# PREVENTING CHRONIC DISEASE

PUBLIC HEALTH RESEARCH, PRACTICE, AND POLICY

## PCD COLLECTION

NEXT STEPS: TRANSLATING EVIDENCE TO ELIMINATE DISPARITIES IN DIABETES AND OBESITY

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EDITORIAL

# Next Steps: Eliminating Disparities in Diabetes and Obesity

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In 2012, 29.1 million Americans, or 9.3% of the population, had diabetes, contributing an estimated $245 billion to US health care costs (1). Type 2 diabetes, which accounts for 90% or more of diabetes cases, affects people of all ages, economic groups, races, and ethnicities (1). However, certain populations, including American Indians, African Americans, and those with socioeconomic disadvantages, have a disproportionate burden of disease and associated complications (1). Despite evidence of effective means to prevent type 2 diabetes through obesity prevention and control, there remains a significant gap between research and practice in real world settings that limits impact. Translational research is needed to inform innovative strategies for preventing and controlling diabetes across high-risk groups.

The Washington University Center for Diabetes Translation Research (WU-CDTR) is 1 of 7 centers across the country funded by the National Institute of Diabetes and Digestive and Kidney Diseases (NIDDK) of the National Institutes of Health whose purpose is to enhance the efficiency, productivity, and effectiveness of diabetes translation research (2). The research is conducted in partnership with the National Congress of American Indians, an organization that represents 566 federally recognized tribal nations (3). The WU-CDTR supports transdisciplinary researchers committed to improving the quality, quantity, and effective translation of research to prevent diabetes and address obesity as a major cause across diverse populations. Researchers study the root causes of diabetes and the impact on translation of evidence-based interventions. These root causes are defined by multiple social constructs that influence health, including poverty, living and working conditions, housing quality, and access to healthy food and safe neighborhoods. Individual constructs, such as health literacy, communication barriers, or cultural differences, are also associated with diabetes disparities (4). Differential experiences and exposure to these dimensions of disparity across the life course contribute to the prevalence of obesity and diabetes among diverse racial and ethnic groups (5). An understanding of these influences is needed to guide implementation research to prevent and control diabetes.

Translational researchers need time to work together to ask questions and solve complex problems. The WU-CDTR and the Washington University Institute of Public Health cosponsored a 1-day conference for researchers, Next Steps: Eliminating Disparities in Diabetes and Obesity. In this context, a review of the 2011 NIDDK strategic plan (6) challenged us to "take stock" of our progress in addressing translational diabetes research relevant to the work of the WU-CDTR. We prioritized 4 questions to guide our review of research activities: 1) What is the influence of life course exposure to poor living environments on diabetes prevention and control? 2) How can structures and policies influence behavior change to prevent diabetes? 3) How can innovations in health communication science and technologies be advanced to test strategies for addressing diabetes disparities? 4) What are key practices for adapting culturally appropriate, evidence-based interventions to real-world settings while expanding reach?

The conference provided a forum for WU-CDTR researchers to discuss, critique, and identify methods for answering these provocative questions. Forty-three researchers representing 14 disciplines and 5 institutions across the country collaborated on a collection of 12 articles in *Preventing Chronic Disease* (*PCD*). These articles document research across various stages of development and inform implementation of evidence-based practices across high-risk populations. Although research on several topics in this collection is in its early stages, we anticipate that these articles will provide practitioners with evidence and leverage points for their efforts in controlling diabetes and obesity. The articles are identified in *PCD*'s table of contents as part of the collection and will be compiled into a single PDF download on the *PCD Collections* page shortly after release (www.cdc.gov/pcd/collections/index.htm). Articles in the collection cover 3 major topics: contextual risk factors, environment and policy issues, and the emerging evidence base for effective interventions.

Three articles on contextual risk factors address the influence of life course exposure to poor living environments on diabetes development and prevalence. Duncan et al (7) describe the link between child maltreatment and diabetes in young adulthood and their differential effects by sex in "Relationship Between Child Abuse and Neglect in Childhood and Diabetes in Adulthood: Differential Effects By Sex, National Longitudinal Study of Adolescent Health." Marley and Metzger (8) describe the influence of neighborhood risk factors, poverty, and stress on diabetes outcomes in "A Longitudinal Study of Structural Risk Factors for Obesity and Diabetes among American Indian Young Adults, 1994–2008." The impact of life course exposure to risk factors in the physical environment and its influence on diabetes is documented by Hipp and Chalise (9) in "Spatial Analysis and Correlates of County-Level Diabetes Prevalence, 2009–2010." These articles provide further evidence of how exposure to poor-quality physical and social environments may place populations at risk for developing obesity and diabetes.

Six articles examine the effect of environmental settings and policies on diabetes and obesity outcomes. The perception of the quality of the home and school settings and its influence on eating behavior is assessed by Clarke et al (10) in "Influence of Home and School Environments on Specific Dietary Behaviors Among Postpartum, High-Risk Teens, 27 States, 2007–2009." Three articles describe developing research on interventions addressing the influence of income in workplaces: "Enhancing Workplace Wellness Efforts to Reduce Obesity: A Qualitative Study of Low-Wage Workers in St Louis, Missouri, 2013–2014" by Strickland et al (11), "Worksite Influences on Obesogenic Behaviors in Low-Wage Workers in St Louis, Missouri, 2013–2014" by Strickland et al (12), and "Review of Measures of Worksite Environmental and Policy Supports for Physical Activity and Healthy Eating" by Hipp et al (13). Two articles describe the influence of policy on diabetes prevention and control. Brown and McBride (14) analyze the state of being uninsured and its influence on health care use in "Impact of the Affordable Care Act on Access to Care for US Adults With Diabetes, 2011–2012." Purnell et al (15) discuss the importance of linking approaches across settings to address diabetes prevention and control: "Outside the Exam Room: Policies for Connecting Clinic to Community in Diabetes Prevention and Treatment."

Two articles examine innovations in health communication science and technologies for addressing diabetes disparities. Harris et al (16) describe emerging evidence on the use of social media and crowdsourcing to influence diabetes-related behavior in "Diabetes Topics Associated With Engagement on Twitter." Caburnay et al (17) address the use of mobile technologies in "Evaluating Diabetes Mobile Applications for Health Literate Designs and Functionality, 2014." These articles explore innovative technologies that hold promise for overcoming communication barriers in reaching diverse audiences.

Sanders Thompson et al (18) review cultural adaptations of diabetes interventions and discuss the need for inclusion of cultural elements unique to racial/ethnic populations in "Use of Culturally Focused Theoretical Frameworks for Adapting Diabetes Prevention Programs: A Qualitative Review." The review provides a road map for identifying key practices in adapting culturally appropriate, evidence-based interventions to real world settings.

Although these articles vary in topic and scope, the authors are consistent in their pursuit of better understanding the multilevel, multisector influences on the physical and social environment and how these environments affect behavior, health, and translational interventions to prevent diabetes. Transdisciplinary approaches such as those represented here are needed to recognize the broader causes of disparities, better inform actions to mitigate the effect of these root causes of disease, and promote sustainable progress in preventing diabetes in diverse populations. Opportunities that encourage the integration of diverse perspectives can lead to transformational research and sustainable impact.

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ORIGINAL RESEARCH

# Relationship Between Abuse and Neglect in Childhood and Diabetes in Adulthood: Differential Effects By Sex, National Longitudinal Study of Adolescent Health

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PEER REVIEWED

## Abstract

### Introduction
Few studies have investigated links between child abuse and neglect and diabetes mellitus in nationally representative samples, and none have explored the role of obesity in the relationship. We sought to determine whether child abuse and neglect were associated with diabetes and if so, whether obesity mediated this relationship in a population-representative sample of young adults.

### Methods
We used data from 14,493 participants aged 24 to 34 years from Wave IV of the National Longitudinal Study of Adolescent Health to study associations between self-reported child abuse (sexual, physical, or emotional abuse) and neglect as children and diabetes or prediabetes in young adulthood. We conducted sex-stratified logistic regression analyses to evaluate associations in models before and after the addition of body mass index (BMI) as a covariate.

### Results
Although the prevalence of diabetes was similar for men and women (7.0% vs 6.7%), men were more likely than women to have prediabetes (36.3% vs 24.6%; omnibus $P < .001$). Among men, recurrent sexual abuse (≥3 lifetime incidents) was significantly associated with diabetes (OR, 3.66; 95% CI, 1.31–10.24), but not with prediabetes. There was no evidence of mediation by BMI. No forms of child abuse or neglect were associated with diabetes or prediabetes among women.

### Conclusions
Recurrent sexual abuse is robustly associated with diabetes in young adult men, independently of other forms of child abuse or neglect and BMI. Future research should explore other potential mechanisms for this association to identify avenues for prevention of diabetes among men who have experienced sexual abuse.

## Introduction

Diabetes mellitus is the seventh leading cause of death in the United States; the disease affects more than 9% of the US population and costs $245 billion per year (1). An additional 86 million Americans aged 20 years or older are estimated to have prediabetes (1). Although 2012 data indicated a leveling off of the prevalence and incidence of diabetes in the population as a whole, increases are still apparent in some subgroups, including young adults aged 20 to 44 years (2), among whom an estimated 6% have diabetes (3). As the public health burden of diabetes continues to rise, efforts to identify risk factors and stem the tide are needed.

Obesity is a major risk factor for diabetes (4); thus, correlates of obesity are likely targets for associations with diabetes. A recent meta-analysis found that obesity was positively associated with sexual, physical, and emotional abuse in childhood (5), and results from the Adverse Childhood Experiences Study showed that the number of adverse experiences (including all forms of abuse and physical neglect) was significantly related to disordered eating, low levels of physical activity, obesity, and diabetes (6,7). Similarly, a 30-year prospective study found significant associations of childhood maltreatment —including neglect and physical, sexual, and emotional abuse — with obesity (7) and elevated hemoglobin A1c (HbA1c) levels, a marker for diabetes (8). One explanation for the relationship between child abuse and neglect and negative health outcomes is that the chronic stress associated with child maltreatment causes detrimental and lasting neurobiologic changes, such as hypothalamic–pituitary–adrenal (HPA) axis dysregulation, that lead to poor health behaviors and outcomes (6, 9, 10). Additionally, child abuse and neglect may result in conflicted relationships, poor self-esteem, and the subsequent adoption of health-risk behaviors (11).

Child maltreatment is common in the United States. It is estimated that 1 in 8 US children will have an officially confirmed maltreatment episode by age 18 (12). Several studies using nationally representative data from the National Longitudinal Study of Adolescent Health (Add Health) have examined associations between child maltreatment and overweight and obesity or weight gain in adolescence and young adulthood (13–17). Add Health is a longitudinal study of a nationally representative sample of US adolescents who were in grades 7 through 12 during the 1994–95 school year. Add Health collects data on adolescents' social, economic, psychological, and physical well-being and has followed a cohort of adolescents into young adulthood in a series of in-home interviews called "waves." These studies using Add Health data had varied results. Three found associations only among particular subgroups; however, results were inconsistent. One study found an association between sexual abuse and obesity in men only (13), 1 study observed a relationship between combined instances of sexual and physical abuse and severe obesity only in nonminority women and men (14), and a third study found that supervisory neglect was associated with body mass index (BMI) at the first wave of data collection (Wave I) in women only (15). Two other studies demonstrated associations in the entire Add Health data between co-occurring physical abuse and neglect and obesity at Wave I (16) and between physical abuse and overweight and obesity at the third wave of data collection (Wave III) (17).

To our knowledge, no study has yet examined associations between child maltreatment and diabetes in a nationally representative sample, and results from studies that used nonrepresentative samples were inconclusive. Furthermore, previous studies did not take obesity into account (18), which would be critical given that obesity, which is a risk factor for diabetes, is associated with childhood maltreatment. Therefore, the objective of this study was to examine whether child maltreatment was associated with diabetes and, if so, whether obesity mediated this relationship in a population-representative sample of young adults.

# Methods

This study used restricted-use data from 14,493 (46.1% male) participants in Wave IV of Add Health. We used variables drawn from participant responses to Waves I, III, and IV in-home interviews. At Wave I, conducted during the 1994–95 school year, a nationally representative sample of 20,745 adolescents in grades 7 through 12 completed in-home interviews. Waves III (2001–02) and IV (2008–09) included all Wave I in-home respondents who could be located, yielding a sample of 15,197 adults aged 18 to 28 years at Wave III, and 15,701 aged 24 to 34 at Wave IV. In addition, at Wave IV, researchers measured height and weight and collected blood for DNA and various biomarker analyses, including fasting or nonfasting blood glucose and HbA1c levels. Details regarding Add Health are available elsewhere (19). Because previous investigations have observed sex-specific associations between childhood maltreatment and obesity, analyses were stratified by sex.

## Key variables

We coded diabetes status from Add Health Wave IV biospecimen data and modeled it as a 3-level variable: 1) diabetes (defined as any of the following: HbA1c ≥6.5%, fasting glucose ≥126 mg/dL, nonfasting blood glucose ≥200 mg/dL, self-reported taking antidiabetic medication, and/or report of receiving a diagnosis of diabetes or high blood glucose by a health care provider); 2) prediabetes or impaired glucose tolerance (HbA1c 5.7%–6.4% and/or fasting glucose 100–125 mg/dL); or 3) no diabetes. We did not use nonfasting blood glucose alone for classification of prediabetes because the American Diabetes Association does not provide guidelines for doing so.

We coded child maltreatment variables from Wave III and Wave IV in-home interview questions (Box) regarding how often respondents experienced specific forms of child maltreatment by adult caregivers. Questions had 5 response options, from "this never happened" to "more than 10 times." Add Health assessed child neglect at Wave III only and emotional abuse at Wave IV only. Although assessments used identical descriptions of childhood sexual abuse and physical abuse at Wave III and Wave IV, questions at Wave III asked about events occurring before the respondent was in 6th grade; Wave IV questions asked about events occurring before age 18. In both interviews, an additional question about the respondent's age when the event first occurred followed positive responses. Because the focus of the current study was child abuse and neglect, we coded events reported at Wave IV as positive only if they first happened before age 12. To distinguish recurrent abuse from abuse that occurred only once or twice, we operationalized each type of maltreatment as a 3-level variable: 3 or more times, 1 to 2 times, or never. These cutpoints coincided with the median number of incidents for respondents who had ever experienced physical abuse, sexual abuse, or neglect.

**Box. Questions Used To Assess Childhood Physical Abuse, Sexual Abuse, and Neglect in Study Sample (N = 14,493), Wave III and Wave IV In-Home Interviews, National Longitudinal Study of Adolescent Health**

**Wave III interview (by the time you started 6th grade)**

How often had your parents or other adult caregivers left you home alone when an adult should have been with you? (Neglect)

How often had your parents or other adult caregivers not taken care of your basic needs, such as keeping you clean or providing food or clothing? (Neglect)

How often had your parents or other adult caregivers slapped, hit, or kicked you? (Physical abuse)

How often had your parents or other adult caregivers touched you in a sexual way, forced you to touch him or her in a sexual way, or forced your to have sexual relations? (Sexual abuse)

**Wave IV interview (before your 18th birthday) (coded as positive if age reported for first event was <12 years)**

How often did a parent or other adult caregiver say things that really hurt your feelings or made you feel like you were not wanted or loved? How old were you the first time this happened? (Emotional abuse)

How often did a parent or adult caregiver hit you with a fist, kick you, or throw you down on the floor, into a wall, or down stairs? How old were you the first time this happened? (Physical abuse)

How often did a parent or other adult caregiver touch you in a sexual way, force you to touch him or her in a sexual way, or force you to have sexual relations? How old were you the first time this happened? (Sexual abuse)

Body mass index (BMI [kg/m$^2$]) was calculated from height and weight measured at Wave IV. We categorized BMI into 5 levels: obese classes III (≥40), II (35.0–39.9), and I (30.0–34.9); overweight (25.0–29.9); and normal weight (<25.0). Because of low numbers, underweight adults (BMI <18.5) were included in the normal-weight category (n = 191; 1.3% of total sample).

We also included covariates that were known to be associated with both childhood maltreatment and diabetes that were not likely to be in the causal pathway between childhood maltreatment and diabetes and were available in the data set. We modeled the 6-category race/ethnicity preconstructed variable from the Wave I data set (ie, white, black, Latino, Asian/Pacific Islander, American Indian/Native American, and other) (13) as a set of indicator variables, with white as the reference category. We dichotomized self-report of highest education attained at Wave IV as receiving versus not receiving a 4-year college degree. We coded financial insecurity in adolescence from the question in the parental interview: "Do you have enough money to pay your bills?" Because 15.0% of respondents did not have parental interview data, we modeled this variable as a set of indicator variables: enough money to pay bills, not enough money to pay bills (the reference category), or parental data missing. Such subjective measures of social status have been identified as strong predictors of health and, for some measures, are more predictive of health than objective measures such as income and education (20,21). Furthermore, without information about household size or region, estimates of income would not be accurate (22). We obtained information on whether respondents had ever smoked daily from the Wave IV interview.

## Data analysis

We analyzed data from 14,493 Add Health Wave IV participants with biomarker data by using survey procedures in Stata version 9.2 (Stata Corp LP) to account for Add Health's complex survey design, stratifying all analyses by sex. First, we used $\chi^2$ analyses to assess bivariate associations of the 3-category diabetes dependent variable (ie, diabetes, prediabetes, or no diabetes) with the 4 child maltreatment variables (ie, sexual abuse, physical abuse, neglect, and emotional abuse) and BMI category and other potential covariates (Table 1). Next, we estimated separate multinomial logistic regression models with 3-category diabetes status as the dependent variable (no diabetes as reference category) for each form of child maltreatment, separately in men and women (models 1–4 [Table 2]). We then estimated a model with all 4 forms of child maltreatment as independent variables (Model 5). To this model, we added the following covariates: age, race/ethnicity, college degree, daily smoking, and childhood financial insecurity (Model 6). Finally, we added BMI category to the model (Model 7) and compared the odds ratios (ORs) of Models 6 and 7. In all models, we conducted post-hoc tests to evaluate differences between the ORs for 1 to 2 versus 3 or more childhood maltreatment incidents for each type of maltreatment.

## Results

Although the prevalence of diabetes was similar for men and women (7.0% vs 6.7%), men were more likely than women to have prediabetes (36.3% vs 24.6%; omnibus $P < .001$). Both men and women with diabetes were more likely than men and women without diabetes to have a BMI in the obese range and to be a member of a racial/ethnic minority group and less likely to report having a college degree. Men, but not women, with diabetes were significantly more likely to have a background of childhood financial insecurity. The prevalence of these variables for respondents with prediabetes was generally between the prevalence for those with and without diabetes (Table 1). In both men and women, a history of daily smoking was inversely associated with diabetes; however, these associations were significant only among women ($P = .001$).

Among men, 4.1% with diabetes reported that they had experienced sexual abuse by a caregiver 3 or more times, compared with 1.3% with prediabetes and 1.2% without diabetes ($P = .013$). No other forms of child maltreatment were significantly associated with diabetes among men. Among women, only emotional abuse was associated with the 3-level diabetes status variable overall ($P = .02$), but the relationship was complex. Although women with diabetes had a higher prevalence of 1 to 2 occurrences of emotional abuse than women with prediabetes or women without diabetes, they had a lower prevalence of 3 or more occurrences of emotional abuse (15.3% vs 18.3% for women without diabetes). Childhood physical abuse was significantly associated with BMI category in men ($P = .012$) and in women ($P = .04$); however, there were no significant associations between BMI category and any other forms of childhood maltreatment in men or women (Table 2).

Men who reported experiencing sexual abuse 3 or more times had 3.63 times greater odds of diabetes than men who did not report sexual abuse (95% CI, 1.53–8.62) (Table 3). The magnitude of this association remained similar after adjusting for other forms of child maltreatment and covariates (OR, 3.66; 95% CI, 1.31–10.24). The addition of BMI category to the model slightly increased the magnitude of association between 3 or more incidents of sexual abuse and diabetes (OR, 3.80; 95% CI, 1.48–9.72), an indication that BMI category did not mediate the association; all BMI categories were significantly, positively associated with diabetes and prediabetes. Negative associations between diabetes and both neglect and emotional abuse were observed but were not consistently significant, and no associations were noted for physical abuse. With one exception (infrequent physical abuse in bivariate model only), no other child maltreatment variables were associated with prediabetes in men.

In contrast to men, among women (Table 3) no associations between diabetes and any child maltreatment variable were observed in any of the models. Rather, women experiencing 1 to 2 occurrences of neglect had a greater risk of prediabetes (OR, 1.31; 95% CI, 1.06–1.63) that remained significant and similar in magnitude even after covariates and BMI were added to the model (OR, 1.29; 95% CI, 1.02–1.63). There was an inverse association between repeated emotional abuse and prediabetes; however, this relationship was no longer significant after adding covariates and BMI to the model.

## Discussion

In this population-based sample of young adults, we found that repeated sexual abuse was significantly associated with diabetes among men, even after adjusting for BMI category. In contrast, there were no associations between retrospective self-reports of any form of childhood maltreatment and diabetes among women. There is limited previous research in this area, and findings from other studies of child maltreatment and diabetes have been mixed. Our results are consistent with those reported in a previous Add Health study that used data from Wave III and found a significant association between sexual abuse and obesity in men but not in women (13).

To our knowledge, this is the first study to investigate the possibility that BMI mediates the association between childhood maltreatment and diabetes. BMI category was positively associated with prediabetes and diabetes in these analyses for both women and men; however, it did not serve as a mediator of the relationship between sexual abuse and diabetes in men, as evidenced by the increase in the magnitude of the OR for sexual abuse after adding BMI category to the model. This finding was not unexpected given that we did not observe an association between sexual abuse and obesity in sexual abuse data from Waves III and IV and BMI data from Wave IV (Table 2), contrary to the results of a previous study (13). Although a meta-analysis showed a significant positive association between sexual abuse and obesity, many of the individual studies included in the meta-analysis did not find a significant association, and ORs from these studies ranged from 0.81 to 3.60 (5). This heterogeneity may be due to differences in the operationalization of sexual abuse and to choice of the comparison group for obesity. Furthermore, findings from previous Add Health studies of associations between sexual abuse and obesity and BMI varied and found significant associations only within particular subgroups (13–15). Taken together, this suggests that if there is an association between sexual abuse and obesity and BMI in Add Health, it is not a robust one.

