Computer use ≥2 hr/d	2,273 (51)	1,155 (53)	1,118 (50)	.11
Diet				
Ate meals prepared away from home ≥3 times/wk	1,973 (52)	1,111 (60)	862 (45)	<.001
Ate frozen meals or pizza in past 30 days ≥3 times/wk	870 (24)	413 (23)	457 (25)	.23
Smoker	973 (53)	527 (49)	446 (57)	.009

[a] Values are number (percentage) unless otherwise indicated. Sample size variations are due to incidental missing values in returned surveys; thus, not all values sum to total respondents.
[b] Weighted and stratified χ^2 tests were used to compare sexes and to generate *P* values.
[c] Calculated as weight in kilograms divided by height in meters squared.
[d] Waist circumference ≥120 cm for men and ≥88 cm for women.

Table 2. Risk of Abdominal Obesity and Obesity[a] by Behavior Among Adults Aged 20 to 64 (N = 4,118) Who Engaged in Work-Related Physical Activity, National Health and Nutrition Examination Survey, 2013–2014[b]

Behavior	Base Model[c] (n = 1,287)		Base Model[c] With Vigorous Work-Related Physical Activity[d] (n = 363)		Base Model[c] With Moderate Work-Related Physical Activity[e] (n = 548)	
	Men	Women	Men	Women	Men	Women
Abdominal Obesity						
Ate meals prepared away from home <3 vs ≥3 times/wk	1.35 (0.88–2.07)	1.58 (0.87–2.85)	1.35 (0.62–2.95)	1.36 (0.68–2.71)	1.06 (0.65–1.75)	1.72 (0.73–4.04)
Ate frozen meals/pizza in past 30 days <3 vs ≥3 times/wk	1.15 (0.71–1.87)	1.27 (0.76–2.11)	1.28 (0.59–2.74)	0.86 (0.21–3.49)	1.27 (0.60–2.70)	1.20 (0.51–2.84)
Sedentary activity ≤359 vs 360–539 min/d	1.24 (0.71–2.19)	0.95 (0.57–1.59)	1.97 (0.90–4.33)	1.40 (0.17–11.52)	1.46 (0.65–3.28)	1.26 (0.53–3.01)
Sedentary activity ≤359 vs ≥540 min/d	1.38 (0.81–2.33)	0.85 (0.38–1.89)	2.35 (0.79–6.99)	0.54 (0.07–4.03)	1.01 (0.45–2.26)	0.65 (0.21–2.02)
Watching television or videos <2 vs ≥2 hr/d	1.96 (1.29–2.98)[f]	1.66 (1.06–2.59)[f]	1.58 (0.77–3.26)	0.96 (0.34–2.73)	2.68 (1.30–5.53)[f]	1.32 (0.71–2.44)
Computer/video game usage <2 vs ≥2 hr/d	1.11 (0.67–1.85)	1.27(0.85–1.89)	0.79 (0.34–1.85)	1.90 (0.83–4.39)	0.70 (0.29–1.69)	1.19 (0.63–2.24)
Vigorous work-related physical activity ≤74 vs ≥75 min/wk	—	—	0.25 (0.08–0.77)[f]	1.26 (0.50–3.19)	—	—
Moderate work-related physical activity ≤149 vs ≥150 min/wk	—	—	—	—	1.31 (0.64– 2.67)	0.86 (0.30– 2.42)
Obesity						
Ate meals prepared away from home <3 vs ≥3 times/wk	1.07 (0.69–1.68)	1.67 (1.08–2.58)[f]	0.89 (0.47–1.69)	1.02 (0.44–2.38)	1.03 (0.61–1.73)	2.37 (1.09–5.13)[f]
Ate frozen meals/pizza in past 30 days <3 vs ≥3 times/wk	1.34 (0.90–2.00)	0.96 (0.55–1.70)	1.45 (0.58–3.59)	1.38 (0.56–3.42)	1.33 (0.76–2.35)	1.48 (0.59–3.70)
Sedentary activity ≤359 vs 360–539 min/d	1.47 (0.82–2.63)	1.41 (1.03–1.93)[f]	1.57 (0.75–3.26)	0.60 (0.16–2.29)	2.19 (0.83–5.74)	1.26 (0.60–2.66)
Sedentary activity ≤359 vs ≥540 min/d)	1.22 (0.63–2.36)	1.14 (0.60–2.16)	1.56 (0.54–4.47)	0.63 (0.11–3.61)	0.97 (0.40–2.34)	0.52 (0.17–1.64)
Watching television or videos <2 vs ≥2 hr/d	2.17 (1.18–4.02)[f]	1.66 (1.12–2.48)[f]	1.83 (0.94–3.56)	1.20 (0.35–4.11)	2.37 (1.09–5.14)[f]	1.28 (0.81–2.02)
Computer or video game use <2 vs ≥2 hr/d	1.15 (0.75–1.75)	1.15 (0.72–1.83)	0.64 (0.27–1.50)	1.44 (0.50–4.13)	0.60 (0.25–1.45)	1.27 (0.71–2.26)
Vigorous work-related physical activity ≤74 vs ≥75 min/wk	—		1.57 (0.65–3.82)	1.11 (0.24–5.05)	—	—
Moderate work-related physical activity ≤149 vs ≥150 min/wk	—	—	—	—	2.46 (1.55–3.90)[f]	0.70 (0.34–1.44)