There is a well-established association between childhood adversity and mental and physical health outcomes (8,15,16,24). Our results suggest that sexual abuse may also have a negative effect on the physical health of men, in particular on cardiovascular disease risk. Fuller-Thomson et al (25), in a population-based adult sample, reported significantly elevated odds of myocardial infarction among men, but not women, who were exposed to childhood sexual abuse than among their unexposed counterparts (25). Various explanations have been offered for this link that may be relevant to our results (24). These include that men could be less likely than women to seek treatment following incidents of abuse and that treatment regimens for men may differ from those for women, leading to poorer adaptation of men following the abuse. This poor adaptation may increase men's psychosocial stress, thereby affecting the HPA stress pathway, making them more vulnerable to adverse cardiovascular events, including precursor outcomes such as diabetes. Further research in this area is needed. The prevalence of officially confirmed childhood sexual abuse and rates of sexual abuse based on retrospective self-report are lower for men than for women (26–28). Thus, efforts to improve the identification of childhood sexual abuse among men and subsequent interventions may not only improve psychosocial outcomes but may also benefit men's long-term physical health.

This study also may be the first to examine associations between childhood maltreatment and prediabetes; however, some of the results were inconsistent and somewhat counterintuitive. For example, women who reported experiencing 1 to 2 neglect incidents were more likely to develop prediabetes, but the OR for 3 or more incidents was close to 1 and not significant; this was also true for both levels of neglect when predicting diabetes. This finding may be due to chance, particularly given that there was not a significant difference between the ORs for 1 to 2 neglect incidents and 3 or more neglect incidents. The negative association between infrequent emotional abuse and diabetes in men was also unexpected and may possibly reflect limitations of the Add Health child maltreatment assessment. Because the assessment of each form of child maltreatment was limited to 1 or 2 questions, it is difficult to place these results into context. A single-item indicator for child maltreatment events may not be adequate in accurately capturing all cases of abuse and does not allow for its in-depth characterization. In addition, the Add Health assessment of sexual abuse asked only about incidents committed by a family member or adult caregiver. Because many perpetrators of sexual abuse, particularly among male victims, are not relatives or caregivers (24,27), people who experienced sexual abuse perpetrated by persons not family members or caregivers would be false negatives on the sexual abuse variable, causing a bias toward the null hypothesis. Misclassification from retrospective reports of child maltreatment, another potential limitation of the assessment, would also probably yield far more false negatives than false positives. Therefore, the true magnitude of association between childhood sexual abuse and diabetes in men may be greater than we observed.

There were also limitations to our categorization of diabetes. First, we were unable to distinguish between type 1 and type 2 diabetes. It is possible that results may have differed by diabetes type, particularly because risk factors for the two types are different (29); however, given estimates that 90% to 95% of adults with diabetes have type 2 diabetes (3), most people with diabetes in the sample probably had type 2 diabetes. Second, the American Diabetes Association currently defines blood glucose cutoffs for classifying prediabetes solely based on fasting blood glucose, but for most Add Health participants, only nonfasting blood glucose levels were available. Thus, we may have missed prediabetes in some people for whom we did not have fasting blood glucose levels: 1.4% of people classified as not having diabetes (n = 123) had nonfasting blood glucose levels in the 140 to 199 mg/dL range and reported 2 to 7 hours since they last ate or drank; some of these may have had prediabetes. Second, 5.2% of women with diabetes (n = 32), but no men, were coded as such solely because they were on antidiabetes medication; it is possible that some of those women were on metformin because of polycystic ovary syndrome rather than for diabetes. Removal of these women from the analysis, however, did not alter the results (data not shown).

Although results were not uniform, our findings indicate that childhood sexual abuse among men is associated with greater risk of diabetes in adulthood. The magnitude of effect remained robust even when controlling for other forms of child maltreatment and obesity. The prevalence of sexual abuse may be underestimated in this sample. Furthermore, given the potential for interactions between different variables examined here, unobserved factors could have altered different associations of diabetes with childhood abuse and neglect. Nonetheless, these findings from a large, nationally representative sample that used a rigorous approach to defining diabetes are a potentially important step in understanding the relationship between childhood adversities and diabetes and may generate future research efforts to develop new hypotheses and interventions to address factors related to the development of diabetes.

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# Tables

**Table 1. Characteristics of Study Sample (N = 14,493) by Sex and Diabetes Status, National Longitudinal Study of Adolescent Health, 2001–2002 and 2008–2009**

| Characteristic[a] | Women | | | | Men | | | |
|---|---|---|---|---|---|---|---|---|
| | Diabetes[b] | Prediabetes[c] | No diabetes | Omnibus *P* Value | Diabetes[b] | Prediabetes[c] | No diabetes | Omnibus *P* Value |
| **N** | 614 | 2,062 | 5,138 | — | 488 | 2,584 | 3,607 | — |
| **Age, y. mean (SD)** | 28.43 (0.18) | 28.44 (0.13) | 28.15 (0.12) | .01 | 28.79 (0.16) | 28.51 (0.13) | 28.33 (0.13) | .001 |
| **Race/ethnicity (Wave I[d])** | | | | | | | | |
| White | 45.10 | 52.12 | 72.76 | <.001 | 42.66 | 57.37 | 75.90 | <.001 |
| Black | 35.60 | 26.67 | 10.60 | | 34.09 | 21.00 | 8.55 | |
| Latino | 13.16 | 15.57 | 10.64 | | 16.07 | 13.70 | 9.97 | |
| Asian/Pacific Islander | 2.31 | 3.07 | 3.36 | | 2.13 | 4.40 | 2.84 | |
| American Indian/Native American | 3.64 | 1.57 | 1.71 | | 4.81 | 2.75 | 1.54 | |
| Other | 0.18 | 1.01 | 0.93 | | 0.23 | 0.78 | 1.21 | |
| **Has college degree** | 20.50 | 25.19 | 36.52 | <.001 | 18.90 | 19.86 | 30.96 | <.001 |
| **Ever smoked daily for 30 days** | 38.96 | 41.02 | 47.30 | .001 | 46.53 | 49.57 | 53.06 | .08 |
| **BMI category** | | | | | | | | |
| Underweight/Normal weight (≤24.9 kg/m$^2$) | 14.45 | 22.03 | 43.83 | <.001 | 16.47 | 24.94 | 33.66 | <.001 |
| Overweight (25.0–29.9 kg/m$^2$) | 18.31 | 22.10 | 25.87 | | 23.92 | 33.17 | 36.66 | |
| Obese class I (BMI 30.0–34.9) | 21.75 | 21.14 | 14.96 | | 23.82 | 21.84 | 19.17 | |
| Obese class II (BMI 35.0–39.9) | 19.47 | 15.87 | 8.57 | | 12.41 | 11.17 | 6.69 | |
| Obese class III (BMI ≥40.0) | 26.02 | 18.87 | 6.83 | | 23.38 | 8.88 | 3.82 | |
| **Childhood financial insecurity (from parent–caregiver interview)** | | | | | | | | |
| Yes | 16.93 | 17.07 | 14.79 | .08 | 19.96 | 16.79 | 11.97 | <.001 |
| No | 63.91 | 68.76 | 70.94 | | 62.07 | 70.53 | 74.01 | |
| Missing | 19.16 | 14.16 | 14.27 | | 17.97 | 12.68 | 14.02 | |
| **Childhood sexual abuse (Waves[d] III, IV)** | | | | | | | | |

Abbreviations: BMI, body mass index; HbA1c, Hemoglobin A1c; SD, standard deviation; —, not applicable.
[a] All values are weighted percentages, unless otherwise noted; all variables were assessed at Wave IV unless otherwise noted with wave number(s) in parentheses.
[b] HbA1c ≥6.5%, fasting glucose ≥126 mg/dL, nonfasting glucose ≥200 mg/dL, self-reported taking antidiabetic medication and/or a positive answer to the question "Has a doctor, nurse or other health care provider ever told you that you have or had high blood sugar or diabetes?"
[c] HbA1c 5.7%–6.4% and/or fasting glucose 100–125 mg/dL.
[d] Waves refer to the series of 4 in-home interviews through which Add Health collected data on adolescents' social, economic, psychological, and physical well-being.

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**Table 1. Characteristics of Study Sample (N = 14,493) by Sex and Diabetes Status, National Longitudinal Study of Adolescent Health, 2001–2002 and 2008–2009**

| Characteristic[a] | Women | | | | Men | | | |
|---|---|---|---|---|---|---|---|---|
| | Diabetes[b] | Prediabetes[c] | No diabetes | Omnibus *P* Value | Diabetes[b] | Prediabetes[c] | No diabetes | Omnibus *P* Value |
| ≥3 times | 5.36 | 4.26 | 4.56 | .79 | 4.10 | 1.30 | 1.17 | .013 |
| 1–2 times | 3.05 | 3.80 | 4.17 | | 3.64 | 4.45 | 3.54 | |
| None | 91.60 | 91.94 | 91.27 | | 92.26 | 94.26 | 95.29 | |
| **Childhood physical abuse (Waves[d] III, IV)** | | | | | | | | |
| ≥3 times | 13.64 | 13.56 | 15.79 | .41 | 15.32 | 15.77 | 15.28 | .36 |
| 1–2 times | 13.01 | 11.52 | 11.22 | | 12.70 | 13.94 | 11.39 | |
| None | 73.35 | 74.92 | 73.00 | | 71.98 | 70.30 | 73.33 | |
| **Childhood emotional abuse** | | | | | | | | |
| ≥3 times | 15.32 | 14.59 | 18.26 | .02 | 9.81 | 12.38 | 13.23 | .26 |
| 1–2 times | 5.08 | 2.74 | 3.22 | | 2.10 | 3.07 | 3.85 | |
| None | 79.61 | 82.67 | 78.52 | | 88.09 | 84.55 | 82.91 | |
| **Neglect (Wave[d] III)** | | | | | | | | |
| ≥3 times | 19.03 | 16.68 | 16.95 | .11 | 14.80 | 17.84 | 17.96 | .62 |
| 1–2 times | 14.94 | 18.58 | 15.49 | | 17.05 | 18.33 | 17.96 | |
| None | 53.62 | 48.54 | 53.10 | | 47.47 | 45.76 | 43.75 | |
| Missing | 12.42 | 16.20 | 14.47 | | 20.68 | 18.07 | 20.53 | |

Abbreviations: BMI, body mass index; HbA1c, Hemoglobin A1c; SD, standard deviation; —, not applicable.
[a] All values are weighted percentages, unless otherwise noted; all variables were assessed at Wave IV unless otherwise noted with wave number(s) in parentheses.
[b] HbA1c ≥6.5%, fasting glucose ≥126 mg/dL, nonfasting glucose ≥200 mg/dL, self-reported taking antidiabetic medication and/or a positive answer to the question “Has a doctor, nurse or other health care provider ever told you that you have or had high blood sugar or diabetes?”
[c] HbA1c 5.7%–6.4% and/or fasting glucose 100–125 mg/dL.
[d] Waves refer to the series of 4 in-home interviews through which Add Health collected data on adolescents’ social, economic, psychological, and physical well-being.

Table 2. Characteristics of Study Sample (N = 14,493) by Sex and Wave IV Body Mass Index (BMI) Category, National Longitudinal Study of Adolescent Health, 2001–2002 and 2008–2009[a]

| Type and Lifetime Frequency of Maltreatment | Underweight/ Normal weight (BMI ≤24.9 kg/ $m^2$) | Overweight (BMI 25.0–29.9 kg/ $m^2$) | Obese Class I (BMI 30.0–34.9 kg/$m^2$) | Obese Class II (BMI 35.0–39.9 kg/$m^2$) | Obese Class III (BMI ≥40.0 kg/ $m^2$) | Omnibus *P* Value |
|---|---|---|---|---|---|---|
| **Men** | | | | | | |
| **Sexual abuse** | | | | | | |
| ≥3 times | 1.35 | 1.39 | 1.58 | 1.45 | 1.53 | .37 |
| 1–2 times | 3.29 | 3.46 | 4.45 | 3.65 | 7.35 | |
| None | 95.36 | 95.15 | 93.96 | 94.91 | 91.12 | |
| **Physical abuse** | | | | | | |
| ≥3 times | 15.84 | 13.87 | 15.27 | 22.36 | 14.19 | .012 |
| 1–2 times | 13.34 | 11.16 | 11.59 | 12.31 | 17.13 | |
| None | 70.82 | 74.97 | 73.14 | 65.33 | 68.68 | |
| **Emotional abuse** | | | | | | |
| ≥3 times | 13.26 | 11.37 | 14.55 | 13.06 | 10.96 | .40 |
| 1–2 times | 4.06 | 3.02 | 2.85 | 4.20 | 3.93 | |
| None | 82.68 | 85.61 | 82.60 | 82.74 | 85.11 | |
| **Neglect** | | | | | | |
| ≥3 times | 17.96 | 16.53 | 18.40 | 17.79 | 18.83 | .83 |
| 1–2 times | 18.12 | 17.17 | 18.67 | 18.21 | 19.36 | |
| None | 45.48 | 44.77 | 43.09 | 46.49 | 45.55 | |
| Missing | 18.43 | 21.53 | 19.84 | 17.51 | 16.26 | |
| **Women** | | | | | | |
| **Sexual abuse** | | | | | | |
| ≥3 times | 3.66 | 4.93 | 6.02 | 4.72 | 4.06 | .45 |
| 1–2 times | 4.45 | 3.84 | 3.63 | 3.62 | 4.26 | |
| None | 91.89 | 91.22 | 90.36 | 91.66 | 91.68 | |
| **Physical abuse** | | | | | | |
| ≥3 times | 14.66 | 16.82 | 13.95 | 13.46 | 15.63 | .04 |
| 1–2 times | 11.34 | 10.26 | 10.30 | 11.16 | 16.25 | |
| None | 74.00 | 72.92 | 75.75 | 75.38 | 68.12 | |
| **Emotional abuse** | | | | | | |
| ≥3 times | 17.20 | 17.96 | 15.96 | 14.29 | 20.34 | .37 |
| 1–2 times | 3.09 | 3.28 | 3.45 | 2.48 | 3.84 | |
| None | 79.71 | 79.03 | 80.59 | 83.23 | 75.82 | |
| **Neglect** | | | | | | |
| ≥3 times | 16.09 | 17.30 | 18.63 | 15.62 | 19.42 | .76 |
| | | | | | | |

[a] All values are weighted percentages unless otherwise noted.

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**Table 2. Characteristics of Study Sample (N = 14,493) by Sex and Wave IV Body Mass Index (BMI) Category, National Longitudinal Study of Adolescent Health, 2001–2002 and 2008–2009[a]**

| Type and Lifetime Frequency of Maltreatment | Underweight/Normal weight (BMI ≤24.9 kg/m$^2$) | Overweight (BMI 25.0–29.9 kg/m$^2$) | Obese Class I (BMI 30.0–34.9 kg/m$^2$) | Obese Class II (BMI 35.0–39.9 kg/m$^2$) | Obese Class III (BMI ≥40.0 kg/m$^2$) | Omnibus *P* Value |
|---|---|---|---|---|---|---|
| 1–2 times | 15.55 | 15.88 | 16.83 | 18.35 | 15.37 | |
| None | 53.95 | 51.96 | 49.27 | 51.85 | 50.85 | |
| Missing | 14.40 | 15.13 | 15.28 | 14.18 | 14.36 | |

[a] All values are weighted percentages unless otherwise noted.

Table 3. Results from Multinomial Logistic Regression Models Predicting Diabetes Status for Men and Women (N = 14,493) Participating in the National Longitudinal Study of Adolescent Health, 2001–2002 and 2008–2009

| Type and Lifetime Frequency of Maltreatment | Men | | Women | |
|---|---|---|---|---|
| | Diabetes, OR (95% CI) | Prediabetes, OR (95% CI) | Diabetes, OR (95% CI) | Prediabetes, OR (95% CI) |
| **Model 1: Sexual abuse only** | | | | |
| ≥3 times | 3.63 (1.53–8.62)[a] | 1.13 (0.61–2.10) | 1.17 (0.76–1.82) | 0.93 (0.64–1.14) |
| 1–2 times | 1.06 (0.47–2.37)[b] | 1.27 (0.86–1.88) | 0.73 (0.34–1.57) | 0.90 (0.62–1.32) |
| Never | 1 [Reference] | 1 [Reference] | 1 [Reference] | 1 [Reference] |
| **Model 2: Physical abuse only** | | | | |
| ≥3 times | 1.02 (0.70–1.49) | 1.08 (0.89–1.31) | 0.86 (0.59–1.24) | 0.84 (0.67–1.05) |
| 1–2 times | 1.14 (0.67–1.93) | 1.27 (1.01–1.61) | 1.15 (0.79–1.69) | 1.00 (0.81–1.24) |
| Never | 1 [Reference] | 1 [Reference] | 1 [Reference] | 1 [Reference] |
| **Model 3: Emotional abuse only** | | | | |
| ≥3 times | 0.70 (0.44–1.10) | 0.92 (0.71–1.18) | 0.83 (0.57–1.20)[b] | 0.76 (0.62–0.93)[a] |
| 1–2 times | 0.51 (0.24–1.11) | 0.78 (0.51–1.19) | 1.56 (0.92–2.62)[c] | 0.81 (0.52–1.26) |
| Never | 1 [Reference] | 1 [Reference] | 1 [Reference] | 1 [Reference] |
| **Model 4: Neglect only** | | | | |
| ≥3 times | 0.77 (0.49–1.19) | 0.96 (0.78–1.18) | 1.11 (0.81–1.52) | 1.08 (0.87–1.33) |
| 1–2 times | 0.88 (0.60–1.28) | 0.98 (0.80–1.20) | 0.96 (0.67–1.37) | 1.31 (1.06–1.63) |
| Missing | 0.93 (0.63–1.38) | 0.85 (0.69–1.04) | 0.85 (0.63–1.15) | 1.22 (0.93–1.61) |
| Never | 1 [Reference] | 1 [Reference] | 1 [Reference] | 1 [Reference] |
| **Model 5: all forms of maltreatment** | | | | |
| **Sexual abuse** | | | | |
| ≥3 times | 4.26 (1.75–10.37)[a] | 1.08 (0.56–2.07) | 1.14 (0.69–1.89) | 0.95 (0.64–1.40) |
| 1–2 times | 1.13 (0.49–2.58)[b] | 1.22 (0.78–1.90) | 0.83 (0.39–1.78) | 0.96 (0.66–1.40) |
| Never | 1 [Reference] | 1 [Reference] | 1 [Reference] | 1 [Reference] |
| **Physical abuse** | | | | |
| ≥3 times | 1.20 (0.80–1.78) | 1.10 (0.88–1.37) | 0.83 (0.53–1.30) | 0.93 (0.72–1.21) |
| 1–2 times | 1.19 (0.73–1.94) | 1.30 (0.99–1.71) | 1.08 (0.74–1.60) | 1.00 (0.81–1.24) |
| Never | 1 [Reference] | 1 [Reference] | 1 [Reference] | 1 [Reference] |
| **Emotional abuse** | | | | |
| ≥3 times | 0.65 (0.42–1.00) | 0.90 (0.70–1.15) | 0.85 (0.57–1.29)[a] | 0.77 (0.60–0.97) |
| 1–2 times | 0.50 (0.23–1.10) | 0.75 (0.49–1.16) | 1.56 (0.93–2.64)[b] | 0.76 (0.48–1.20) |
| Never | 1 [Reference] | 1 [Reference] | 1 [Reference] | 1 [Reference] |
| **Neglect** | | | | |
| ≥3 times | 0.68 (0.42–1.12) | 0.92 (0.73–1.15) | 1.09 (0.77–1.55) | 1.14 (0.91–1.43) |

Abbreviations: BMI, body mass index; CI, confidence interval.
[a,b] Values with different superscripts are significantly different from one another in pairwise post-hoc tests ($P$ < .05).
[c] Adjusted for age, race/ethnicity, college degree, ever smoked daily, and childhood financial insecurity.

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**Table 3. Results from Multinomial Logistic Regression Models Predicting Diabetes Status for Men and Women (N = 14,493) Participating in the National Longitudinal Study of Adolescent Health, 2001–2002 and 2008–2009**

| Type and Lifetime Frequency of Maltreatment | Men | | Women | |
|---|---|---|---|---|
| | Diabetes, OR (95% CI) | Prediabetes, OR (95% CI) | Diabetes, OR (95% CI) | Prediabetes, OR (95% CI) |
| 1–2 times | 0.80 (0.53–1.21) | 0.90 (0.72–1.12) | 0.98 (0.68–1.41) | 1.29 (1.04–1.60) |
| Missing | 0.95 (0.62–1.43) | 0.89 (0.71–1.11) | 0.87 (0.63–1.20) | 1.22 (0.95–1.56) |
| Never | 1 [Reference] | 1 [Reference] | 1 [Reference] | 1 [Reference] |
| **Model 6: all forms of maltreatment and covariates[c]** | | | | |
| **Sexual abuse** | | | | |
| ≥3 times | 3.66 (1.31–10.24)[a] | 0.95 (0.50–1.83) | 1.04 (0.63–1.72) | 0.91 (0.61–1.35) |
| 1–2 times | 0.74 (0.33–1.67)[b] | 0.98 (0.62–1.55) | 0.70 (0.32–1.50) | 0.86 (0.59–1.26) |
| Never | 1 [Reference] | 1 [Reference] | 1 [Reference] | 1 [Reference] |
| **Physical abuse** | | | | |
| ≥3 times | 1.11 (0.73–1.70) | 1.01 (0.82–1.25) | 0.77 (0.50–1.20) | 0.88 (0.68–1.14) |
| 1–2 times | 1.25 (0.77–2.03) | 1.30 (0.99–1.72) | 1.02 (0.69–1.51) | 0.97 (0.78–1.20) |
| Never | 1 [Reference] | 1 [Reference] | 1 [Reference] | 1 [Reference] |
| **Emotional abuse** | | | | |
| ≥3 times | 0.74 (0.47–1.16) | 0.97 (0.75–1.25) | 1.02 (0.68–1.54) | 0.88 (0.69–1.12) |
| 1–2 times | 0.45 (0.20–1.04) | 0.73 (0.46–1.16) | 1.57 (0.90–2.72) | 0.75 (0.47–1.21) |
| Never | 1 [Reference] | 1 [Reference] | 1 [Reference] | 1 [Reference] |
| **Neglect** | | | | |
| ≥3 times | 0.60 (0.37–1.00) | 0.87 (0.69–1.09) | 1.00 (0.68–1.46) | 1.06 (0.84–1.34) |
| 1–2 times | 0.79 (0.52–1.22) | 0.89 (0.70–1.12) | 0.98 (0.67–1.42) | 1.29 (1.02–1.63) |
| Missing | 0.74 (0.47–1.16) | 0.79 (0.64–0.98) | 0.68 (0.49–0.94) | 1.02 (0.80–1.29) |
| Never | 1 [Reference] | 1 [Reference] | 1 [Reference] | 1 [Reference] |
| **Model 7: all forms of maltreatment, covariates[c] and BMI** | | | | |
| **Sexual abuse** | | | | |
| ≥3 times | 3.80 (1.48–9.72)[a] | 0.93 (0.49–1.77) | 1.03 (0.62–1.71) | 0.90 (0.61–1.32) |
| 1–2 times | 0.64 (0.30–1.37)[b] | 0.92 (0.58–1.48) | 0.71 (0.32–1.59) | 0.89 (0.58–1.37) |
| Never | 1 [Reference] | 1 [Reference] | 1 [Reference] | 1 [Reference] |
| **Physical abuse** | | | | |
| ≥3 times | 1.15 (0.76–1.75) | 0.99 (0.81–1.22) | 0.76 (0.48–1.21) | 0.87 (0.66–1.14) |
| 1–2 times | 1.19 (0.74–1.91) | 1.31 (1.00–1.71) | 0.95 (0.66–1.36) | 0.92 (0.73–1.14) |
| Never | 1 [Reference] | 1 [Reference] | 1 [Reference] | 1 [Reference] |
| **Emotional abuse** | | | | |

Abbreviations: BMI, body mass index; CI, confidence interval.
[a,b] Values with different superscripts are significantly different from one another in pairwise post-hoc tests (*P* < .05).
[c] Adjusted for age, race/ethnicity, college degree, ever smoked daily, and childhood financial insecurity.