Abbreviation: —, not applicable.

[a] Abdominal obesity was defined as a waist circumference ≥120 cm for men and ≥88 cm for women. Obesity was defined as a body mass index (calculated as weight in kilograms divided by height in meters squared) of ≥30.

[b] Values are odds ratio (95% confidence interval). Odds ratios were calculated by using logistic regression.

[c] Includes all demographic variables (age, race/ethnicity, education, employment, and marital status), 2 food intake variables (consumption of meals prepared away from home and consumption of frozen meals or pizza at home), and variables for general sedentary activity, television and video viewing, and computer use.

[d] Activity that causes large increases in heart rate or breathing.

[e] Activity that causes small increases in heart rate or breathing.

[f] Significant at *P* < .05.

Table 3. Risk of Abdominal Obesity and Obesity[a] by Behavior Among Adults Aged 20 to 64 (N = 4,118) Who Engaged in Recreational and Transportation Physical Activity, National Health and Nutrition Examination Survey, 2013–2014[b]

Behavior	Base Model[c] With Vigorous Recreational Physical Activity[d] (n = 266)		Base Model[c] With Moderate Recreational Physical Activity[e] (n = 498)		Base Model[c] With Transportation Physical Activity[f] (n = 335)	
	Men	Women	Men	Women	Men	Women
Abdominal Obesity						
Ate meals prepared away from home <3 vs ≥3 times/wk	0.98 (0.43–2.22)	1.27 (0.21–7.46)	1.13 (0.72–2.40)	1.55 (0.55–4.39)	1.43 (0.60–3.44)	1.85 (0.34–10.04)
Ate frozen meals/pizza in past 30 days <3 vs ≥3 times/wk	1.21 (0.37–3.96)	3.56 (2.18–5.81)[g]	0.47 (0.19–1.18)	1.81 (0.55–3.87)	1.26 (0.37–4.30)	1.31 (0.34–5.08)
Sedentary activity ≤359 vs 360–539 min/d	1.64 (0.93–2.92)	0.86 (0.21–3.50)	1.24 (0.72–2.11)	0.52 (0.15–1.85)	1.24 (0.45–3.46)	0.57 (0.13–2.47)
Sedentary activity ≤359 vs ≥540 min/d	0.59 (0.11–3.26)	1.73 (0.61–4.95)	2.05 (0.72–5.81)	0.26 (0.07–1.01)	2.84 (0.93–8.64)[g]	0.13 (0.03–0.54)[g]
Watching television or videos <2 vs ≥2 hr/d	3.79 (0.85–16.85)	0.48 (0.10–2.42)	1.95 (0.94–4.05)	1.17 (0.54–2.52)	3.24 (1.28–8.20)[g]	1.40 (0.49–4.06)
Computer or video game use <2 vs ≥2 hr/d	1.36 (0.45–4.12)	1.83 (0.50–6.75)	0.93 (0.40–2.18)	1.26 (0.61–2.59)	0.47 (0.19–1.18)	2.29 (0.61–8.65)
Vigorous recreational physical activity ≤74 vs ≥75 min/wk	0.31 (0.11–0.88)[g]	0.60 (0.13–2.81)	—	—	—	—