(continued on next page)

(continued)

**Table 3. Results from Multinomial Logistic Regression Models Predicting Diabetes Status for Men and Women (N = 14,493) Participating in the National Longitudinal Study of Adolescent Health, 2001–2002 and 2008–2009**

| Type and Lifetime Frequency of Maltreatment | Men | | Women | |
|---|---|---|---|---|
| | Diabetes, OR (95% CI) | Prediabetes, OR (95% CI) | Diabetes, OR (95% CI) | Prediabetes, OR (95% CI) |
| ≥3 times | 0.70 (0.44–1.09) | 0.97 (0.75–1.26) | 1.00 (0.67–1.48) | 0.86 (0.67–1.09) |
| 1–2 times | 0.44 (0.20–0.99) | 0.71 (0.45–1.12) | 1.67 (0.97–2.86) | 0.77 (0.47–1.27) |
| Never | 1 [Reference] | 1 [Reference] | 1 [Reference] | 1 [Reference] |
| **Neglect** | | | | |
| ≥3 times | 0.63 (0.38–1.04) | 0.89 (0.70–1.12) | 0.95 (0.64–1.43) | 1.03 (0.81–1.32) |
| 1–2 times | 0.84 (0.53–1.33) | 0.88 (0.70–1.12) | 0.97 (0.65–1.45) | 1.29 (1.02–1.63) |
| Missing | 0.82 (0.54–1.25) | 0.81 (0.65–1.01) | 0.72 (0.51–1.00) | 1.06 (0.83–1.35) |
| Never | 1 [Reference] | 1 [Reference] | 1 [Reference] | 1 [Reference] |
| **BMI category** | | | | |
| Obese class III | 12.02 (7.21–20.03) | 2.98 (1.98–4.50) | 9.24 (6.05–14.11) | 4.48 (3.42–5.87) |
| Obese class II | 3.80 (2.33–6.19) | 2.16 (1.63–2.87) | 5.71 (3.40–9.59) | 3.27 (2.46–4.34) |
| Obese class I | 2.60 (1.65–4.09) | 1.55 (1.22–1.96) | 3.56 (2.46–5.75) | 2.45 (1.99–3.03) |
| Overweight | 1.35 (0.85–2.16) | 1.25 (1.04–1.52) | 2.01 (1.26–3.20) | 1.67 (1.34–2.10) |
| Normal weight | 1 [Reference] | 1 [Reference] | 1 [Reference] | 1 [Reference] |

Abbreviations: BMI, body mass index; CI, confidence interval.
[a,b] Values with different superscripts are significantly different from one another in pairwise post-hoc tests (*P* < .05).
[c] Adjusted for age, race/ethnicity, college degree, ever smoked daily, and childhood financial insecurity.

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ORIGINAL RESEARCH

# A Longitudinal Study of Structural Risk Factors for Obesity and Diabetes Among American Indian Young Adults, 1994–2008

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PEER REVIEWED

## Abstract

### Introduction
American Indian young adults have higher rates of obesity and type 2 diabetes than the general US population. They are also more likely than the general population to have higher rates of structural risk factors for obesity and diabetes, such as poverty, frequent changes of residence, and stress. The objective of this study was to investigate possible links between these 2 sets of problems.

### Methods
Data from the American Indian subsample of the National Longitudinal Study of Adolescent to Adult Health (Add Health) were used to examine potential links between obesity and type 2 diabetes and structural risk factors such as neighborhood poverty, housing mobility, and stress. We used logistic regression to explore explanatory factors.

### Results
American Indians in the subsample had higher rates of poor health, such as elevated hemoglobin A1c levels, self-reported high blood glucose, self-reported diabetes, and overweight or obesity. They also had higher rates of structural risk factors than non-Hispanic whites, such as residing in poorer and more transient neighborhoods and having greater levels of stress. Self-reported stress partially mediated the increased likelihood of high blood glucose or diabetes among American Indians, whereas neighborhood poverty partially mediated their increased likelihood of obesity.

### Conclusion
Neighborhood poverty and stress may partially explain the higher rates of overweight, obesity, and type 2 diabetes among American Indian young adults than among non-Hispanic white young adults. Future research should explore additional neighborhood factors such as access to grocery stores selling healthy foods, proximity and safety of playgrounds or other recreational space, and adequate housing.

## Introduction

Rates of overweight, obesity, and type 2 diabetes are growing in the United States across all racial and ethnic groups and among children and adolescents (1–4). However, American Indian adolescents and young adults are more likely than adolescents and young adults of other races and ethnicities to have these conditions (4,5). American Indian adolescents are more likely to be overweight or obese (42%) than non-Hispanic whites (26.7%), Latinos (37.6%), and African Americans (41.1%) (2). From 1990 to 1998, type 2 diabetes diagnoses increased by 71% among American Indian children, adolescents, and young adults and prevalence increased by 68% (from 1.23 per 1,000 to 5.42 per 1,000) among American Indian adolescents aged 15 to 19 (5). Overweight and obesity can have serious consequences for health, including cardiovascular disease, type 2 diabetes, and other conditions that can contribute to lower quality of life, disability, and premature death (6).

Structural determinants and conditions of daily life make up the social determinants of health and are responsible for many poor health outcomes, and increasingly, researchers recognize the effects of various social determinants that contribute to overall health (7–9). A growing body of research suggests that disease and ill health are largely the result of the "circumstances in which people are born, grow, live, work, and age, and the systems put in place to deal with illness" (9). Despite evidence of the associations among social determinants and health, empirical research on possible links between neighborhood factors and obesity, overweight, and type 2 diabetes among American Indians is scarce

(3,10–13). The objective of this study was to explore the associations between the structural determinants of neighborhood factors, parent education and obesity, and perceived stress with overweight, obesity, and type 2 diabetes among American Indian young adults.

# Methods

## Survey design

This study used data from the first and fourth waves of the National Longitudinal Study of Adolescent to Adult Health (Add Health), a nationally representative study following adolescents into early adulthood (14). These waves were chosen to capitalize on the rich neighborhood data available in Wave 1 and the multiple outcomes related to type 2 diabetes and obesity in Wave 4.

Wave 1 comprised adolescents in grades 7 through 12 (ages 12–19) in school year 1994–1995. Participants originated from a stratified random sample of 20,745 adolescents attending 80 high schools and 52 middle schools. The schools were stratified into 80 clusters, by variables such as region (Northeast, Midwest, South, West), urbanicity (urban, suburban, rural), school type (public, private, parochial), and other characteristics. In addition to the surveys of the adolescents themselves, 17,670 parents also completed interviews at Wave 1. Wave 4 followed up with those adolescents when they were young adults aged 24 to 32 in 2007–2008. The Wave 4 follow-up included 76% of the original sample (n = 15,701).

Attrition between Waves 1 and 4 differed by race and ethnicity. The Wave 4 response rate was highest for white participants (79%) and lowest for Asian participants (66%). The response rate was slightly below average for American Indian participants (73%). To adjust for this differential response, all analyses used Add Health's longitudinal sampling weights designed for the Wave 4 sample ("pweights" in Stata [StataCorp LP]). These weights adjust for complex sample design, selection, and nonresponse, including adjustment for differential response by race, education level, and marital status (15). Overall, complete data were available for 12,657 respondents.

## Measures

### Dependent variables

Analyses included 4 outcomes: glycated hemoglobin (HbA1c), self-reported high blood glucose or type 2 diabetes, overweight/obesity, and obesity. For HbA1c, whole-blood spot assays were collected via finger pricks, and levels were determined from colorimetric methods. HbA1c values greater than 5.7 were considered elevated.

In addition to the direct measure of HbA1c, we examined self-reports of high blood glucose or type 2 diabetes, measured with a single item, "Has a doctor, nurse, or other health care provider ever told you that you have or had high blood sugar or diabetes?" We used direct measures of height and weight to calculate body mass index (BMI, $kg/m^2$). Overweight/obesity was defined as a BMI greater than or equal to 25.0 and obesity as a BMI greater than or equal to 30.0.

### Race and ethnicity

Racial and ethnic classifications were based on self-report at Wave 1. Our primary group of interest, American Indians, included participants who selected "Native American" solely or in combination with another racial or ethnic group. The Hispanic category included those self-reporting as Hispanic solely or in combination with another group (not including Native American). The white, black, and Asian categories comprised those self-reporting as each of those groups not in combination with another group. Because of small sample sizes, participants self-reporting as other combinations of racial and ethnic groups were classified as "other."

### Context measures

Three measures of neighborhood characteristics were included in the analyses: neighborhood collective efficacy (ie, social cohesion), neighborhood poverty rate, and neighborhood mobility. Neighborhood collective efficacy was reported by adolescents in Wave 1 (16) and was calculated as the sum of 3 dichotomous (true/false) items: "You know most of the people in your neighborhood," "In the past month, you have stopped on the street to talk with someone who lives in your neighborhood," and "People in this neighborhood look out for each other." For each item, a no response was scored as zero, and a yes response was scored as 1. Data for the second and third neighborhood measures were from 1990 Census block group data. Neighborhood poverty rate is the percentage of people living below the official poverty threshold ($13,254 for a family of 4 in 1990). "Neighborhood mobility" was measured as the percentage of occupied housing units into which people moved during the previous 5 years. In addition to the neighborhood measures, dummy variables were included to reflect participants' school location in suburban, rural, or urban locations at Wave 1.

### Additional variables

A robust set of control variables and mediators was included. Control variables from Wave 1 were adolescent-reported age, sex, and parent's highest level of educational attainment (for 2-parent families, data were used for the parent with the higher level of education). From Wave 4, we included the Cohen Perceived Stress Scale (PSS) (17,18). The PSS score was calculated as the sum of 4 items (range, 0–16). Participants reported how often during the previous 30 days they 1) were unable to control important things in their lives, 2) felt confident in their ability to handle their personal problems (reversed), 3) felt things were going their way (reversed), and 4) felt that difficulties were piling up so high that they were unable to overcome them. Each item was scored as 0 (never), 1 (almost never), 2 (sometimes), 3 (fairly often), or 4 (very often).

### Statistical analysis

We calculated descriptive statistics (percentages, means, and 95% confidence intervals) for the full sample and American Indian subsample. We calculated adjusted odds ratios (AORs) and $P$ values (significance set at an $\alpha$ level of .05) from a series of logistic regression models predicting elevated HbA1c, self-reported high blood glucose, and self-reported diabetes. Logistic regression models, neighborhood predictors, and perceived stress were entered as $z$ scores for ease of comparison across coefficients. Finally, Sobel tests were conducted as a test of mediation. All analyses were implemented in Stata version 12 (StataCorp LP). Procedures for data access and analysis were implemented as approved by the institutional review board at Northwestern University and in agreement with the sensitive data security plan approved by Add Health data managers.

## Results

Our analytic sample comprised 11,110 participants, including 393 participants who self-identified as American Indian (Table 1). At Wave 1, the full sample resided in neighborhoods with a poverty rate of 13.9%, whereas the American Indian subsample resided in neighborhoods with an average neighborhood poverty rate of 19.2%. Neighborhood mobility was higher for the American Indian subsample than for the full sample; 49.3% in the subsample and 46.5% in the full sample of neighbors resided in the neighborhood for less than 5 years. The mean score for neighborhood collective efficacy was 0.75 for both the American Indian subsample and the full sample. At Wave 4, the mean score on the Cohen PSS was higher among American Indians (score, 5.6) than among the full sample (score, 4.8.)

The American Indian subsample was more likely than the full sample to have health problems across multiple indicators at Wave 4: 43.8% of the American Indian subsample had elevated HbA1c levels, compared with 30.6% of the full sample; 5.2% of the American Indian subsample reported having been told they had high blood glucose or type 2 diabetes, compared with 2.6% of the full sample; 76.8% of the American Indian subsample was overweight/obese or obese, compared with 66.6% of the full sample; and 42.5% of the American Indian sample was obese, compared with 37.4% of the full sample.

All racial/ethnic minority groups included in our logistic regression models were more likely than non-Hispanic whites to have elevated HbA1c (Table 2). In Model 1 (no control variables), American Indians were 2.66 times as likely as non-Hispanic whites to have elevated HbA1c ($P < .01$); in Model 2 (controls for sex, age, parent education, and parent obesity), they were 2.47 times as likely ($P < .01$). In Model 3 (further addition of controls for neighborhood variables, urbanicity, and perceived stress), the adjusted odds ratio (AOR) of American Indians having elevated HbA1c was further attenuated to 2.41; one of the 3 neighborhood variables (neighborhood collective efficacy) was significantly associated with elevated HbA1c (AOR, 1.07; $P = .04$); perceived stress was not. In Model 4 (addition of overweight/obesity and obesity), both overweight/obesity and obesity predicted elevated HbA1c ($P < .01$ for both). In this model, the likelihood of elevated HbA1c among American Indians was attenuated with the inclusion of overweight/obesity and obesity but remained significant (AOR, 2.38; $P < .01$). Post hoc tests showed that overweight/obesity and obesity may partially mediate the relationship between being American Indian and having elevated HbA1c (Sobel $z = 2.42$, $P = .02$ for overweight/obesity; Sobel $z = 1.83$, $P = .07$ for obesity).

In Model 5 (Table 2), American Indians were 2.39 times as likely as non-Hispanic whites to self-report high blood glucose or diabetes ($P = .02$), similar to the findings for elevated HbA1c. However, compared with the control variables for HbA1c, the control variables for high blood glucose and diabetes mediated associations more strongly. In Model 6 (controls for sex, age, parent education, and parent obesity), the AOR for American Indians decreased 1.95 ($P = .07$); in Model 7 (further addition of controls for neighborhood variables, urbanicity, and perceived stress), the AOR decreased to 1.83 ($P = .12$), and in Model 8 (addition of overweight/obesity and obesity), it further decreased to 1.82 ($P = .14$). Although none of the 3 neighborhood indicators was significantly associated with high blood glucose or diabetes, perceived stress was (AOR, 1.09; $P < .01$). One standard deviation increase in perceived stress was associated with a 9% increase in the likelihood of high blood glucose or diabetes, and post hoc tests confirmed perceived stress as a mediator (Sobel $z = 2.23$; $P = .03$). Obesity did not mediate the association between being American Indian and self-reporting high blood glucose or diabetes (Sobel $z = 1.76$, $P = .08$).

In models predicting overweight/obesity or obesity (Models 1–3) and obesity (Models 4–6) (Table 3), American Indians were more likely than non-Hispanic whites to be overweight/obese or obese, and this association was attenuated by the inclusion of covariates. In Model 6 (controls for all variables), neighborhood poverty was significantly associated with obesity (AOR, 1.17, $P < .01$). Neighborhood poverty was a partial mediator of the association between being American Indian and being obese (Sobel $z$, 2.01; $P = .05$)

## Discussion

Studies investigating social determinants or structural risk factors and the incidence of type 2 diabetes, overweight/obesity, and obesity are increasingly common (3,10–13,19). Numerous studies examined social determinants or structural risk factors such as the built environment or neighborhood surroundings and their associations with such health outcomes as obesity and type 2 diabetes among racial/ethnic minority populations (20,21). However, unlike other studies, our research investigated social determinants or structural risk factors that might explain the higher incidence of type 2 diabetes, overweight/obesity, and obesity among American Indians. Type 2 diabetes, overweight, and obesity are growing health concerns for American Indian adolescents and young adults. Consistent with findings from previous studies, our study provides evidence that American Indian young adults have higher rates of elevated HbA1c levels, self-reported type 2 diabetes or high blood glucose, and overweight/obesity or obesity than have non-Hispanic whites (1,3). American Indians in our subsample also had higher rates of risk factors for poor health: they were more likely to live in neighborhoods with higher rates of poverty and housing mobility than the full sample. In addition, American Indians had higher rates of perceived stress.

Controlling for other variables, American Indian race/ethnicity was positively associated with a greater likelihood of elevated HbA1c (compared with non-Hispanic whites), and overweight/obesity and obesity partially mediated elevated HbA1c. These results are consistent with previous research (22,23). Only one of our neighborhood measures was significantly associated with HbA1c, and it was not associated in the hypothesized direction: greater neighborhood collective efficacy predicted higher HbA1c. Previous research demonstrated an association between higher collective efficacy and decreased risk of obesity and overweight among adolescents (24). However, our Census measures were based on 1990 statistics, whereas other Wave 1 data were collected in 1994–1995. Future research should continue to explore these potential links, using more precise neighborhood indicators.

American Indians were also more likely than non-Hispanic whites to report high blood glucose or diabetes. The inclusion of control and risk factors did not mediate these associations, with the exception of stress. Perceived stress was a significant mediator of the likelihood of self-reported high blood glucose or diabetes among American Indians. Research suggests that stress may influence the onset of type 2 diabetes (25).

Consistent with other findings, neighborhood characteristics such as poverty were associated with an increased risk of high BMI in non–American Indian population groups (10,26–28). Controlling for other variables, American Indians in our study were more likely to be overweight or obese than non-Hispanic whites; high BMI among American Indians was partially mediated by neighborhood poverty. Neighborhood poverty is a risk factor for poor health; future research should examine other factors associated with neighborhood poverty, such as access to grocery stores, safety, and walkability, among American Indians (19,20,21,26).

Although our study focused on the American Indian subsample, it is also interesting to compare our findings on American Indians and blacks. Without any control variables, the AOR for elevated HbA1c was 2.66 for American Indians and 4.86 for blacks, but in the prediction of self-reported high blood glucose or diabetes, the AORs were 2.39 for American Indians and 1.48 for blacks. Because the outcomes in these models reflect *being told* by a doctor, nurse, or other health care provider that one has high blood glucose or diabetes, these findings suggest that American Indians are more likely to be screened and treated for diabetes — by the Indian Health Service or others — so that they are more aware of their diabetes risk and perhaps more likely to be managing their condition. We did not measure insulin use or health insurance coverage in our study, but those issues are important for understanding differences among racial/ethnic subgroups.

This study has several limitations. First, we could not identify causal relationships between our predictors and outcomes of interest. Despite the use of longitudinal data and a robust set of control variables, our analytic strategy did not rule out the possibility of omitted variable bias. Second, our definition of the category "American Indian" combined data on participants self-reporting solely as American Indian and data on those self-identifying as American Indian in combination with one or more other groups. Future studies could investigate these American Indian subgroups separately. Third, despite the inclusion of several social determinants of health and a perceived stress indicator that might partially explain how context affects health, we did not formally test the complex pathways linking these variables to our outcomes. Future research might employ structural equation modeling or other path analyses to explore these relationships more precisely.

Despite these limitations, our study extends knowledge via several key strengths. First, the study focuses on American Indian young adults, filling a gap in the literature (1,3,5,10–13,29). Much of the research examining diabetes among American Indians is dated and does not use data from large samples such as Add Health. Second, although we do not make any claims about causal relationships, the use of longitudinal data suggests that the associations between social determinants and health outcomes persist over time; this persistence points out the need for future research in this area. Third, our analytic approach of staging control variables demonstrates the extent to which certain risk factors may play a mediating role above and beyond other control variables. We hope that future research will build on this effort to estimate the effects of an improved set of social determinants among American Indian and Alaska Native populations, especially neighborhood and housing risk factors, such as safety and overcrowding.

This study emphasizes the need to further investigate the social determinants of overweight, obesity, type 2 diabetes, and elevated HbA1c. Our research suggests that neighborhood factors and stress partially explain elevated risk for overweight, obesity, and type 2 diabetes among American Indians and that future research should include additional neighborhood factors, such as access to grocery stores selling healthy foods, proximity and safety of playgrounds or other recreational space, and adequate housing. Because neighborhood characteristics such as social capital and perceived safety are associated with lower levels of obesity in children (10,11,20,24), future research should also examine these potentially protective factors at the individual, family, and community levels.

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# Tables

**Table 1. Descriptive Statistics for Full Sample and American Indian Subsample, National Longitudinal Study of Adolescent to Adult Health, 1994–2008**

| Characteristic | Full Sample (n = 11,110) | American Indian Subsample (n = 393) |
|---|---|---|
| **Neighborhood (Wave 1), mean (95% CI)** | | |
| Neighborhood collective efficacy[a] | 0.75 (0.74–0.77) | 0.75 (0.71–0.79) |
| Neighborhood poverty[b] | 13.9 (12.2–15.6) | 19.2 (13.2–25.1) |
| Neighborhood mobility[c] | 46.5 (45.0–48.0) | 49.3 (46.5–52.0) |
| **Urbanicity, % (95% CI)** | | |
| Urban | 25.4 (18.5–33.9) | 32.8 (21.0–47.3) |
| Suburban | 58.2 (48.2–67.5) | 45.7 (31.1–61.1) |
| Rural | 16.4 (9.5–26.9) | 21.4 (8.3–45.0) |
| **Family (Wave 1), % (95% CI)** | | |
| Parent has ≥high school diploma | 86.3 (83.9–88.4) | 80.2 (73.6–85.5) |
| Parent has ≥college diploma | 33.3 (30.0–36.9) | 18.2 (13.2–24.6) |
| Parent is obese | 22.9 (21.7–24.1) | 36.3 (29.8–43.3) |
| **Individual stress and health (Wave 4)** | | |
| Perceived stress, mean score[d] (95% CI) | 4.8 (4.7–4.9) | 5.6 (5.2–6.0) |
| HbA1c value, mean (95% CI) | 5.6 (5.5–5.6) | 5.7 (5.6–5.8) |
| HbA1c ≥5.7, % (95% CI) | 30.6 (28.4–32.8) | 43.8 (36.4–51.5) |
| Ever told have high blood glucose or diabetes, % (95% CI) | 2.6 (2.2–3.0) | 5.2 (2.8–9.3) |
| Mean body mass index, kg/m$^2$ (95% CI) | 29.1 (28.8–29.5) | 30.7 (29.0–32.3) |
| Overweight or obese, % (95% CI) | 66.6 (64.9–68.3) | 76.8 (69.9–82.6) |
| Obese, % (95% CI) | 37.4 (35.5–39.2) | 42.5 (33.7–51.8) |

Abbreviations: HbA1c, glycated hemoglobin; CI, confidence interval.
[a] A measure of social cohesion scored on a scale of 0 to 3, with a higher score indicating better neighborhood efficacy.
[b] Percentage of people living below the official poverty threshold, based on 1990 Census block group data.
[c] Measured as the percentage of occupied housing units into which people moved during the previous 5 years, based on1990 Census block group data.
[d] Cohen Perceived Stress Scale (PSS) (17,18). Scored on a scale of 0 to 16, with higher scores indicating greater stress.

Table 2. Adjusted Odds Ratios From Logistic Regression Models of HbA1c and Self-Reported High Blood Glucose or Diabetes Among Young Adults (n = 11,110), National Longitudinal Study of Adolescent to Adult Health, 1994–2008

| Characteristic | HbA1c (Direct Measurement) | | | | Diagnosis of High Blood Glucose or Diabetes (Self-Reported) | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 | Model 8 |
| **Race/ethnicity** | | | | | | | | |
| White [Reference] | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| American Indian | 2.66[a] | 2.47[a] | 2.41[a] | 2.38[a] | 2.39[b] | 1.95 | 1.83 | 1.82 |
| Black | 4.86[a] | 4.94[a] | 4.68[a] | 4.62[a] | 1.48[b] | 1.31 | 1.19 | 1.10 |
| Hispanic | 2.20[a] | 2.07[a] | 2.15[a] | 2.00[a] | 1.57 | 1.25 | 1.26 | 1.13 |
| Asian | 2.06[a] | 2.30[a] | 2.42[a] | 2.69[a] | 0.43 | 0.50 | 0.50 | 0.58 |
| Other race/ethnicity | 2.25[a] | 2.33[a] | 2.38[a] | 2.44[a] | 0.71 | 0.66 | 0.65 | 0.62 |
| **Male** | — | 1.78[a] | 1.78[a] | 1.80[a] | — | 0.74 | 0.78 | 0.80 |
| **Age** | — | 1.07[a] | 1.08[a] | 1.07[a] | — | 1.08 | 1.08 | 1.07 |
| **Parent education** | | | | | | | | |
| <High school diploma [Reference] | — | 1.00 | 1.00 | 1.00 | — | 1.00 | 1.00 | 1.00 |
| High school diploma | — | 0.82[b] | 0.83[b] | 0.82[b] | — | 0.60 | 0.64 | 0.63 |
| Some college | — | 0.72[a] | 0.75[a] | 0.76[a] | — | 0.56[b] | 0.61 | 0.63 |
| College diploma | — | 0.63[a] | 0.66[b] | 0.70[a] | — | 0.40[a] | 0.45[a] | 0.49[a] |
| >College diploma | — | 0.61[a] | 0.65[a] | 0.71[b] | — | 0.28[a] | 0.32[b] | 0.38 |
| **Parent is obese** | — | 1.52[a] | 1.52[a] | 1.25[a] | — | 1.72[a] | 1.70[a] | 1.36 |
| **Neighborhood characteristics[c]** | | | | | | | | |
| Neighborhood collective efficacy[d] | — | — | 1.07[b] | 1.07[b] | — | — | 1.02 | 1.01 |
| Neighborhood poverty[e] | — | — | 1.06 | 1.03 | — | — | 1.04 | 1.00 |
| Neighborhood mobility[f] | — | — | 1.00 | 1.01 | — | — | 0.92 | 0.93 |
| **Urbanicity** | | | | | | | | |
| Suburban [Reference] | — | — | 1.00 | 1.00 | — | — | 1.00 | 1.00 |
| Rural | — | — | 1.14 | 1.14 | — | — | 0.95 | 0.94 |
| Urban | — | — | .96 | 1.00 | — | — | 1.09 | 1.14 |
| Perceived stress[c, g] | — | — | 1.01 | 1.01 | — | — | 1.09[a] | 1.09[a] |
| **Weight status** | | | | | | | | |

Abbreviation: —, not applicable; HbA1c, glycated hemoglobin.
[a] $P < .01$.
[b] $P < .05$.
[c] Calculated as *z* scores, normed such that the mean equals zero and standard deviation equals 1. Coefficients can be interpreted as the adjusted odds ratio associated with a 1 standard deviation increase in the predictor.
[d] A measure of social cohesion scored on a scale of 0 to 3, with a higher score indicating better neighborhood efficacy.
[e] Percentage of people living below the official poverty threshold, based on 1990 Census block group data.
[f] Measured as the percentage of occupied housing units into which people moved during the previous 5 years, based on1990 Census block group data.
[g] Measure of stress based on the Cohen Perceived Stress Scale (PSS) (17,18). Scored on a scale of 0 to 16, with higher scores indicating greater stress.

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(continued)

**Table 2. Adjusted Odds Ratios From Logistic Regression Models of HbA1c and Self-Reported High Blood Glucose or Diabetes Among Young Adults (n = 11,110), National Longitudinal Study of Adolescent to Adult Health, 1994–2008**

| Characteristic | HbA1c (Direct Measurement) | | | | Diagnosis of High Blood Glucose or Diabetes (Self-Reported) | | | |
|---|---|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 | Model 8 |
| Neither overweight or obese [Reference] | — | — | — | 1.00 | — | — | — | 1.00 |
| Overweight/obesity | — | — | — | 1.47[a] | — | — | — | 1.03 |
| Obese | — | — | — | 2.88[a] | — | — | — | 3.47[a] |
| **Constant** | 0.29 | 0.09 | 0.07 | 0.05 | 0.03 | 0.01 | 0.01 | 0.004 |

Abbreviation: —, not applicable; HbA1c, glycated hemoglobin.
[a] $P < .01$.
[b] $P < .05$.
[c] Calculated as *z* scores, normed such that the mean equals zero and standard deviation equals 1. Coefficients can be interpreted as the adjusted odds ratio associated with a 1 standard deviation increase in the predictor.
[d] A measure of social cohesion scored on a scale of 0 to 3, with a higher score indicating better neighborhood efficacy.
[e] Percentage of people living below the official poverty threshold, based on 1990 Census block group data.
[f] Measured as the percentage of occupied housing units into which people moved during the previous 5 years, based on1990 Census block group data.
[g] Measure of stress based on the Cohen Perceived Stress Scale (PSS) (17,18). Scored on a scale of 0 to 16, with higher scores indicating greater stress.

**Table 3. Adjusted Odds Ratios From Logistic Regression Models of Overweight and Obesity, National Longitudinal Study of Adolescent to Adult Health (n = 11,110), 1994–2008**

| Characteristic | Overweight/Obesity | | | Obesity | | |
|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
| **Race/ethnicity** | | | | | | |
| White [Reference] | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| American Indian | 1.87[a] | 1.62[b] | 1.65[a] | 1.38[b] | 1.15 | 1.09 |
| Black | 1.54[a] | 1.51[a] | 1.45[a] | 1.63[a] | 1.58[a] | 1.34[a] |
| Hispanic | 1.75[a] | 1.70[a] | 1.78[a] | 1.48[a] | 1.43[a] | 1.47[a] |
| Asian | 0.67 | 0.81 | 0.84 | 0.51[a] | 0.64[b] | 0.67 |
| Other race/ethnicity | 0.96 | 0.94 | 0.96 | 1.11[a] | 1.07 | 1.08 |
| **Male** | — | 1.48[a] | 1.46[a] | — | 0.93 | 0.93 |
| **Age** | — | 1.06[a] | 1.06[a] | — | 1.05[a] | 1.05[a] |
| **Parent education** | | | | | | |
| <High school diploma [Reference] | — | 1.00 | 1.00 | — | 1.00 | 1.00 |
| High school diploma | — | 0.97 | 0.97 | — | 1.02 | 1.07 |
| Some college | — | 0.85 | 0.86 | — | 0.84 | 0.90 |
| College diploma | — | 0.68[a] | 0.69[a] | — | 0.67[a] | 0.74[a] |
| >College diploma | — | 0.58[a] | 0.59[a] | — | 0.52[a] | 0.59[a] |
| **Parent is obese** | — | 2.43[a] | 2.44[a] | — | 2.47[a] | 2.48[a] |
| **Neighborhood characteristics[c]** | | | | | | |
| Neighborhood collective efficacy[d] | — | — | 1.02 | — | — | 1.02 |
| Neighborhood poverty[e] | — | — | 1.06 | — | — | 1.17[a] |
| Neighborhood mobility[f] | — | — | 0.99 | — | — | 0.96 |
| **Urbanicity** | | | | | | |
| Suburban [Reference] | — | — | 1.00 | — | — | 1.00 |
| Rural | — | — | 1.04 | — | — | 1.01 |
| Urban | — | — | 0.87 | — | — | 0.88 |
| **Perceived stress *z* score[c, g]** | — | — | 0.98 | — | — | 1.00 |
| **Constant** | 1.78 | 0.63 | 0.70 | 0.54 | 0.25 | 0.24 |

[a] $P < .01$.
[b] $P < .05$.
[c] Calculated as *z* scores, normed such that the mean equals zero and standard deviation equals 1. Coefficients can be interpreted as the adjusted odds ratio associated with a 1 standard deviation increase in the predictor.
[d] A measure of social cohesion scored on a scale of 0 to 3, with a higher score indicating better neighborhood efficacy.
[e] Percentage of people living below the official poverty threshold, based on 1990 Census block group data.
[f] Measured as the percentage of occupied housing units into which people moved during the previous 5 years, based on1990 Census block group data.
[g] Measure of stress based on the Cohen Perceived Stress Scale (PSS) (17,18). Scored on a scale of 0 to 16, with higher scores indicating greater stress.

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ORIGINAL RESEARCH

# Spatial Analysis and Correlates of County-Level Diabetes Prevalence, 2009–2010

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PEER REVIEWED

## Abstract

### Introduction
Information on the relationship between diabetes prevalence and built environment attributes could allow public health programs to better target populations at risk for diabetes. This study sought to determine the spatial prevalence of diabetes in the United States and how this distribution is associated with the geography of common diabetes correlates.

### Methods
Data from the Centers for Disease Control and Prevention and the US Census Bureau were integrated to perform geographically weighted regression at the county level on the following variables: percentage nonwhite population, percentage Hispanic population, education level, percentage unemployed, percentage living below the federal poverty level, population density, percentage obese, percentage physically inactive, percentage population that cycles or walks to work, and percentage neighborhood food deserts.

### Results
We found significant spatial clustering of county-level diabetes prevalence in the United States; however, diabetes prevalence was inconsistently correlated with significant predictors. Percentage living below the federal poverty level and percentage nonwhite population were associated with diabetes in some regions. The percentage of population cycling or walking to work was the only significant built environment–related variable correlated with diabetes, and this association varied in magnitude across the nation.

### Conclusion
Sociodemographic and built environment–related variables correlated with diabetes prevalence in some regions of the United States. The variation in magnitude and direction of these relationships highlights the need to understand local context in the prevention and maintenance of diabetes. Geographically weighted regression shows promise for public health research in detecting variations in associations between health behaviors, outcomes, and predictors across geographic space.

## Introduction

More than 25 million Americans have diabetes, and another 80 million have prediabetes; taken together, approximately 1 in 3 Americans have diabetes or prediabetes (1). Diabetes is associated with obesity and physical inactivity; many built environment factors — attributes of the proximate environment — such as access to healthy foods (2), crime level (3), the rural–urban matrix (4–6), and walking (4) are correlated with diabetes prevalence. One of the great challenges in understanding the associations between built environment attributes and diabetes is that both factors vary across the United States. Although studies of diabetes have found spatial variations in incidence and prevalence, there is a paucity of information on how the spatial prevalence of diabetes may or may not be associated with the spatial prevalence of built environment attributes. The importance of understanding the covariance of diabetes with its correlates was made salient by Siordia and colleagues (7), who found that the relationship between poverty and diabetes prevalence varied across the United States, with poverty highly correlated with diabetes in some regions but not in others (7). This finding provided the impetus for our hypothesis that the relationship between diabetes prevalence and county-level built environment attributes is nonstationary (ie, the relationship varies across space).

The objective of our study was to determine how and where diabetes prevalence is associated with built environment attributes at the county level in the contiguous United States. This information could allow programs and interventions to better target populations and attributes of the built environment associated with high diabetes prevalence.

# Methods

Our study used geographically weighted regression (GWR), a tool that is increasingly used by public health researchers to understand the nuances of such issues as access to health care, disease distribution, and spatial variation in magnitude of health outcome predictors (8–10).

## Data sources

We used county-level cross-sectional secondary data from various publicly available sources. Geographic information systems (GIS) shapefiles of contiguous US counties were downloaded from the Topographically Integrated Geographic Encoding and Referencing (TIGER) files available from the US Census Bureau (11) and imported into the ArcGIS 10.2 software (ESRI). Data on diabetes prevalence, obesity rates, and physical inactivity were collected from the Centers for Disease Control and Prevention's (CDC's) Diabetes Interactive Atlas (12), which is based on data from the Behavioral Risk Factor Surveillance System (BRFSS). CDC defines diabetes prevalence as the estimated percentage of adults with diagnosed diabetes, after adjusting for age. BRFSS does not differentiate between type 1 and type 2 diabetes. CDC defines obesity prevalence as the estimated percentage of obese adults (body mass index ≥30) after adjusting for age. The prevalence of physical inactivity is an estimated percentage of adults who are physically inactive. Physically inactive adults are those who have not participated in any physical activity or exercise in the preceding 30 days (http://www.cdc.gov/diabetes/library/glossary.html). All BRFSS data are based on self-report. Data on walking or cycling to work were collected from the US Census; this variable was defined as the percentage of employed adults per county who stated they either walked or cycled to work in the previous week.

Data for the sociodemographic variables — percentage nonwhite population, percentage Hispanic population, percentage living below the federal poverty level, education level, population density, and percentage unemployed — were from the US Census Bureau's American Community Survey 5-year estimates (2006–2010) (13). The variable for percentage nonwhite population refers to the percentage of people who did not identify themselves as white and does not include Hispanics who identify themselves as white. Percentage Hispanic population refers to the percentage of people who identified themselves as Hispanic (both white and nonwhite). The percentage of people living below the federal poverty level was determined according to income thresholds defined by the US Census Bureau, which differ by family composition. The education variable was defined as the percentage of people who reported having less than a high school diploma. Population density was defined as the number of people per square mile in a county. Unemployment was determined as the percentage of civilians aged 16 years or older that did not have work for the reference week. Data on food deserts were collected from the Department of Agriculture (USDA); the food desert variable was defined as the percentage of census tracts (per county) that are food deserts (http://www.ers.usda.gov/data-products/food-access-research-atlas/download-the-data.aspx). USDA defines a census tract as a food desert if 33% of the population lives far (urban, >1 mile; rural, >10 miles) from a supermarket or a grocery store. All variables were determined at the county level. There were 3,109 counties included in the study. Counties in Alaska and Hawaii were excluded because we could not test the influence of proximity; these states do not border other US states, and in Hawaii, no county borders another.

## Geographically weighted regression

We used GWR in addition to ordinary least squares (OLS) regression because the spatial data used in our study violates 2 major assumptions of global regression. First, global OLS regression assumes observations are independent of each other. However, spatial data often are clustered, suggesting stronger relationships between proximate observations (14). Clustering can result in correlation among regression residuals across space, or spatial autocorrelation, and biased parameter estimates (15). Second, OLS regression assumes spatial stationarity of the relationship between independent and dependent variables (16). In other words, it assumes coefficients will be constant across a sample area. However, the context of a particular area can influence the magnitude and direction of the relationship and produce a range of coefficients (17). GWR relaxes these assumptions and enables the analysis of spatially relevant data. Unlike OLS regression models, which produce global models across space, GWR produces numerous local models. It simultaneously conducts multiple regressions so that there is one regression model per spatial data point (eg, a county). Observations closer to a particular data point will have more weight in the estimation than observations farther away.

### Methodological steps in model building

The first step in the model building process is to map the dependent variable and explore spatial heterogeneity. If the dependent variable is not clustered, there is no need to build a spatially explicit model. Without clustering, the global model will be similar to the local model (17). We used the Moran's Index (*I*) in ArcGIS to map the clustering of diabetes prevalence across counties in the United States. Moran's *I* ranges from −1.0, perfectly dispersed (eg, a checkerboard pattern), to a +1.0, perfectly clustered. A *z* score and *P* value are generated as outputs along with Moran's *I*.

Initial data exploration and model specification using OLS was completed using SPSS 22 software (IBM Corporation). Three factors motivated the decision to first specify the OLS model: 1) we wished to identify variables significantly correlated with the dependent variable before specifying the regression model; 2) the GWR software used for spatial analysis does not provide a variance inflation factor (VIF) to assess multicollinearity; and 3) the GWR software does not enable the researcher to extract regression residuals to assess spatial autocorrelation for the global model.

In the OLS regression we included only variables significantly correlated with the dependent variable, diabetes prevalence. Residuals from the global OLS model were mapped and analyzed for spatial autocorrelation using Moran's *I*. The same set of variables was then used to specify a GWR model using the GWR4 software (http://geodacenter.asu.edu/gwr). While conducting GWR, we used the adaptive kernel, which was produced using the bi-square weighting function. The adaptive kernel uses varying spatial areas but a fixed number of observations for each estimation, a method most appropriate when the distribution of observations varies across space. In our case, observations (counties) are much smaller and closer together in the Northeast and Southeast than they are in the Midwest and West Coast. Finally, a process that minimizes the Akaike Information Criteria (AIC) was used to determine the best kernel size. The parameter estimates and *t* values produced by the software were exported and mapped using ArcGIS 10.2 (ESRI).

The residuals of GWR models are assumed to be normally distributed; a further assumption is that they are not spatially autocorrelated or clustered across space. Such clustering suggests that the local model underestimates or overestimates diabetes prevalence in particular areas. The residuals from the GWR model were analyzed using Moran's *I* to assess spatial autocorrelation. The clustering of residuals for OLS and GWR models were compared to assess the value of using GWR.

### Comparison of OLS and GWR model performance

We used 3 tools to compare the OLS and GWR models. First, we compared the adjusted $R^2$ of the basic OLS model and the GWR model. A higher adjusted $R^2$ in the GWR model than in the OLS model for the same set of variables suggests that location plays an important role in explaining the variance of diabetes prevalence. Second, we compared the corrected AIC (AICc) for both models. AICc is a widely used measure of goodness-of-fit that adjusts for degrees of freedom (18). It can be used to compare models with the same dependent variable but different independent variables. AICc can also be used to compare a global model with local models (17) because AICc does not assume models must be nested (18). The values of AICc are not absolute, but relative, so that they are meaningful only when compared between models. The model with a smaller AICc is deemed a better fit. The final analytical step was to compare residuals of both models for their distribution and spatial autocorrelation.

## Results

Diabetes prevalence in the United States at the county level ranged from 3.8% to 17.8% and was significantly clustered (Moran's $I$ = 0.35; $z$ = 540.2; $P$ < .001). We found clusters of high diabetes prevalence in the Southeast and clusters of low diabetes prevalence in Colorado. Diabetes prevalence was significantly correlated with numerous independent variables. Because the percentage of neighborhood food deserts was not significantly correlated at the county level, it was not included in the OLS model. The following 9 variables were included in the OLS model: population density, percentage nonwhite, percentage Hispanic, percentage living below the federal poverty level, percentage with less than high school education, percentage unemployed, percentage obese, percentage physically inactive, and percentage that walked or cycled to work. The OLS model was significant ($F_{9,3099}$ = 495.87, $P$ < .001). The model explained 58.8% of the variance in county-level diabetes prevalence. The VIF for all variables was less than 4.0, a commonly used cutoff point, suggesting no multicollinearity (Table 1).

The residuals of the OLS model were spatially autocorrelated (Moran's $I$ = 0.13; z = 26.4; $P$ < .001). The OLS model overestimated diabetes prevalence for Colorado and New Mexico counties. Similarly, it underestimated the outcomes for Alabama and West Virginia counties.

The GWR model produced coefficients for each county (Table 2, Figure 1, Figure 2). The change in both magnitude and direction of the coefficients suggests spatial nonstationarity of the relationship between the predictors and diabetes prevalence. The direction of the relationship in most counties was as expected. Only a few counties had opposite relationships for the predictors in the GWR model. In most counties, walking or cycling to work was associated with lower diabetes prevalence. However, a few clusters of rural counties in Minnesota, North Dakota, and South Dakota show an association between walking or cycling to work and higher diabetes prevalence. Such nonstationarity demands a more nuanced analysis with a contextual focus. For example, high rates of walking or cycling to work are often associated with multimodal transportation that also includes public transit, which is less likely to be available in rural communities (19).