Moderate recreational physical activity ≤149 vs ≥150 min/wk	—	—	0.44 (0.22–0.89)[g]	0.38 (0.23–0.67)[g]	—	—
Transportation physical activity ≤149 vs ≥150 min/wk	—	—	—	—	0.58 (0.23–1.46)	0.71 (0.54–3.44)
Obesity						
Ate meals prepared away from home <3 vs ≥3 times/wk	0.83 (0.54–1.28)	3.22 (0.72–14.41)	1.28 (0.65–2.50)	1.61 (0.75–3.44)	1.64 (0.69–3.87)	1.75 (0.79–3.89)
Ate frozen meals/pizza in past 30 days <3 vs ≥3 times/wk	1.16 (0.54–2.49)	2.27 (0.72–7.11)	0.87 (0.42–1.83)	1.14 (0.71–1.82)	1.79 (0.62–5.11)	1.69 (0.46–6.17)
Sedentary ≤359 vs 360–539 min/d	2.10 (0.82–5.36)	1.67 (0.25–11.30)	1.52 (0.90–2.56)	1.59 (0.93–2.73)	1.25 (0.51–3.07)	0.88 (0.28–2.74)
Sedentary ≤359 vs ≥540 min/d	0.85 (0.14–5.26)	1.29 (0.17–9.79)	1.80 (0.46–7.02)	0.60 (0.24–1.51)	3.06 (0.97–9.58)	0.40 (0.13–1.25)
Watching television or videos <2 vs ≥2 hr/d	3.87 (1.53–9.78)[g]	0.81 (0.14–4.61)	1.98 (0.84–4.69)	1.11 (0.46–2.70)	3.28 (1.20–8.96)[g]	1.23 (0.51–2.99)
Computer or video game use <2 vs ≥2 hr/d	0.89 (0.33–2.40)	0.70 (0.05–9.53)	1.01 (0.48–2.14)	0.83 (0.38–1.81)	0.59 (0.25–1.42)	1.94 (0.82–4.57)
Vigorous recreational physical activity ≤74 vs ≥75 min/week	0.39 (0.14–1.08)	0.85 (0.15–4.74)	—	—	—	—
Moderate recreational physical activity ≤149 vs ≥150 min/week	—	—	0.97 (0.40–1.86)	0.48 (0.27–0.84)[g]	—	—
Transportation physical activity ≤149 vs ≥150 min/wk	—	—	—	—	0.73 (0.32–1.67)	0.59 (0.22–1.59)

Abbreviation: —, not applicable.

[a] Abdominal obesity was defined as a waist circumference ≥120 cm for men and ≥88 cm for women. Obesity was defined as a body mass index (calculated as weight in kilograms divided by height in meters squared) of ≥30.

[b] Values are odds ratio (95% confidence interval). Odds ratios were calculated by using logistic regression.

[c] Includes all demographic variables (age, race/ethnicity, education, employment, and marital status), 2 food intake variables (consumption of meals prepared away from home and consumption of frozen meals or pizza at home), and variables for general sedentary activity, television and video viewing, and computer use.

[d] Activity that causes large increases in heart rate or breathing.

[e] Activity that causes small increases in heart rate or breathing.

[f] Walking or bicycling for getting to and from places.

[g] Significant at *P* < .05.