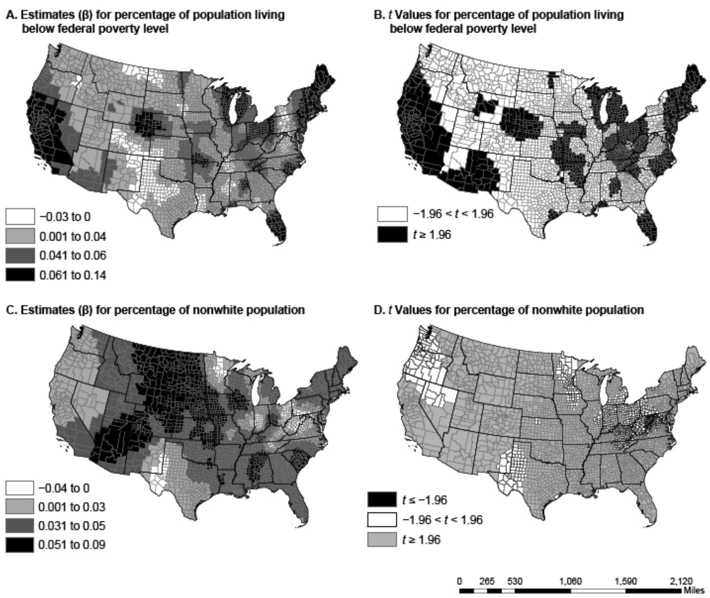


**Figure 1.** Spatial variation in parameter estimates and *t* values in US counties for the percentage of people living below the federal poverty level (maps A and B) and the percentage of nonwhite population (maps C and D). Data sources: American Community Survey (2006–2010) (13) and Centers for Disease Control and Prevention (12).

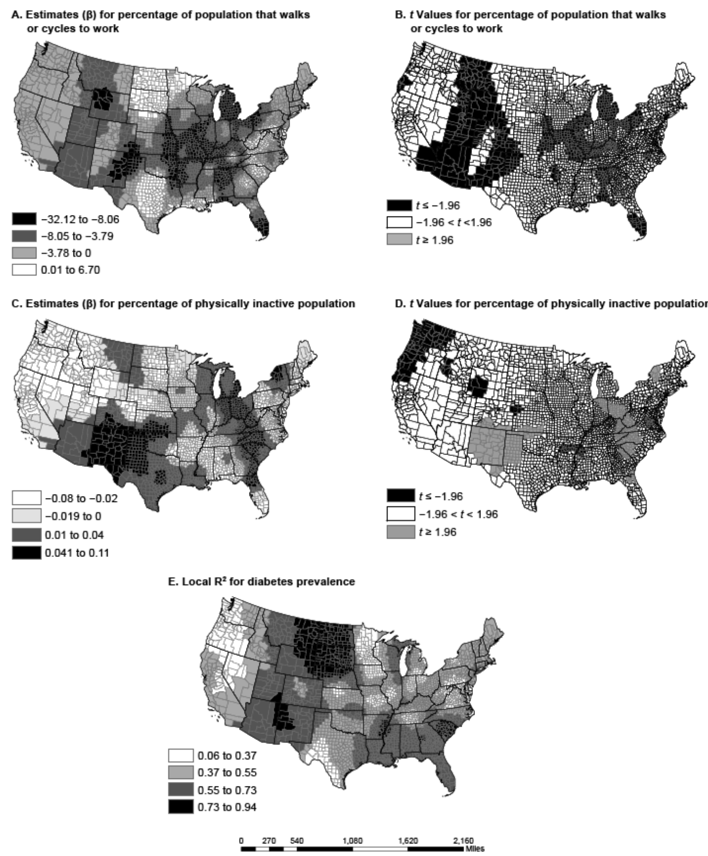


**Figure 2.** Spatial variation in parameter estimates and *t* values in US counties for percentage of employed population walking or cycling to work (maps A and B) and the percentage of the population that is physically inactive (maps C and D); local R-squared for full geographically weighted regression model (Map E). Data sources: American Community Survey (2006–2010) (13) and Centers for Disease Control and Prevention (12).

The adjusted $R^2$ for the local GWR model ranged from 0.06 to 0.94; the adjusted $R^2$ in the OLS model was 0.58. Explicitly, the global OLS $R^2$ of 0.58 masks a wide distribution of local associations between the predictors and diabetes prevalence. Without GWR, we would have been unable to estimate local models. In counties in North Dakota, South Dakota, and Montana, the GWR model explained up to 94% of the variance in diabetes prevalence. However, in Washington and Oregon, the model did not explain much of the variance (6%–37%), a spatial variation that would have been missed with the OLS model alone. Residuals for the

GWR model, although significant, were less spatially autocorrelated than residuals for the OLS model (Moran's $I = 0.01$; $z = 3.74$; $P < .001$). Compared with OLS, the GWR model greatly improved model fit. The GWR model explained more variance in diabetes prevalence and reduced the AICc ($\Delta R^2 = 0.22$; ΔAICc = 2,008.4).

# Discussion

Poverty level, physical inactivity, and walking or cycling to work were each significantly associated with county-level diabetes prevalence, relationships that were spatially nonstationary across the United States. The variation in parameter estimates from GWR suggests the need to apply this spatial analysis tool to other diabetes studies that have been restricted to global models (2,4). In the global OLS model, 58.8% of county-level diabetes prevalence was explained by race, poverty, obesity, physical inactivity, and walking or cycling to work. However, at an individual county level, the explanatory percentage ranged from 6% to 94%, and the individual county-level models were significantly clustered. This clustering suggests that local contexts, policies, programs, and built environment attributes are associated with diabetes prevalence and that the amplitude of such contexts, policies, programs, and environments varies across the nation.

The dissimilarity in variable coefficients was not a factor of one county alone but was a factor of multiple proximal counties, perhaps because of policy and programmatic spillover from neighboring counties and diffusion of innovation (20). The percentage of nonwhite population in a county had the greatest effect in the Southeast and the Rockies, from Arizona and New Mexico to Idaho and Montana. States in these regions have a high proportion of African Americans, Hispanics, or Native Americans, races/ethnicities with disproportionately high rates of diabetes (21). In several regions (including the Midwest, the Ohio Valley, and New England), poverty had a greater association with diabetes prevalence than any other variable. Physical inactivity had the greatest effect in the Southeast and the Southwest, a pattern similar to that of obesity prevalence (22). Walking or cycling to work was most associated with diabetes prevalence in the Mississippi Valley, the panhandles of Texas and Oklahoma, and south Florida, areas not generally associated with walking or cycling because of their hot summers.

The relationships among nonwhite populations, poverty, physical inactivity, and diabetes are not new (3,4,7). Others found these relationships have a spatial component (23). With the exception of recent work by Siordia and colleagues (7), there has been no investigation into the nonstationarity of these relationships. Similarly, the strong association between walking or cycling to work and diabetes is consistent with findings of other studies (24), but it has not been investigated for spatial heterogeneity or nonstationarity. That there is a significant association between nonwhite populations, poverty, physical inactivity, and diabetes and that this relationship has a spatial but nonstationary association highlights the need for local, context-specific diabetes prevention programs.

There are limitations to GWR and our analyses. GWR equates the local regression coefficients based on those geographic areas (eg, counties) most proximate to the area of interest. That is, the regression equation and coefficients for a county in Missouri are most influenced by bordering counties and other nearby counties, but not influenced by counties in Colorado or North Carolina. This concept is essential for local planning and related to Tobler's first law of geography, that "everything is related to everything else, but near things are more related than distant things" (25). However, the distance of influence (of predictors or potential interventions) is theoretically unknown and perhaps inconsistent across a geographic area (eg, the continental United States). We chose to use an adaptive kernel bandwidth, which accounted for differences in the size of counties and therefore the distance of influence. This choice should have helped adjust for the fact that, for example, North Carolina has 100 small counties and California has 58 larger counties spread over 3 times the landmass of North Carolina. Because of this discrepancy, the data point (county) was an estimate based on proximate counties as defined by the kernel type. GWR is also limited by the edge effect, whereby counties located on the edges of the United States (ie, coastal regions and the borders with Canada and Mexico) do not have the 360° influence of counties in the nation's interior.

There are also limitations to our findings. The local $R^2$s accounted for 6% to 94% of county-level diabetes prevalence. In large geographic areas in the Mid-Atlantic, upper Midwest, and Northwest, the 9 variables included in the model explained less than one-third of the variance in diabetes prevalence, which means that most factors associated with county-level diabetes prevalence in these geographic areas must have been missing from our model.

The primary strength of this study is the use of GWR in the analysis of the spatial distribution and correlates of diabetes prevalence. Siordia and colleagues (7) introduced the concept of spatial nonstationarity to the relationship between poverty and diabetes. Here, we extend their work by incorporating additional socioeconomic variables and built environment correlates with diabetes. GWR adds value to public health research and practice by emphasizing location-specific theories of health outcomes and tailored policies for intervention. It scrutinizes the assumption of global relationships between various predictors and health outcomes. Using GWR, public health researchers and practitioners can gain a nuanced understanding of health-related issues and respond to the notion that "all health is local" (25,26). In doing so, they can provide clarity for designing and funding context-specific public health programs and policies, especially for national programs that have local reach, including those of the CDC and the American Diabetes Association (ADA). Our analyses could also be used by local public health departments and ADA offices for resources such as MIYO (Make It Your own - http://www.miyoworks.org/) to tailor messages and materials for their target audiences. The use of GWR is a key advancement in public health research and practice because many health behaviors and outcomes vary spatially (eg, obesity) as do many common predictors (eg, race/ethnicity) (27).

Shedding light on spatial variations can provide new insights into well-established relationships. The methodology of GWR needs to be expanded to additional public health efforts to understand the impact of environment and place on health and how these relationships may vary across space. For diabetes prevalence, we presented an initial step in this direction, but much work remains before we understand why these variations exist and why race/ethnicity, poverty, physical inactivity, and active commuting have little explanatory effect in some regions but explain up to 94% of diabetes prevalence in other regions.

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# Tables

**Table 1. Results From Ordinary Least Square Model of US County-Level Diabetes Prevalence, 2009–2010**

| Characteristic | β | SE | *t* Value | *P* Value | Variance Inflation Factor |
|---|---|---|---|---|---|
| Intercept | 4.80 | 0.190 | 24.94 | <.001 | — |
| Population density | 0.000192 | 0 | 8.93 | <.001 | 1.45 |
| Percentage nonwhite population | 0.043 | 0.002 | 26.22 | <.001 | 1.42 |
| Percentage Hispanic population | −0.03 | 0.002 | −18.32 | <.001 | 1.11 |
| Percentage living below federal poverty level | 0.10 | 0.004 | 23.65 | <.001 | 1.46 |
| Percentage unemployed | −0.89 | 0.360 | −2.48 | .01 | 2.95 |
| Percentage with less than a high school education | 0.44 | 0.110 | 3.97 | <.001 | 3.00 |
| Percentage obese | 0.063 | 0.009 | 6.99 | <.001 | 2.22 |
| Percentage physically inactive | 0.03 | 0.007 | 5.86 | <.001 | 2.15 |
| Percentage that walks or cycles to work | −12.46 | 0.580 | −21.38 | <.001 | 1.47 |

Abbreviation: SE, standard error.

Table 2. Results From Geographically Weighted Regression Model of US County-Level Diabetes Prevalence, 2009–2010

| Characteristic | β | | Percentage of Counties by 95% of *t* Statistic | | |
|---|---|---|---|---|---|
| | Min | Max | $t \leq -1.96$ | $-1.96 < t < 1.96$ | $t \geq 1.96$ |
| Intercept | 1.60 | 10.7 | 0 | 0 | 100 |
| Population density | −0.003 | 0.01 | 13.2 | 86.2 | 0.70 |
| Percentage nonwhite population | −0.04 | 0.09 | 1.00 | 21.6 | 77.4 |
| Percentage Hispanic population | −0.22 | 0.16 | 30.4 | 68.0 | 1.50 |
| Percentage living below federal poverty level | −0.02 | 0.14 | 0.00 | 60.2 | 39.8 |
| Percentage unemployed | −45.4 | 23.4 | 21.4 | 78.1 | 0.60 |
| Percentage with less than a high school education | −6.66 | 15.0 | 0.10 | 76.3 | 23.6 |
| Percentage obese | −0.07 | 0.16 | 0.00 | 71.0 | 29.0 |
| Percentage physically inactive | −0.08 | 0.11 | 5.00 | 81.9 | 13.1 |
| Percentage that walks or cycles to work | −32.1 | 6.69 | 29.2 | 70.7 | 0.20 |

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ORIGINAL RESEARCH

# Influence of Home and School Environments on Specific Dietary Behaviors Among Postpartum, High-Risk Teens, 27 States, 2007–2009

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PEER REVIEWED

## Abstract

### Introduction
The objective of this study was to determine whether perceptions of the home and school food environments are related to food and beverage intakes of postpartum teens.

### Methods
Our study was a baseline, cross-sectional analysis of 853 postpartum teens enrolled in a weight-loss intervention study across 27 states from 2007 through 2009. Eight-item scales assessed perceived accessibility and availability of foods and beverages in school and home environments. Associations between environments and intakes were assessed by using $\chi^2$ and using logistic regression with generalized estimating equations (GEE), respectively.

### Results
Overall, 52% of teens perceived their school food environment as positive, and 68% of teens perceived their home food environment as positive. A positive school environment was independently associated with fruit consumption and 100% fruit juice consumption. A positive home environment was independently associated with fruit, vegetable, and water consumption and infrequent consumption of soda and chips ($\chi^2$ $P < .05$). Having only a positive school environment was associated with fruit consumption (GEE odds ratio [OR], 3.1; 95% confidence interval [CI], 1.5–6.5), and having only a positive home environment was associated with fruit (GEE OR, 2.9; 95% CI, 1.6–5.6), vegetable (GEE OR, 3.1; 95% CI, 1.5–6.2), and water (GEE OR, 2.6; 95% CI, 1.7–4.0) consumption and infrequent consumption of soda (GEE OR, 0.5; 95% CI, 0.3–0.7). Results for positive home and school environments were similar to those for positive home only.

### Conclusion
Home and school environments are related to dietary behaviors among postpartum teens, with a positive home environment more strongly associated with healthful behaviors.

## Introduction

Nearly one-third of adolescents are overweight or obese and thus are at greater risk for obesity and its long-term health consequences, such as diabetes, in adulthood (1,2). This risk is significantly heightened for postpartum, teenaged mothers who have sociodemographic and behavioral risk factors for overweight and obesity, such as low socioeconomic status and poor diet (3). Both the school and home environments influence dietary behaviors of teenagers, particularly in low-income and racial/ethnic minority populations (4,5). Aspects of food environments that may be particularly important include availability and accessibility of healthful foods such as fruits and vegetables, low-fat snacks, and low-calorie beverages (4,6–8).

More recent evidence suggests that school-based interventions and policies may not be sufficient to overcome risks posed in other settings (9,10). Reports from the Institute of Medicine suggest that although the school environment is a key target for obesity prevention programs, emphasis is also needed on the role of parents or caregivers in shaping dietary behaviors in the home (7,11).

Little is known about how postpartum teens perceive their food environments and whether those perceptions are related to their dietary behaviors (4,12). In previous work with high-risk, postpartum teens, we found a stronger relationship between the perceived home food environment (vs school) and healthful dietary behaviors (Tabak R, Joshu C, Clarke M, Schwarz C, Haire-Joshu D, unpublished data). Here we aim to build on these findings by examining the associations between perceived school and home food environments and consumption of specific food and beverage items and examining whether relationships vary by body mass index (BMI) and participation in nutrition assistance programs. We hypothesize that positive perceptions of food environments will be associated with healthful food and beverage intakes, and that these associations will differ by type of environment.

# Methods

## Study population

This cross-sectional study includes baseline data from postpartum teens enrolled in the Moms for a Healthy Balance Weight-loss Intervention Study (BALANCE), a group-randomized, nested cohort study with an intervention component designed to reduce postpartum weight retention in young mothers (13). BALANCE was developed in partnership with Parents as Teachers (PAT), a child development–parent education program supported by federal and state funds and delivered free of charge to over 200,000 families in all 50 states (14). For this study, we selected 27 states on the basis of the number of adolescent parents expected in the state.

Detailed methods on the BALANCE intervention have been described elsewhere (13). Briefly, trained PAT parent educators delivered an evidence-based curriculum via home visits, group activities, and online resources. Adolescents were eligible to participate if they were enrolled in the PAT Teen Program, were less than 1 year postpartum, and were not pregnant or planning to become pregnant. We enrolled 1,325 eligible adolescent mothers from 2007 through 2009, and the study concluded in 2010. A total of 141 of the 1,325 teen participants randomized did not complete the baseline assessment, and 45 were missing baseline data for the calculation of BMI, leaving a total of 1,139 with complete data. For this analysis, teens who were underweight at baseline (n = 19) as well as those who reported they were not currently in school (n = 221) were excluded. An additional 46 teen participants did not have information on food environments, leaving a total of 853 included in this analysis. The institutional review board of Saint Louis University and Washington University in St Louis approved this study, and informed consent was obtained from all participants.

## Measures

Teen mothers self-reported characteristics including age, race/ethnicity, current education level, length of time since giving birth (postpartum status), breastfeeding status at baseline, and participation in the Supplemental Nutrition Assistance Program (SNAP) and the National School Lunch Program (NSLP).

Trained staff measured height and weight at baseline in accordance with the National Health and Nutrition Examination Survey (NHANES) study procedures (15). Weight, height, and age data were used to calculate age-appropriate BMI categories, following the Centers for Disease Control and Prevention algorithm (16). BMI was dichotomized as normal (<85th percentile) and overweight/obese (≥85th percentile).

Questionnaire items measuring perceived access of 4 healthful items (fruits and vegetables, low-fat products, low-calorie beverages, and low-calorie snacks) were used to characterize the home and school food environments (17,18). For each environment, 8 statements assessed the availability and selection of healthful items at home (eg, “it is easy to find/there is a large selection of low-fat products in my home”) and ease of purchase and selection of healthful items at school (eg, “it is easy to purchase/there is a large selection of low-fat products in school”). Ratings were scored on a 5-point Likert scale (1 = “strongly agree” to 5 = “strongly disagree”). A mean score of the 8 items was created for the school and home food environments (Cronbach’s $\alpha$ = 0.897 and 0.902, respectively) and dichotomized as less than 3.0 being a positive environment and 3.0 or higher being a negative environment.

Dietary behaviors were assessed using the Snack and Beverage Food Frequency Questionnaire (SBFFQ) developed from our previous work (19,20). A validation study and pilot testing were completed with 60 teen participants. The SBFFQ examined the young mothers’ intake of 31 items during the prior 7 days by asking on how many days, how many times per week, and how much of the item she consumed. Items that were consumed by less than 25% of teens were excluded. Because of the nature and distribution of the data, data on the frequency of specific food and beverage items were collapsed into binary categories of infrequent (0–3 d/wk) and frequent (4–7 d/wk) consumption as a more conservative approach (21).

## Statistical analyses

Descriptive statistics were calculated to evaluate baseline characteristics of all postpartum teens and by positive and negative school and home food environments. Differences in baseline characteristics by environment were assessed by using Pearson $\chi^2$ tests and *t* tests. Relationships between environments and frequency of food and beverage consumption were assessed by using Pearson $\chi^2$ tests. To evaluate the relative strength of association between home and school environments and dietary behaviors, we created the following categories: "negative school and home," "positive school only," "positive home only," and "positive school and home." We used multiple logistic regression with generalized estimating equations (GEE) to account for clustering within a state. Potential confounders including NSLP and SNAP participation, race/ethnicity, age, and postpartum status, were identified on the basis of a priori knowledge and assessed by using a backward selection procedure. Final regression models were adjusted for race/ethnicity, age, and postpartum status, and results were calculated as GEE odds ratios (ORs) and 95% confidence intervals (CIs). To determine whether there were any differences by baseline weight status or participation in nutrition assistance programs, all models were stratified by BMI (ie, normal weight vs overweight/obese) and NSLP or SNAP participation. Data were analyzed by using Stata (Stata Intercooled, version 13; Stata Corp LP).

# Results

The mean age of the postpartum teens was 17 years (range, 12–20) and there were no significant age differences by perceived school or home environment (Table 1). Most teens identified as white (44%), black (29%), or Hispanic (20%). Racial distribution varied significantly by home environment, with a greater proportion of white teens reporting a positive home environment ($\chi^2$ $P < .05$). Slightly more than half of the teens had a normal BMI, and no significant differences were observed between home or school environment and BMI. Participation in SNAP and NSLP was common (30% and 40%, respectively) and varied significantly by home environment, with a greater proportion of postpartum teens reporting a negative home environment also reporting receiving SNAP and/or NSLP benefits ($\chi^2$ $P < .05$). Most teens were from neighborhoods in rural or suburban settings, and neighborhood location varied significantly by school environment; teens living in a suburban neighborhood were more likely to perceive a negative school environment ($\chi^2$ $P < .05$). Approximately 75% of teens were 3 months or more postpartum and 12% reported that they were currently breastfeeding.

Overall, the item most likely to be consumed more than 3 days per week was chips, followed by cereal (Table 2). A positive school environment was significantly associated with eating fruit more than 3 days per week, while a positive home environment was significantly associated with eating cereal, fruit, and vegetables on more than 3 days per week and chips and chocolate on 0 to 3 days per week ($\chi^2$ $P < .05$). When we stratified by baseline BMI, the relationships between a positive home environment and frequency of chips and chocolate consumption were significant only among normal-weight teens ($\chi^2$ $P < .05$). When we stratified by NSLP and SNAP participation, patterns of frequency of intake of food items were similar to the patterns observed for all teens except 1) the relationship between positive school environment and frequency of fruit consumption was significant only for teens participating in NSLP ($\chi^2$ $P < .01$), and 2) the relationship between a positive home environment and frequency of fruit consumption was significant only among teens not receiving SNAP benefits ($\chi^2$ $P < .01$).

Overall, the beverage item most likely to be consumed more than 3 times per week was water, followed by regular soda (Table 2). A positive school environment was significantly associated with frequent consumption of 100% fruit juice as well as 2 types of sugar-sweetened beverages: fruit punch and sports drinks ($\chi^2$ $P < .05$). A positive home environment was significantly associated with frequent water, 100% fruit juice, and whole or 2% milk consumption, and infrequent regular soda consumption ($\chi^2$ $P < .05$). We found similar results when we stratified by baseline BMI; however, the significant relationship between a positive home environment and whole or 2% milk consumption was observed only for overweight/obese teens ($\chi^2$ $P < .05$). When we stratified by NSLP and SNAP participation, patterns of frequency of intake of beverage items were similar to the patterns observed for all teens except that a positive school environment was significantly associated only with drinking 100% fruit juice more than 3 days per week among teens who did not participate in NSLP ($\chi^2$ $P < .05$).

When compared with teens reporting negative school and home environments, a positive school environment only was significantly associated with increased odds of frequent fruit consumption (GEE OR, 3.1; 95% CI, 1.5–6.5) (Table 3). Compared with teens reporting negative school and home environments, a positive home environment only was significantly associated with frequent consumption of cereal (GEE OR, 2.3; 95% CI, 1.4–3.7), fruit (GEE OR, 2.9; 95% CI, 1.6–5.6), and vegetables (GEE OR, 3.1; 95% CI, 1.5–6.2) and infrequent consumption of chips (GEE OR, 0.5; 95% CI, 0.3–0.8), and a positive home and school environment was associated with increased odds of frequent cereal (GEE OR, 1.7; 95% CI, 1.1–2.8), fruit (GEE OR, 2.9; 95% CI, 1.6–5.4), and vegetable (GEE OR, 3.2; 95% CI, 1.7–6.2) consumption.

Reporting only a positive school environment was not significantly associated with frequent consumption of any beverage items. Compared with teens reporting negative school and home environments, teens reporting a positive home environment only had increased odds of frequent water (GEE OR, 2.6; 95% CI, 1.7–4.0) and 100% fruit juice (GEE OR, 1.9; 95% CI, 1.2–2.9) consumption and infrequent consumption of regular soda (GEE OR, 0.5;

95% CI, 0.3–0.7). Compared with teens reporting negative school and home environments, teens reporting both positive home and school environments had similar results to those reporting only a positive home environment. Teens reporting both a positive home and school environment had significantly greater odds of frequent 100% fruit juice (GEE OR, 2.3; 95% CI, 1.5–3.6) and water consumption (GEE OR, 1.8; 95% CI, 1.2–2.6) and infrequent consumption of regular soda (GEE OR, 0.7; 95% CI, 0.5–1.0) than those reporting both negative home and school environments. Relative relationships between school and home food environments and food and beverage item consumption did not vary by baseline BMI. Significant associations between the positive school food environment and frequent consumption of healthful items such as fruit (GEE OR, 4.8; 95% CI, 1.6–14.6) and 100% fruit juice (GEE OR, 2.4; 95% CI, 1.1–5.6) were observed only among teens participating in the NSLP. The relationships between a positive home environment and both positive home and school environments did not differ substantially by NSLP participation. The relationship between the positive school food environment and dietary intake did not differ by SNAP participation, but significant associations between a positive home environment and infrequent consumption of unhealthful items such as chips (GEE OR, 0.4; 95% CI, 0.2–0.8) and soda (GEE OR, 0.2; 95% CI, 0.1–0.5) were observed only among teens who received SNAP benefits. The same patterns were generally observed for both positive home and school environments.

# Discussion

Our findings indicate that the school and home food environments have differential relationships with food and beverage intakes. Our findings were similar to those from other studies: we found that a perceived positive school environment was primarily related to healthful eating behaviors such as frequent fruit or 100% fruit juice intake but not unhealthful eating behaviors (22,23). In contrast, a perceived positive home environment was associated with frequent consumption of a wider variety of healthful items as well as infrequent consumption of unhealthful food and beverage items such as soda and chips. Our findings regarding the impact of positive school and home food environments suggest that for certain items consumed by teens, the major benefit lies within the home environment. This study contributes to our understanding of the relationship between both the home and school food environment and dietary behaviors of this understudied population of postpartum teens.

Numerous studies have documented the impact of policy and behavioral interventions promoting healthful school food environments on positive dietary change in youth (8,13,24). Increased access to fruit and various juices may be a result of enhanced school wellness and nutrition policies, which promote access to and availability of select foods (13,25). In addition, school meal programs such as NSLP that promote fruit and vegetable intake in school environments provide opportunities for increased fruit and vegetable consumption among low-income teens (26). However, easy access to and availability of high-calorie and high-fat snacks and sugar-sweetened beverages (ie, "competitive foods") that had been commonly sold in vending machines and at after-school fundraisers may have limited the effectiveness of school food policies and the influence of a positive school environment on teens' eating behaviors (24,27). Our results as well as findings from other studies indicate that while a positive school environment may be related to frequent intake of certain healthful food and beverage items, it was not associated with infrequent intake of unhealthful items such as sweet and salty snacks and sugar-sweetened beverages (4,22,23,28). These findings support the importance of recent changes in school food policies that limit access to unhealthful snacks by requiring improvements in the nutrition content of vending machine foods.

Unlike childhood obesity interventions in the school setting, interventions conducted in the home have not been common. Many of these interventions have focused on individual behavior change without addressing the home food environment, limiting their impact on dietary intake and other obesity-related outcomes (7,10). Results from our study are consistent with the literature suggesting the home environment has an important relationship with dietary intake among adolescents (9,29). The home food environment represents a substantial part of the full environmental context in which a postpartum teen grows, develops, eats, and behaves and is guided by "family policies" informed by tradition and culture as well as neighborhood and economic environment (7,29). Additionally, new mothers may be particularly aware of and sensitive to the health quality of their home setting (13). Our findings suggest the multiple and variable influences of a positive home environment have the added benefit of reducing unhealthful behaviors among postpartum teens.

To our knowledge, ours is the first study to examine whether associations between the school and home environments and food and beverage intake differ by participation in nutrition assistance programs. Other studies have shown mixed associations between SNAP and NSLP participation and dietary behaviors (9,30). Our findings suggest that the relationship between the food environment and frequency of consumption of certain items may be stronger among postpartum teens receiving nutrition assistance than those who did not receive assistance. Future research is needed to determine whether there are differences in the relationship between the environment and dietary behavior among teens that do and do not participate in nutrition assistance programs.

Our study has several limitations. This was a cross-sectional analysis; thus, we cannot evaluate causal relationships. Furthermore, reliance on self-reported data for dietary intake may be subject to recall bias and measurement error such as underreporting of items consumed. We attempted to limit potential misclassification by collapsing food and beverage frequency into dichotomous categories, but misclassification is a concern when using SBFFQ data (6,20). Although we were not able to compare data on the school and home environments with objective measures, studies have shown that perceived quality of home- and school-based settings independently influences dietary behavior (4,12). Therefore, we consider using perceptions of the school and home food environments a strength of this study, particularly because we are among the first to address perceptions of the school and home food environments and how they are related to behavior. Additional strengths of this study include a large and nationally representative sample of postpartum teens, an understudied population with a high risk for overweight and obesity.

Our study highlights the importance of both the school and home food environments and their differential relationships with dietary behaviors among teens at high risk for obesity. Further work targeting interventions across both home and school environments simultaneously are needed. In addition, it is important to understand whether different subpopulations respond differently to environmental influences to tailor effective obesity interventions and policies. Improving the home environment may be particularly important among this population of teen mothers who directly control the food environment of their infants. Environmental interventions in this high-risk and hard-to-reach population may not only be important for reducing the risk of adult-onset obesity in the teenaged mother but may also have substantial impact in minimizing the intergenerational transfer of obesity-related behaviors to offspring (13).

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# Tables

**Table 1. Characteristics of 853 Postpartum Teens and Their School and Home Food Environments,[a] 27 States, 2007–2009**

| Characteristic | Total[b] | School | | Home | |
|---|---|---|---|---|---|
| | | Positive | Negative | Positive | Negative |
| **Total N (%)** | 853 (100.0) | 442 (51.8) | 411 (48.2) | 577 (67.6) | 276 (32.4) |
| **Age, y, mean (SD)** | 17.4 (1.1) | 17.3 (1.1) | 17.4 (1.0) | 17.4 (1.0) | 17.4 (1.1) |
| **Race/ethnicity, n (%)[c]** | | | | | |
| White | 379 (44.4) | 193 (43.7) | 186 (45.3) | 264 (45.7) | 115 (41.7) |
| Black | 247 (29.0) | 131 (29.6) | 116 (28.2) | 151 (26.2) | 96 (34.8) |
| Hispanic | 173 (20.3) | 86 (19.5) | 87 (21.2) | 121 (21.0) | 52 (18.8) |
| Other/missing | 54 (6.3) | 32 (7.2) | 22 (5.3) | 41 (7.1) | 13 (4.7) |
| **BMI[d], n (%)** | | | | | |
| Normal | 480 (56.3) | 248 (56.1) | 232 (56.4) | 314 (54.4) | 166 (60.1) |
| Overweight/obese | 373 (43.7) | 194 (43.9) | 179 (43.6) | 263 (45.6) | 110 (39.9) |
| **Education, n (%)** | | | | | |
| 9th grade | 88 (10.6) | 53 (12.4) | 35 (8.7) | 55 (9.8) | 33 (12.3) |
| 10th grade | 148 (17.9) | 80 (18.7) | 68 (17.0) | 100 (17.9) | 48 (17.9) |
| 11th grade | 251 (30.3) | 125 (29.2) | 126 (31.5) | 172 (30.7) | 79 (29.5) |
| 12th grade | 341 (41.2) | 170 (39.7) | 171 (42.8) | 233 (41.6) | 108 (40.3) |
| **SNAP benefits[c], n (%)** | 254 (30.0) | 133 (30.3) | 121 (29.6) | 155 (27.1) | 99 (36.0) |
| **NSLP benefits[c], n (%)** | 346 (40.8) | 188 (42.8) | 158 (38.6) | 214 (37.4) | 132 (48.0) |
| **Neighborhood[e], n (%)** | | | | | |
| Rural | 345 (40.4) | 186 (46.2) | 159 (41.7) | 237 (44.8) | 108 (42.4) |
| Suburban | 260 (33.2) | 116 (28.8) | 144 (37.8) | 176 (33.3) | 84 (32.9) |
| Urban | 179 (22.8) | 101 (25.1) | 78 (20.5) | 116 (21.9) | 63 (24.7) |
| **Time since giving birth, n (%)** | | | | | |
| <3 months | 158 (25.1) | 81 (25.6) | 77 (24.5) | 116 (27.0) | 42 (20.9) |
| 3–6 months | 193 (30.6) | 107 (33.9) | 86 (27.4) | 130 (30.3) | 63 (31.3) |
| >6 months | 279 (44.3) | 128 (40.5) | 151 (48.1) | 183 (42.7) | 96 (47.8) |
| **Breastfeeding[c], n (%)** | 96 (11.7) | 56 (13.2) | 40 (10.1) | 81 (14.6) | 15 (5.6) |

Abbreviations: BMI, body mass index; NSLP, National School Lunch Program; SNAP, Supplemental Nutrition Assistance Program.
[a] See the Methods section for a description of how positive and negative perceptions were determined.
[b] Counts may not sum to overall total because of missing data.
[c] Significantly different for home environment, $\chi^2$ $P < .05$.
[d] Weight, height, and age data were used to calculate age-appropriate BMI categories, following the Centers for Disease Control and Prevention algorithm (16).
[e] Significantly different for school environment, $\chi^2$ $P < .05$.

Table 2. Association Between Frequency of Food and Beverage Items Consumed and School and Home Food Environments[a] for 853 Postpartum Teens, 27 States, 2007–2009

| | | School | | Home | |
|---|---|---|---|---|---|
| Item Consumed | Total, N (%) | Positive, n (%) | Negative, n (%) | Positive, n (%) | Negative, n (%) |
| **Chips[b]** | | | | | |
| 0–3 d/wk | 624 (73.2) | 319 (72.2) | 305 (74.2) | 434 (75.2) | 190 (68.8) |
| 4–7 d/wk | 229 (26.8) | 123 (27.8) | 106 (25.8) | 143 (24.8) | 86 (31.2) |
| **Crackers** | | | | | |
| 0–3 d/wk | 802 (94.0) | 410 (92.8) | 392 (95.4) | 538 (93.2) | 264 (95.7) |
| 4–7 d/wk | 51 (6.0) | 32 (7.2) | 19 (4.6) | 39 (6.8) | 12 (4.3) |
| **Granola bars** | | | | | |
| 0–3 d/wk | 812 (95.2) | 417 (94.3) | 395 (96.1) | 545 (94.5) | 267 (96.7) |
| 4–7 d/wk | 41 (4.8) | 25 (5.7) | 16 (3.9) | 32 (5.5) | 9 (3.3) |
| **Cakes** | | | | | |
| 0–3 d/wk | 764 (89.6) | 394 (89.1) | 370 (90.0) | 522 (90.5) | 242 (87.7) |
| 4–7 d/wk | 89 (10.4) | 48 (10.9) | 41 (10.0) | 55 (9.5) | 34 (12.3) |
| **Cookies** | | | | | |
| 0–3 d/wk | 785 (92.0) | 402 (91.0) | 383 (93.2) | 531 (92.0) | 254 (92.0) |
| 4–7 d/wk | 68 (8.0) | 40 (9.0) | 28 (6.8) | 46 (8.0) | 22 (8.0) |
| **Chocolate[b]** | | | | | |
| 0–3 d/wk | 750 (87.9) | 389 (88.0) | 361 (87.8) | 520 (90.1) | 230 (83.3) |
| 4–7 d/wk | 103 (12.1) | 53 (12.0) | 50 (12.2) | 57 (9.9) | 46 (16.7) |
| **Hard candy** | | | | | |
| 0–3 d/wk | 794 (93.1) | 412 (93.2) | 382 (92.9) | 542 (93.9) | 252 (91.3) |
| 4–7 d/wk | 59 (6.9) | 30 (6.8) | 29 (7.1) | 35 (6.1) | 24 (8.7) |
| **French fries** | | | | | |
| 0–3 d/wk | 738 (86.5) | 381 (86.2) | 357 (86.9) | 505 (87.5) | 233 (84.4) |
| 4–7 d/wk | 115 (13.5) | 61 (13.8) | 54 (13.1) | 72 (12.5) | 43 (15.6) |
| **Pizza** | | | | | |
| 0–3 d/wk | 811 (95.1) | 415 (93.9) | 396 (96.4) | 551 (95.5) | 260 (94.2) |
| 4–7 d/wk | 42 (4.9) | 27 (6.1) | 15 (3.6) | 26 (4.5) | 16 (5.8) |
| **Cereal[b]** | | | | | |
| 0–3 d/wk | 646 (75.7) | 335 (75.8) | 311 (75.7) | 418 (72.4) | 228 (82.6) |
| 4–7 d/wk | 207 (24.3) | 107 (24.2) | 100 (24.3) | 159 (27.6) | 48 (17.4) |
| **Fruit[b,c]** | | | | | |
| 0–3 d/wk | 712 (83.5) | 357 (80.8) | 355 (86.4) | 468 (81.1) | 244 (88.4) |

[a] See the Methods section for a description of how positive and negative perceptions were determined.
[b] Significantly different for home environment, $\chi^2$ $P < .05$.
[c] Significantly different for school environment, $\chi^2$ $P < .05$.

(continued on next page)

(continued)

**Table 2. Association Between Frequency of Food and Beverage Items Consumed and School and Home Food Environments[a] for 853 Postpartum Teens, 27 States, 2007–2009**

| Item Consumed | Total, N (%) | School | | Home | |
|---|---|---|---|---|---|
| | | Positive, n (%) | Negative, n (%) | Positive, n (%) | Negative, n (%) |
| 4–7 d/wk | 141 (16.5) | 85 (19.2) | 56 (13.6) | 109 (18.9) | 32 (11.6) |
| **Vegetables[b]** | | | | | |
| 0–3 d/wk | 722 (84.6) | 367 (83.0) | 355 (86.4) | 468 (81.1) | 254 (92.0) |
| 4–7 d/wk | 131 (15.4) | 75 (17.0) | 56 (13.6) | 109 (18.9) | 22 (8.0) |
| **Water[b]** | | | | | |
| 0–3 d/wk | 251 (29.4) | 130 (29.4) | 121 (29.4) | 144 (25.0) | 107 (38.8) |
| 4–7 d/wk | 602 (70.6) | 312 (70.6) | 290 (70.6) | 433 (75.0) | 169 (61.2) |
| **Regular soda[b]** | | | | | |
| 0–3 d/wk | 456 (53.5) | 229 (51.8) | 227 (55.2) | 337 (58.4) | 119 (43.1) |
| 4–7 d/wk | 397 (46.5) | 213 (48.2) | 184 (44.8) | 240 (41.6) | 157 (56.9) |
| **100% Fruit juice[b,c]** | | | | | |
| 0–3 d/wk | 597 (70.0) | 292 (66.1) | 305 (74.2) | 381 (66.0) | 216 (78.3) |
| 4–7 d/wk | 256 (30.0) | 150 (33.9) | 106 (25.8) | 196 (34.0) | 60 (21.7) |
| **Fruit punch[c]** | | | | | |
| 0–3 d/wk | 712 (83.5) | 358 (81.0) | 354 (86.1) | 477 (82.7) | 235 (85.1) |
| 4–7 d/wk | 141 (16.5) | 84 (19.0) | 57 (13.9) | 100 (17.3) | 41 (14.9) |
| **Sports drinks[c]** | | | | | |
| 0–3 d/wk | 787 (92.3) | 397 (89.8) | 390 (94.9) | 530 (91.9) | 257 (93.1) |
| 4–7 d/wk | 66 (7.7) | 45 (10.2) | 21 (5.1) | 47 (8.1) | 19 (6.9) |
| **Whole or 2% milk[b]** | | | | | |
| 0–3 d/wk | 472 (55.3) | 234 (52.9) | 238 (57.9) | 304 (52.7) | 168 (60.9) |
| 4–7 d/wk | 381 (44.7) | 208 (47.1) | 173 (42.1) | 273 (47.3) | 108 (39.1) |
| **Sweet tea** | | | | | |
| 0–3 d/wk | 711 (83.4) | 371 (83.9) | 340 (82.7) | 483 (83.7) | 228 (82.6) |
| 4–7 d/wk | 142 (16.6) | 71 (16.1) | 71 (17.3) | 94 (16.3) | 48 (17.4) |

[a] See the Methods section for a description of how positive and negative perceptions were determined.
[b] Significantly different for home environment, $\chi^2$ $P < .05$.
[c] Significantly different for school environment, $\chi^2$ $P < .05$.

**Table 3. GEE Logistic Regression Analysis[a] of Food Environments[b] and Frequency of Food and Beverage Consumption Among 853 Postpartum Teens, 27 States, 2007–2009**

| Item Consumed | Negative School and Home (n = 179) | GEE OR (95% CI) | | |
|---|---|---|---|---|
| | | Positive School Only (n = 97) | Positive Home Only (n = 232) | Positive School and Home (n = 345) |
| **Food** | | | | |
| Chips | 1 [Reference] | 0.8 (0.4–1.3) | 0.5 (0.3–0.8)[c] | 0.8 (0.5–1.1) |
| Crackers | 1 [Reference] | 1.9 (0.6–6.1) | 1.7 (0.6–4.7) | 2.3 (0.9–5.9)[d] |
| Granola bars | 1 [Reference] | 3.8 (0.9–17.0)[d] | 3.5 (0.9–13.6)[d] | 3.4 (0.9–12.8)[d] |
| Cakes | 1 [Reference] | 1.0 (0.5–2.2) | 0.6 (0.3–1.3) | 0.8 (0.5–1.5) |
| Cookies | 1 [Reference] | 1.3 (0.5–3.1) | 0.9 (0.4–1.9) | 1.2 (0.6–2.4) |
| Chocolate | 1 [Reference] | 1.6 (0.9–3.1) | 0.7 (0.4–1.3) | 0.6 (0.3–1.0) |
| Hard candy | 1 [Reference] | 1.1 (0.5–2.6) | 0.7 (0.3–1.5) | 0.7 (0.3–1.3) |
| Fries | 1 [Reference] | 1.1 (0.5–2.1) | 0.7 (0.4–1.3) | 0.8 (0.5–1.4) |
| Pizza | 1 [Reference] | 1.5 (0.5–4.1) | 0.5 (0.2–1.4) | 1.2 (0.5–2.5) |
| Cereal | 1 [Reference] | 1.2 (0.7–2.4) | 2.3 (1.4–3.7)[e] | 1.7 (1.1–2.8)[c] |
| Fruit | 1 [Reference] | 3.1 (1.5–6.5)[e] | 2.9 (1.6–5.6)[e] | 2.9 (1.6–5.4)[b] |
| Vegetables | 1 [Reference] | 1.3 (0.5–3.3) | 3.1 (1.5–6.2)[e] | 3.2 (1.7–6.2)[b] |
| **Beverage** | | | | |
| Water | 1 [Reference] | 1.3 (0.8–2.1) | 2.6 (1.7–4.0)[e] | 1.8 (1.2–2.6)[e] |
| Regular soda | 1 [Reference] | 1.4 (0.8–2.3) | 0.5 (0.3–0.7)[e] | 0.7 (0.5–1.0)[c] |
| 100% Fruit juice | 1 [Reference] | 1.5 (0.8–2.6) | 1.9 (1.2–2.9)[e] | 2.3 (1.5–3.6)[e] |
| Fruit punch | 1 [Reference] | 1.4 (0.7–2.7) | 1.1 (0.6–1.9) | 1.5 (0.9–2.6) |
| Sports drinks | 1 [Reference] | 2.1 (0.8–5.5) | 1.1 (0.4–2.6) | 2.0 (1.0–4.4)[d] |
| Whole or 2% milk | 1 [Reference] | 1.2 (0.8–2.2) | 1.5 (1.0–2.2)[e] | 1.6 (1.1–2.3)[c] |
| Sweet tea | 1 [Reference] | 0.6 (0.3–1.1) | 0.7 (0.4–1.2) | 0.8 (0.5–1.3) |

Abbreviations: GEE, generalized estimating equations; OR, odds ratio; CI, confidence interval.
[a] Adjusted for race, age, and length of time since giving birth.
[b] See the Methods section for a description of how positive and negative perceptions were determined.
[c] $P < .01$.
[d] $P < .1$, significant for trend.
[e] $P < .05$.

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ORIGINAL RESEARCH

# Enhancing Workplace Wellness Efforts to Reduce Obesity: A Qualitative Study of Low-Wage Workers in St Louis, Missouri, 2013–2014

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PEER REVIEWED

## Abstract

### Introduction
The objective of this study was to examine workplace determinants of obesity and participation in employer-sponsored wellness programs among low-wage workers.

### Methods
We conducted key informant interviews and focus groups with 2 partner organizations: a health care employer and a union representing retail workers. Interviews and focus groups discussed worksite factors that support or constrain healthy eating and physical activity and barriers that reduce participation in workplace wellness programs. Focus group discussions were transcribed and coded to identify main themes related to healthy eating, physical activity, and workplace factors that affect health.

### Results
Although the union informants recognized the need for workplace wellness programs, very few programs were offered because informants did not know how to reach their widespread and diverse membership. Informants from the health care organization described various programs available to employees but noted several barriers to effective implementation. Workers discussed how their job characteristics contributed to their weight; irregular schedules, shift work, short breaks, physical job demands, and food options at work were among the most commonly discussed contributors to poor eating and exercise behaviors. Workers also described several general factors such as motivation, time, money, and conflicting responsibilities.

### Conclusion
The workplace offers unique opportunities for obesity interventions that go beyond traditional approaches. Our results suggest that modifying the physical and social work environment by using participatory or integrated health and safety approaches may improve eating and physical activity behaviors. However, more research is needed about the methods best suited to the needs of low-wage workers.

## Introduction

Obesity, a major risk factor for diabetes, affects more than one-third of adults in the United States and is associated with several demographic and socioeconomic factors, including low income (1). Several studies have found that obesity rates are generally higher among working class occupations than professional occupations, even after controlling for demographic factors (2,3).

From a sociological perspective, the environments in which people live and work are strong influences on obesity and diabetes (4,5). The work environment is especially important because many adults spend a significant amount of time at work and because obesity affects employers through reduced productivity and absenteeism as well as increased health care costs and disability (6). Numerous studies acknowledge the negative health consequences of workplace factors such as stress, low autonomy, poor coworker and managerial support, and unhealthy physical work environments (2,7). These workplace risk factors may be more common in low-wage and working-class jobs and may explain some occupational differences in obesity prevalence (2,8).

Promoting health through worksite wellness programs is a national priority. The Affordable Care Act creates new incentives to promote employer wellness programs and encourage opportunities to support healthier workplaces (9). The National Institutes of Health and the Centers for Disease Control and Prevention have targeted worksites as a priority location for health interventions because they offer an efficient means of delivering and evaluating programs and provide opportunities to reach socially disadvantaged populations (10,11). However, data for the effectiveness of workplace health programs are limited and may not be generalizable to all types of workers (6,11–13). National data show that blue-collar and service workers are less likely to work for an employer who offers health promotion activities and are less likely to participate in such programs when offered (14).

This study focused on a little-studied health disparity — workplace health promotion among low-wage workers. The objective of the study was to examine through interviews and focus groups 1) worksite culture, environment, and policies that influence healthy eating and physical activity; and 2) barriers that reduce worker participation in workplace health promotion programs. An understanding of how the workplace affects health behaviors is can inform design of effective interventions to reduce and prevent obesity.

# Methods

We partnered with a large health care system and a national labor union representing retail workers to recruit study participants. Qualitative data collection included interviews with key informants (eg, employer representatives, union leaders, benefits administrators) and worker focus groups with both partner organizations. The workforce in the union was relatively homogenous with regard to income and included workers in jobs such as cashier and merchandise stocker. Within the health care system, we targeted hospital work departments and locations that employed a large proportion of low-wage workers, including housekeepers, patient care technicians, and food service workers. This study was approved by the Washington University institutional review board.

We interviewed 10 individuals from the union partner: 4 local union leaders, 5 store representatives, and 1 health benefits administrator. Key informants were recruited in person or through email, and interviews were conducted in person or over the telephone. We asked about current and previous wellness initiatives offered to employees, employee participation in these initiatives, and potential barriers to participation. Informants were also asked about workplace factors that influenced health behaviors (ie, physical activity and healthy eating) and employee attitudes about health and wellness.

We conducted a total of 9 focus groups involving 61 workers. Twenty hospital employees (4 men and 16 women) participated in 4 groups. Forty-one unionized retail workers including 12 men and 29 women participated in 5 focus groups. Focus group participants were recruited through their work department, store, or local union hall. The research team attended union meetings to recruit members in person and posted flyers in break rooms at selected stores and hospital departments. We used a semistructured script to guide focus group discussions. The scripts covered 11 broad domains with follow-up questions and prompts for each domain (Table 1). All group discussions were audio recorded and transcribed. Transcriptions were entered into QSR International's NVivo 10 software (QSR International Pty Ltd), and all were coded by 2 independent raters using a predefined code book based on the domains in the focus group script. After initial coding and consensus of all transcripts, we applied a phenomenological approach for data analysis to find the "essence" or common themes across individual experiences (15). The purpose of the thematic analysis was to answer 2 questions: "what impacts healthy eating and physical activity" and "what can be modified at the workplace?" Through systematic review and discussion, codes were merged and grouped under main themes. Each transcript was reread and re-coded for consistency.

# Results

## Key informant interviews

The informants indicated that very few wellness programs related to weight management were offered to retail workers. The union-sponsored health plan covered some costs for nutritional counseling, but that benefit was not well advertised. The employer-sponsored initiatives such as an onsite gym or weight loss programs were primarily available to employees in the corporate offices, not to workers in retail stores. Both the union and employer representatives recognized the need for workplace wellness programs but were unsure about how to proceed with developing and implementing a program to reach their diverse and widespread workforce.

Informants described various programs available to employees but noted several barriers to effective program implementation, including lack of management commitment at some levels, limited budgets, and communication and advertising limitations. One informant described results of a focus group conducted among employees of 1 hospital department regarding awareness of existing wellness programs and preferred methods of communication; results indicated that most workers were unaware of the wellness program and did not regularly use company email, which was the primary method of communicating information about the wellness program. Workers preferred to get information via personal email, text message, or in person. Workplace wellness efforts within the health care organization varied by worksite; some sites were more successful in promoting and delivering their wellness initiatives than others. Informants thought the size of organization and motivation of appointed representatives for each location influenced program success. An informant from a smaller hospital mentioned several successful wellness initiatives at her location, including an onsite gym, exercise classes, and 2 weight-loss challenges each year, and an informant from a larger hospital discussed struggles to find effective communication methods to reach all worker groups.

### Worker focus groups

The final list of themes from the focus group analysis included 10 work-related themes and 10 general themes (Table 2). Workers commonly discussed how their job characteristics contributed to their health. For example, they mentioned that physical demands and stress of their jobs left them too exhausted or unmotivated to exercise or plan healthy meals (Table 3). Many also described how the physical environment affected their health (eg, small work area, concrete floors). Past or current company programs and priorities was another common theme identified, although details varied by group. Overall, the retail workers talked about lack of wellness programs; some mentioned store weight-loss competitions and previous company campaigns but felt that their employers and union did not prioritize health and wellness. Responses of the health care worker groups differed; those working in a large hospital setting were much less aware of wellness initiatives and felt less company or management support for health promotion. Many were aware of the onsite gym and the weight-loss program, but cost, work schedule, and home responsibilities made it difficult to participate. Conversely, a group working in a smaller clinic felt tremendous upper-management support and described numerous workplace supports, including a produce garden at the worksite, access to exercise equipment, afternoon stretch breaks, and healthy potluck lunches.

Workers also discussed schedules and breaks as having a significant impact on their healthy eating and physical activity. For many retail workers, their schedules varied week-to-week, making it difficult to maintain any routine. Workers from both organizations stated that short and interrupted breaks made it difficult to eat healthy. They discussed how food options —healthy or unhealthy and purchased or provided for free (eg, incentive lunches, holiday parties) — affected their eating behaviors at work. Workers from both organizations felt that their workplaces had a lack of quick, convenient, and low-cost healthy food options. Moreover, in all groups we heard that free food was almost always unhealthy. Nearly all workers commented that social support and accountability to coworkers would improve their ability to initiate and maintain healthy behaviors.

General themes were those that may be related to the workplace but also extended into workers' personal lives. For example, workers often discussed how intrapersonal factors (eg, motivation, willpower) and home life (eg, responsibilities, family support) affected their health behaviors both in the workplace and at home. Workers often discussed how their jobs influenced their health in terms of not having the money, time, or energy to exercise or plan healthy meals. Some workers also discussed the roles that health issues and transportation played in initiating and sustaining healthy behaviors.

## Discussion

This study highlights factors related to obesity as described by 2 low-wage work groups; our findings are consistent with results from a similar study among low-wage workers in various industries (8). The workplace was often viewed as a barrier to healthy eating and physical activity; however, workers supported the concept of workplace health promotion and offered suggestions for overcoming many of the identified barriers. As demonstrated in this study, the workplace may be effective in engaging populations at risk for obesity and related illnesses, though it may be necessary to go beyond traditional workplace wellness approaches. Using more innovative methods may increase program reach, effectiveness, and sustainability.

Policy changes have increasingly been recognized as essential components of worksite health promotion (16) and are more sustainable than individual-level behavior interventions (17). Policies promoting a culture and environment conducive to reducing obesity can be a strong catalyst to behavior change. These can include top-level policies, such as offering a health care plan that has wellness options or implementing organizational policies that provide for access to low-cost healthy foods at the worksite, encourage active transportation to and from work, or allow for flexible work schedules to encourage lunch or break-time physical activity. The work environment (both indoor and outdoor) is also an important component of behavior change and can have a significant impact on behavior choice (18). An environment that encourages less sedentary work and more physical activity could include well-placed and maintained stairwells for stair use versus elevators or distant parking.

Changes solely in the workplace environment may not be enough to encourage healthy behaviors (19). Health behavior decisions are affected by the social context in which they are made, such that the social support and social norms surrounding a health issue have a substantial effect on how that health behavior is perceived. Changing social norms and fostering a supportive work environment for the desired behavior is a necessary complement to the other levels of intervention. Social norms have been studied as a way to promote nutrition (20) and physical activity (21).

Workplace participatory approaches may foster social support and help to overcome organizational and employee barriers to program success. Most worksite weight-loss programs have relied on a top-down approach, rather than a participatory approach based on employee involvement in the design of interventions (22). In workplaces where employees generally have little influence on their work environment, similar to those sampled in this study, participatory approaches can result in better program implementation and subsequent health improvement (22). The recently described Healthy Workplace Participatory Program (HWPP) includes work environment changes, as well as healthy eating and physical activity interventions (23). A small study based on HWPP found promising changes in behaviors and weight loss in a pre–post evaluation of a participatory worksite intervention (24). To our knowledge, this HWPP-based study is the only controlled study to date using a worker health participatory program to attain weight loss. Future research should implement and evaluate workplace participatory interventions for weight loss.

Workplace wellness programs should also use effective communication strategies to engage workers from diverse work groups and backgrounds. As demonstrated with the health care system in this study, many low-wage workers were not aware of the wellness programs that were available to them. The same programs, however, have good participation from other work groups in the health care organization, primarily because of the method of communication. Rapid changes in information technology have enabled new interventions that use mobile telephones and other mobile devices (mHealth). These techniques show great promise for weight reduction in low-income populations (25), and such interventions are readily scalable to larger populations (13).

Although we did not directly ask about incentives, several participants discussed monetary incentives as a possible motivator to eat healthy and exercise. The use of incentives is common in workplace wellness programs; employers could maximize the benefits of incentives by incorporating lessons from behavioral economics. For example, the increasingly popular approach of delivering incentives through health insurance premium adjustments is unlikely to be as effective as more frequent and immediate rewards for behavior. This is because people tend to discount the future, meaning that they respond more readily to immediate than delayed costs and benefits (26). The participants in our study commonly discussed cost as a barrier to eating healthy and exercising. As suggested by others (27), low-income workers may be more likely to change and sustain healthy behaviors if provided with financial support for healthy food and participation in other weight-loss activities. Employers should also be aware of the limitations of incentives for behavior change. Recent reviews have shown behavioral effects to be relatively short-lived after incentives are removed (27), and considerable attrition is found in workplace programs for weight loss (28). More research is needed to determine the optimal timing, magnitude, and structure of incentives, but results to date suggest that incentives may need to be an ongoing feature of the workplace to have maximum impact.

Finally, employers may consider integrating traditional occupational safety and health programs (ie, those that focus on health hazards unique to the workplace) with health promotion and wellness programs (ie, those that focus exclusively on lifestyle factors off the job). The Total Worker Health program was launched by the National Institute of Occupational Safety and Health (NIOSH) to support the development and adoption of research and best practices to integrate these approaches and address health and safety risks at multiple levels, including the work environment (physical and organizational) and individual behaviors. This integrative approach may lead to greater adoption of interventions by management and workers and hence to improvements in the health of workers (11), but more research is needed to evaluate both the development process and the effectiveness of integrated programs (29).

The results of this study can help inform future worksite interventions for low-wage workers; however, our study has several limitations. First, we collected data from key informants who could be contacted or agreed to be interviewed. Second, although the participants in the focus groups represented a range of positions and worker groups, they were limited to those available during the implementation of the focus group discussions. Although using a convenience sample may be a limitation, those who elected to participate in the interviews or focus groups were able to provide helpful insights on the topic. Future intervention planning would need to be preceded by additional input from a broader participant base. Third, the information we collected may not be generalizable to other health conditions or work settings. Despite these limitations, the key informants and focus group participants provided rich and potentially actionable information on addressing obesity at the worksites of these worker populations.

Workplaces can provide an effective venue for engaging low-income populations at risk for obesity and related illnesses. Results of this study suggest that future worksite interventions for low-wage workers can improve reach, effectiveness, and sustainability if they embrace more innovative methods than those used in current workplace wellness programs. Future interventions should address workplace policies and environment and social norms that affect health behavior decisions. Communication strategies and financial incentives should be better aligned with the needs of low-wage workers. Workplace participatory programs are a promising approach to engage workers in health improvement.

## Acknowledgments

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# Tables

Table 1. Focus Group Domains and Questions, Qualitative Study of Low-Wage Workers, St. Louis, Missouri, 2013–2014

| Domain | Questions | Examples, Clarification, Follow-ups, Probes |
|---|---|---|
| Work schedule | Tell us about a typical work day. | How many hours do you usually work? What opportunities do you have for breaks? |
| Healthy eating priority | Is eating healthy a personal priority for you? | Do you try to eat healthy? What do you do at home to eat healthy? Are you satisfied with your diet? |
| Eating at work | When do you eat while at work? What do you eat while at work? | How do you decide what you will eat while at work? |
| Exercise priority | Is regular exercise a personal priority for you? | Do you try to exercise? How often, where do you exercise? Are you satisfied with your level of physical activity? |
| Physical activity at work | What kind of physical activity/exercise do you do at work? | Do you do anything in addition to your normal work routine to be more physically active? (eg, take the stairs, walk during break times) |
| Worksite health facilitators | What aspects of work at [organization] seem to help you or your coworkers stay healthy while at work? | Current wellness or safety programs that are helpful? Helpful aspects about physical environment or company policies that promote health? What qualities of your job make you feel good? Keep you fit? Do your work relationships contribute to health? How? |
| Worksite health barriers | Which aspects of your work or work environment get in the way of being healthy? | Are there things about your work tasks or the way work is organized that make it difficult for you to take care of your health? What aspects of work prevent you from engaging in healthy activities outside of work? |
| Health concerns | What health issues are you most concerned about for yourself? | How concerned are you about missing work due to illness/injury? |
| Current wellness programs | Are you aware of any health and wellness programs currently or previously offered to employees? (ie, weight-loss, smoking cessation) | Have you or any of your coworkers participated in any of these wellness programs? |
| Communication | How does your employer communicate important information to you? | What about health information? |
| Future workplace programs | How likely are you to participate in workplace wellness programs in the future? What about nutrition and exercise programs, specifically? | What factors might influence your decision to participate? (ie, cost, location, other). How can your employer/union do a better job of promoting wellness in employees? |

**Table 2. Main Focus Group Themes and Number of Associated Coded References, Qualitative Study of Low-Wage Workers, St. Louis, Missouri, 2013–2014**

| Theme (N)[a] | Topics Included |
|---|---|
| **Work-related theme** | |
| Job characteristics (196) | Physical and mental demands, stress, physical environment, safety, workplace rules |
| Company priorities and programs (165) | Company health promotion programs, perception of company priorities for employee health |
| Food options (105) | Food options at work (free or available for purchase) |
| Communication (92) | Communication of health information, preferred methods of communication |
| Work schedule (75) | Schedule, time of day worked |
| Social support/accountability (72) | Desire for social support or being held accountable, camaraderie |
| Management support (48) | Perception of management support, employee–management relationships |
| Facilities (45) | Aspects of current facility related to health or suggestions for changes to facilities |
| Breaks (40) | Relationship between breaks and health behaviors |
| Other (24) | Knowledge from job, suggestions for general workplace changes |
| **General theme** | |
| Intrapersonal (168) | Motivation, willpower, impulse, desire to be healthy/look good |
| Financial (132) | Company discounts, cost of food, gym memberships |
| Home life (94) | Cooking at home, food restrictions, outside environment, other priorities/responsibilities |
| Time (75) | Not enough time, availability of quick options |
| Energy (53) | Lack of energy, need energy |
| Food preferences (49) | How eating habits/preferences affect food choices |
| Planning (45) | Lack of routine, difficulties of planning, reasons behind planning or not planning |
| Convenience (33) | Convenience of food options, wellness programs; choices that require little effort |
| Personal health (20) | Physical and mental health as barriers to eating well or participating in physical activity |
| Transportation (16) | Influence of transportation on participation in wellness programs |

[a] N = number of times this theme was referenced.

**Table 3. Sample Comments and Coded Themes, Qualitative Study of Low-Wage Workers, St. Louis, Missouri, 2013–2014**

| Comment | Theme Coded |
| --- | --- |
| "If any employer is really serious about wanting a healthier work environment and employees then they have to make sure they have the proper rest time. I am squishing my two 15-minute breaks together to make my half-hour lunch." | Company priorities and programs, breaks |
| "I think I would [go to the workplace gym] because I think somebody would go with me from here. You'd have a buddy. You have so many friends inside of [the store]. I mean I have friends at other [stores] and I could be like 'Hey, meet me at our gym.'" | Social support-accountability, company priorities and programs |
| "When I first started working here I thought it was the oddest thing that I would walk to the cafeteria and I would see nurses, techs, eating when they are walking, eating at the elevator . . . but now I know why they do that, you know, 'cause sometimes that is all the time they get." | Breaks, time, job characteristics |
| "And that's another thing, they got a lot of good different varieties during the day, but at night, there is not much to choose from." | Work schedule, food options |
| "But it is funny because they put [smoking cessation ads] in the break room but the smokers don't go in the break room, they go outside. So nobody saw it." | Communication |
| "And I have to say, she [upper-level manager] don't throw it down your throat . . . I don't think anybody does. They put the option out there and it's your choice to participate or not. They give us the resources to use and they say here, now it is up to you They will promote something [monthly] that most of us probably didn't know . . . to help us." | Company priorities and programs, management support |
| "I feel like not having set schedules makes it kinda hard to exercise, because sometimes you work early in the morning, sometimes you'll work late at night. Throws off your sleep schedule." | Work schedule |
| "If you're too tired and you're stressed out, you don't want to do anything but eat that fattening food and curl up in a little ball and go to bed. You don't plan for tomorrow; you just have to get through the day." | Planning, energy |
| "I'm a food addict, I'll admit it; I like food. I have all intents and purposes of going to the salad bar and picking the good lettuce, the good stuff, the good fruits, the good vegetables, but man as soon as that [BBQ smoker] hits me, I'm gone!" | Intrapersonal, food preferences |
| "I prepare my lunch every morning. I work and then I actually walk every day . . . up to 5, 6, 7 miles every day . . . except for today because all of us had double shifts. So that's it, I have the will power, I'm not gonna lie. Most people don't know me, but I've dropped a ton of weight. I was quite large and I just made a goal this year that I was gonna take care of myself." | Intrapersonal, planning, work schedule |

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ORIGINAL RESEARCH

# Worksite Influences on Obesogenic Behaviors in Low-Wage Workers in St Louis, Missouri, 2013–2014

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PEER REVIEWED

## Abstract

### Introduction
More than one-third of US adults are obese. Workplace programs to reduce obesity and improve overall health are not available or accessible to all workers, particularly low-wage workers among whom obesity is more prevalent. The goal of the study was to identify modifiable workplace factors and behaviors associated with diet and exercise to inform future workplace interventions to improve health.

### Methods
We distributed paper and online surveys to 2 groups of low-wage workers, hospital workers and retail sales workers, at the worksites. The surveys assessed obesity, obesogenic behaviors, workplace factors, and worker participation in workplace health programs (WHPs). Descriptive and regression analyses were conducted to examine workplace factors associated with obesogenic behaviors.

### Results
A total of 529 surveys were completed (219 hospital workers and 310 retail workers). More than 40% of workers were obese and 27% were overweight. In general, workers had poor diets (frequent consumption of sugary and high-fat foods) and engaged in little physical activity (only 30.9% met recommended physical activity guidelines). Access to and participation in workplace health programs varied greatly between hospital and retail sales workers. We identified several modifiable workplace factors, such as food source and work schedule, that were associated with diet, exercise, or participation in workplace health programs.

### Conclusion
This study illustrates the high prevalence of obesity and obesogenic behaviors workers in 2 low-wage groups. The differences between work groups indicated that each group had unique facilitators and barriers to healthy eating and exercise. An understanding of how socioeconomic, demographic, and work-related factors influence health will help to identify high-risk populations for intervention and to design interventions tailored and relevant to the target audiences.

## Introduction

More than one-third of US adults are obese (1), and obesity is a major contributor to increased medical costs and lost productivity (2–4). Obesity is associated with low income and education, even after controlling for other risk factors (4,5). Even modest weight loss is associated with improved health outcomes for such conditions as diabetes (6,7), and many evidence-based guidelines now recommend lifestyle interventions for weight management and disease prevention (8,9). Worksite wellness programs that incorporate weight management interventions are becoming more common (3) and can be an effective means of reaching low-wage populations (4,10,11).

Low-wage workers have less access to workplace wellness programs and are less likely to use them, creating an overlooked health disparity (10,12,13). Furthermore, low-wage jobs often entail shift work, irregular schedules, and little autonomy over work schedule (2), which may contribute to obesogenic behaviors, yet most existing worksite programs do not address such workplace factors (3,14–16). Understanding how the workplace influences obesity and how existing structures can be used to change behavior will inform the development of more effective wellness programs to target obesity and reduce health disparities (3,10).

This study examined some workplace determinants of obesogenic behaviors in 2 groups of low-wage workers. Additionally, we examined factors related to participation in existing workplace health programs (WHPs). The goal of the study was to identify modifiable workplace factors and behaviors associated with diet and exercise to inform future workplace interventions to improve health.

# Methods

## Study population and recruitment

We worked with a large health care system and 2 local chapters of a national union representing retail workers to recruit participants. The health care system and the union represent large, fast-growing segments of the low-wage workforce, and both expressed interest in improving their workplace wellness efforts. Workers were recruited and surveyed from November 2013 through June 2014. We targeted hospital departments with high proportions of low-wage workers, including housekeepers, food service workers, patient care technicians, and unit secretaries; retail workers were primarily employed by 3 regional retail chains. We attempted to recruit all workers within targeted departments, stores, or union meetings and worked with supervisors, store managers, and union leaders to distribute paper surveys packets. Packets included a recruitment letter, consent form, and survey. Participants could return paper surveys in person to a research team member at a specified time and location or by mail using a prepaid envelope; they were compensated for their time. A small number of surveys were offered online to hospital employees who did computer work. All participants were at least 18 years of age and spoke English. This study was approved by the Washington University Institutional Review Board.

## Survey development and administration

The survey assessed various domains including demographics, job characteristics, and work environment (eg, schedule, wages, social support, employer's value of workers' health), availability of and participation in WHPs, health behaviors (eg, diet, physical activity, willingness to change health behaviors), and health status (eg, height, weight, overall health, health conditions). To measure the 3 primary outcomes of diet, physical activity, and participation in WHPs, we used well-established survey tools: the Rapid Eating Assessment for Participants Short Version (REAP-S) (17), the 2-question physical activity assessment (18), and 16 items from the Worksite and Energy Balance Survey (WEBS) to measure availability and participation in WHPs (such as health fairs, exercise programs and facilities, flexible time for physical activity, and incentives to walk or bike to work) (19). The survey also included the SF-8 to measure health status (20), the Supervisor and Coworker Support scales from the Job Content Questionnaire (21), questions from the WEBS survey to determine food source at work, a question from the National Health and Nutrition Examination Survey Occupation Questionnaire Section (22) to assess work schedule, and a revised version of the Stanford Brief Activity Survey to determine physical activity at work (23).Willingness to change eating behaviors was measured by using a question from the REAP-S; we created a similar question for physical activity. Prior to distribution, we conducted pilot testing of the survey among both hospital and retail workers to ensure clarity, relevance, and readability. The survey took approximately 15 to 20 minutes to complete.

## Data analysis

Body mass index (BMI) (weight in kg/height in $m^2$) was calculated by using self-reported height and weight. Aggregate scores for the Job Content Questionnaire and the SF-8 physical and mental well-being scores were calculated by using published procedures (20,21). To assess food sources at work, participants reported the number of days that they brought food from home, purchased food at their workplace, or purchased takeout food to eat at work. Since workers often brought and purchased food on the same day, we assessed food sources in 2 ways: 1) we categorized the primary food source as the source of food more than 60% of the time, and 2) we calculated the proportion of time workers used each source. Work groups were compared using Pearson $\chi^2$ and analysis of variance (ANOVA); significance was assessed at $P \leq .05$.

We examined possible predictors of 3 outcomes: diet, exercise, and WHP participation. To assess diet, we used the REAP-S total score (17), which reflects how often a participant engages in healthy and unhealthy eating behaviors. Scores ranged from 13 to 39 with a lower score indicating healthier behaviors. We also examined REAP-S subscores for consumption of fatty foods and sugary foods. To categorize people as either meeting or not meeting the recommended level of exercise (24), we estimated total physical activity minutes per week on the basis of answers to the 2 physical activity questions. Participation and availability of WHPs was calculated as a positive response for participation in any 1 of the 16 programs queried.

Student's *t* test was conducted on dichotomous predictors of REAPS-S total score, and Spearman correlations were conducted for interval and ordinal predictors. Univariate logistic regression was conducted for predictors of exercise and WHP participation, yielding odds ratios and 95% confidence intervals. For each outcome, significant predictors ($P \leq .05$) in the univariate analyses were included in multivariate models. We analyzed the REAP-S total score by using multivariate ordinary least squares regression and used multivariate logistic regression to analyze exercise and WHP participation. Analyses were conducted using IBM SPSS version 20 and R version 3.1.0 (IBM Corporation).

# Results

A total of 219 hospital workers (30.0% response rate) and 310 retail workers (57.5% response rate) completed the survey. The median wage was $11.26 per hour; 46% of respondents had an annual household income below $30,000 (Table 1). Mean BMI was 29.5 (standard deviation [SD], 7.2), 67.8% had a BMI at or above 25, and 41.1% were obese (BMI ≥30), which was above the national prevalence of 34.9% for 2011–2012 (1). Nearly half of respondents reported having 1 or more of the following diseases: hypertension, arthritis, high cholesterol, or diabetes. Mental and physical health, as shown by the SF-8 scores, were slightly worse than values for the general US population (25).

## Obesogenic behaviors

The overall population had a REAP-S total score of 25.5 (SD, 4.5), indicating that many respondents had unhealthy eating habits. Compared with nonobese participants, obese participants had significantly higher scores on the REAP-S (25.1 vs 26.0, $P = .04$) and the fatty foods subscale (8.0 vs 8.4, $P = .047$); there was no significant difference in the sugar subscale. The source of food at work varied greatly; about 23.3% primarily brought from home, 38.8% primarily bought food at work, 24% split between bringing and buying, and 13.1% did not regularly eat at work.

Overall, only 30.9% reported getting the recommended level of exercise, lower than the 46.1% found in a national sample (26). Obese workers were less likely to get recommended levels of exercise than nonobese workers (23.8% vs 35.8%, $P = .006$). More than one-third (35.7%) reported spending most of their work day either sitting or standing, whereas 28.7% said they spend most of the day walking, 28.9% said they spend most of the day lifting or pushing heavy objects or moving most of their body, and 4.3% said they do hard physical labor most of the day.

Most participants reported willingness to change both eating habits and physical activity to be healthier (reporting at least a 4 on a scale of 1 to 5 with 1 being "not at all willing" and 5 being "very willing"); many said they had already changed eating patterns or physical activity in the last year because of health concerns.

## Work environment

More than half (55.8%) of respondents did not regularly work day shifts, and 32.4% reported working irregular schedules. Overall, participants felt that their supervisors and coworkers were supportive as indicated by high Supervisor and Coworker Support scales scores. Additionally, most workers agreed or strongly agreed that their companies valued healthy workers. Participation in any WHP was 36.7%; among those who reported that WHPs were offered, the participation rate was 54.8%. Availability of WHPs was not associated with lower rates of obesity, but those who participated in 1 or more programs were less likely to be obese than those who did not (49.7% vs 60.7%).

## Predictors of healthy diet

In univariate analyses, a lower REAP-S score, (ie, healthier diet) was associated with older age, higher wages, greater number of hours worked, higher rate of bringing food from home, having some college education, participating in a WHP, and working for the hospital system rather than for retail stores (Table 2). Minority status, nonday shifts, irregular shifts, and higher rates of buying food at work or getting takeout were associated with unhealthier diet. The final multivariate models had a $R^2$ value for the REAP-S total score of 0.24 for all workers (Table 3). Bringing food from home was the strongest predictor of healthy diet for all workers. Older age, lower wages, nonminority status, some college education, and participation in a WHP were also predictors of healthy diet.

## Predictors of exercise

Fewer predictors of exercise were found via univariate analysis (Table 2). For all workers, younger age, higher rate of bringing food, lower rate of buying food, having more physical activity at work, and participating in WHPs were all significant predictors of exercise. In the multivariate logistic regression model, only physical activity at work and WHP participation were significant predictors of exercise for all workers (Table 3).

## Predictors of WHP

Univariate logistic regression analyses of the 354 workers who indicated that their company offered 1 or more WHPs showed that younger age, being female, being a minority, and working for the hospital predicted WHP participation, whereas working nonday shifts and having irregular schedules were associated with nonparticipation (Table 2). In the multivariate model for all workers, younger age, minority status, and being a hospital worker predicted participation in WHP.

### Group differences

Several differences between the work groups may inform future interventions. Table 1 shows comparisons between hospital workers and retail workers. Retail workers were more likely to work nonday shifts, have irregular schedules, and sit or stand in 1 place most of the day compared with hospital workers (Table 1). Hospital workers were more likely to believe that their company valued healthy workers than retail workers and also reported greater availability of WHPs. Significant ($P \leq .05$) univariate associations with diet, exercise, and WHP participation for hospital workers and retail workers are noted in Table 2.

The $R^2$ values for the multivariate models predicting the overall REAP-S score were 0.26 for hospital workers, and 0.22 for retail workers. For hospital workers, bringing food from home and nonminority status were associated with a healthier diet; bringing food from home, participation in a WHP, younger age, and nonminority status were predictors of healthier diet in retail workers (Table 3).

In the multivariate models, WHP participation was the only significant predictor of exercise in retail workers (odds ratio [OR] 2.16, $P = .03$); there were no significant predictors of exercise for hospital workers. Although participation in any WHP was not a significant predictor of exercise in hospital workers, participation in 4 programs was associated with exercise in these workers: workplace exercise programs (OR, 3.12; $P = .04$), reduced price gym memberships (OR, 4.30; $P = .008$), signs encouraging the use of stairs (OR, 4.35; $P = .02$), and brochures or a poster encouraging healthy behaviors (OR, 3.00; $P = .009$).

## Discussion

Our study group of low-wage workers had slightly poorer health than the general US population, but this is probably typical of low-wage American workers. Obesogenic behaviors such as a diet high in fat and infrequent exercise were common and were associated with poor health outcomes (ie, high rates of obesity and illness). Despite their obesogenic behaviors, most workers indicated they were willing to change their diet and exercise habits to be healthier. Employer or union-based interventions may help workers achieve their desired behaviors and healthy weight.

We identified several modifiable workplace factors associated with diet. Food source was the strongest predictor of diet; bringing food from home more often was associated with healthier eating, whereas buying food at the worksite was associated with unhealthy eating. Preparing food ahead of time may allow workers to plan healthy food options rather than making spontaneous, unhealthy purchases when they are hungry or have little time. Additionally, bringing food from home may help with portion control, as cafeteria or restaurant food is often sold in large portions. Employers can encourage workers to bring their own food to work by providing microwave ovens and refrigerators, organizing healthy potlucks, and offering suggestions for healthy recipes and tips for easy meal planning. Alternatively, employers could provide healthier food options for purchase that are highly visible, readily available, and low in cost. Irregular work schedules, nonday shifts, and nonparticipation in a WHP were also predictors of unhealthy diet; these factors are all potential targets for interventions.

Consistent with previous findings, our results indicated that participating in a WHP was associated with more exercise outside of work (11); greater physical activity at work was also a predictor of meeting weekly exercise recommendations. This study had limited power to detect significant predictors for each work group. However, 1 difference is worth noting: hours worked had opposite associations for the 2 work groups. Working more hours per week was positively associated with exercise in hospital workers, but negatively associated in the retail group, though this association was not significant for retail workers. Schedule regularity may partly explain this finding, because many of the retail workers in this study reported having irregular schedules. Among workers with irregular schedules, those who met the recommended guidelines for exercise worked fewer hours than those who did not (32.6 h vs 36.1 h, $P = .03$); there were no significant association in workers with regular schedules. Thus, it may be the combination of irregular schedules and longer work hours that interferes with exercising. Additionally, irregular schedules may influence the ability to plan ahead and maintain diet and exercise routines. Irregular and unpredictable work schedules are becoming more common for retail workers, imposing a particular burden on low-wage workers (27). Future research should examine the health implications of irregular schedules.

Differences observed between hospital workers and retail workers highlight the complexity of obesity and behavior change as well as the need for tailored approaches to workplace health programs. Designing programs that are tailored to the needs of employees may result in greater reach and adoption of interventions, ultimately producing behavior change. One way of creating interventions that are relevant to a work group is a participatory approach, in which workers provide input into the types of interventions that would be useful and appealing to them. This approach has been successful in safety and ergonomic interventions but little studied or tested for workplace health behavior interventions (28). Socioeconomic and demographic factors play a strong role in health behaviors and health status. Although employers can target WHP efforts to high-risk populations, improvements in health among low-wage workers may ultimately require more systematic changes, such as better pay and benefits, more regular work schedules, and compensated time for participation in health activities (29).

Our study has several limitations. First, response rates in both groups were low because of limitations in our recruitment and follow-up methods. Some managers allowed us to talk to workers directly, but most would only distribute the survey and reminders on our behalf. Second, all data were self-reported by the workers and may be subject to poor recall or social desirability bias. Questions regarding WHP offerings measured workers' awareness of the availability of these programs. Retail workers' reports of few WHP offerings were generally accurate; hospital workers had more available WHPs but were often unaware of programs that were available to them. Improved communication may be effective in increasing program awareness and, eventually, participation. Third, the REAP-S scale was designed for use in clinical settings rather than in general population studies. We chose this measure because it is brief, designed for lower literacy people (17), and assesses compliance with dietary guidelines. Although it is more limited than longer dietary questionnaires, it measures specific healthy and unhealthy behaviors that could be targeted for intervention. Similarly, we chose 2 simplified questions measuring exercise so as not to burden participants with a lengthy survey. Consequently, we found few significant predictors of exercise, which may be a result of using an insensitive measure. Fourth, our brief survey did not ask about many important risk factors for obesity and obesogenic behaviors; some of these factors were explored in a qualitative analysis of these populations that is reported separately (30). Finally, some of our study findings are probably industry-specific and may not be generalizable to other low-wage populations.

In summary, our study highlights the high prevalence of obesity and obesogenic behaviors among 2 low-wage worker groups and describes workplace influences on healthy behaviors. Between-group differences suggest that interventions should be tailored to different worker groups. From these results, we recently started an intervention based on the Healthy Workforce Participatory Program (31) in a retail store we worked with in this project. We will use previous qualitative data (Strickland et al, unpublished data, August 2014) and results from this study to inform a participatory worker group intervention that will elicit worker input for changes at the worksite to support healthy behaviors.

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# Tables

**Table 1. Demographics, Health Status, and Potential Predictors of Obesogenic Behaviors in Low-wage Hospital and Retail Workers, St. Louis, Missouri, 2013–2014**

| Demographics | All Workers (n = 529)[a] | Hospital Workers (n = 219)[a] | Retail Workers (n = 310)[a] | *P* Value |
|---|---|---|---|---|
| Age, mean (SD), y | 43.0 (14.9) | 41.8 (13.9) | 43.8 (15.5) | .14 |
| Female | 66.0 | 76.7 | 58.4 | <.001 |
| Racial/ethnic minority | 50.6 | 63.6 | 41.4 | <.001 |
| Some college | 58.8 | 58.7 | 58.9 | .97 |
| Hourly wage, median, $ | 11.26 | 11.00 | 11.70 | .87 |
| Household income < $30,000/y | 46.5 | 56.9 | 39.1 | <.001 |
| **Health status** | | | | |
| BMI, mean (SD), kg/m$^2$ | 29.5 (7.2) | 30.5 (7.6) | 28.7 (6.9) | .005 |
| Normal weight (BMI<25.0) | 32.2 | 27.4 | 35.5 | .05 |
| Overweight (BMI 25.0–29.9) | 26.7 | 21.9 | 30.2 | .03 |
| Obese (BMI ≥30.0) | 41.1 | 50.7 | 34.2 | <.001 |
| Current smoker | 16.6 | 12.8 | 19.3 | .05 |
| SF-8 physical score, mean (SD) | 49.1 (8.4) | 48.7 (8.6) | 49.3 (8.3) | .39 |
| SF-8 mental score, mean (SD) | 49.0 (10.3) | 49.5 (10.3) | 48.7 (10.3) | .38 |
| Diabetes | 9.8 | 12.3 | 8.1 | .11 |
| Hypertension | 21.9 | 25.6 | 19.4 | .09 |
| High cholesterol | 17.0 | 18.7 | 15.8 | .38 |
| Arthritis | 21.0 | 23.3 | 19.4 | .27 |
| Have ≥1 conditions listed above[b] or other diseases | 48.0 | 49.3 | 47.1 | .62 |
| Have ≥2 conditions listed above[b] or other diseases | 21.7 | 24.7 | 19.7 | .17 |
| Missed work because of health problem in last 4 weeks | 13.2 | 15.5 | 11.5 | .18 |
| **Diet** | | | | |
| REAP-S score, mean (SD) | 25.5 (4.5) | 25.0 (4.5) | 25.9 (4.5) | .03 |
| Often consume sugary drinks and/or sweets | 45.8 | 39.7 | 50.0 | .02 |
| Often eat fatty foods | 55.5 | 55.6 | 55.4 | .96 |
| Bring food from home | 23.3 | 27.1 | 20.6 | .08 |
| Buy food at work | 38.8 | 36.9 | 40.2 | .45 |
| Do not eat regularly at work | 13.1 | 8.4 | 16.3 | .008 |

Abbreviations: BMI, body mass index; REAP, Rapid Eating Assessment for Participants Short Version; SD, standard deviation; WHP, workplace health program.
[a] Values are percentages unless otherwise noted.
[b] Conditions included are diabetes, hypertension, high total cholesterol, and arthritis.

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**Table 1. Demographics, Health Status, and Potential Predictors of Obesogenic Behaviors in Low-wage Hospital and Retail Workers, St. Louis, Missouri, 2013–2014**

| Demographics | All Workers (n = 529)[a] | Hospital Workers (n = 219)[a] | Retail Workers (n = 310)[a] | *P* Value |
|---|---|---|---|---|
| **Activity level** | | | | |
| Get recommended level of exercise | 30.9 | 40.8 | 35.5 | .22 |
| Sit or stand at work | 35.7 | 29.0 | 40.3 | .009 |
| **Work environment** | | | | |
| Hours worked per week, mean (SD) | 36.8 (9.5) | 38.9 (7.6) | 35.3 (10.3) | <.001 |
| Nonday shifts | 55.8 | 45.4 | 63.2 | <.001 |
| Irregular shifts | 32.4 | 6.0 | 51.3 | <.001 |
| Supervisor and Coworker Support scales score (21), mean (SD) | 23.3 (4.3) | 22.9 (4.7) | 23.6 (3.9) | .06 |
| Company values worker health | 78.7 | 85.4 | 74.1 | .002 |
| One or more WHPs offered | 66.9 | 92.2 | 49.0 | <.001 |
| Participated in ≥1 WHPs | 54.8 | 73.8 | 29.6 | <.001 |

Abbreviations: BMI, body mass index; REAP, Rapid Eating Assessment for Participants Short Version; SD, standard deviation; WHP, workplace health program.
[a] Values are percentages unless otherwise noted.
[b] Conditions included are diabetes, hypertension, high total cholesterol, and arthritis.

Table 2. Univariate Results for Predictors of Diet, Exercise, and Participation in Workplace Health Programs Among Low-wage Hospital and Retail Workers,[a] St. Louis, Missouri, 2013–2014

| Predictor | Diet (REAP-S Score) (n = 529) | Recommended Exercise Level (n = 529) | Participated in 1 or More WHPs (If Offered) (n = 354) |
|---|---|---|---|
| | Spearman *r* (*P* Value) | Logistic Regression Odds Ratio (*P* Value) | Logistic Regression Odds Ratio (*P* Value) |
| Age | −0.19 (<.001)[b] | 0.98 (.004)[b] | 0.98 (.01)[b] |
| Wage | −0.17 (.001)[b,c] | 0.97 (.13) | 1.00 (.96)[b] |
| Hours worked per week | −0.14 (.002)[b] | 1.00 (.74)[c] | 1.02 (.16) |
| Social support at work | 0.03 (.57) | 1.04 (.14) | 1.01 (.71) |
| Bring food from home, rate | −0.33 (<.001)[b,c] | 2.01 (.02)[c] | 1.16 (.65) |
| Buy food, rate | 0.28 (<.001)[b,c] | 0.49 (.02)[c] | 0.94 (.84) |
| Buy takeout, rate | 0.13 (.006)[c] | .98 (.98) | 0.62 (.54) |
| **Difference in mean score (*P* Value)** | | | |
| Female | −0.73 (.09)[c,d] | 0.67 (.051) | 1.68 (.02) |
| Racial/ethnic minority | 2.13 (<.001)[b, c,d] | 1.42 (.08) | 2.11 (.001)[b] |
| Some college | −1.09 (.01)[c,d] | 1.18 (.40) | 0.82 (.37) |
| Hospital worker | −0.9 (.03)[d] | 1.26 (.24) | 6.69 (<.001) |
| Nonday shifts | 0.98 (.02)[d] | 1.25 (.27) | 0.48 (.001) |
| Irregular shifts | 0.94 (.03)[d] | 0.77 (.22) | 0.24 (<.001) |
| Physical activity at work | 0.57 (.12)[d] | 1.82 (.01)[b] | 1.17 (.49) |
| Company values health | −0.65 (.19)[d] | 1.42 (.16) | 1.27 (.39) |
| WHP offered | −0.82 (.06)[d] | 1.10 (.64) | NA |
| Participated in WHP | −1.32 (.002)[b, d] | 1.79 (.004)[b] | NA |

Abbreviations: NA, not applicable; REAP-S, Rapid Eating Assessment for Participants Short Version; WHP, workplace health program.
[a] Numbers represent both worker groups.
[b] Significant predictors among retail workers ($P \leq .05$).
[c] Significant predictors among hospital workers ($P \leq .05$).
[d] Difference in mean REAP-S scores between dichotomous categories

**Table 3. Multivariate Regression Results for Predictors of Diet, Exercise, and Participation in Workplace Health Programs, St. Louis, Missouri, 2013–2014**

| Predictors | Value |
|---|---|
| **Diet[a]** | |
| Age | −0.05 (.006) |
| Wage | 0.09 (.03) |
| Hours worked per week | −0.03 (.29) |
| Bring food from home, rate | −3.43 (<.001) |
| Buy takeout food, rate | −1.96 (.32) |
| Racial/ethnic minority | 2.27 (<.001) |
| Some college | −0.91 (.04) |
| Hospital worker | −0.10 (.85) |
| Nonday shift | 0.51 (.27) |
| Participated in WHP | −1.44 (.006) |
| **Exercise[b]** | |
| Age | 0.98 (0.97–1.00) |
| Buy food, rate | 0.66 (0.13–3.40) |
| Bring food from home, rate | 1.73 (0.34–8.85) |
| Physical activity at work | 1.69 (1.06–2.72) |
| Participated in WHP | 1.67 (1.08–2.60) |
| **Participation in WHP[b]** | |
| Age | 0.98 (.096–0.99) |
| Female | 1.09 (0.63–1.89) |
| Racial/ethnic minority | 1.73 (1.06–2.85) |
| Hospital worker | 5.09 (2.77–9.38) |
| Nonday shifts | 0.67 (0.37–1.22) |
| Irregular shifts | 0.79 (0.36–1.71) |

Abbreviation: WHP, workplace health program.
[a] Predictors of diet according to Rapid Eating Assessment for Participants Short Version total score; values are unstandardized coefficients (*P* value); $R^2$ = 0.24.
[b] Values are odds ratio (95% confidence interval).

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SYSTEMATIC REVIEW

# Review of Measures of Worksite Environmental and Policy Supports for Physical Activity and Healthy Eating

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PEER REVIEWED

## Abstract

### Introduction
Obesity prevention strategies are needed that target multiple settings, including the worksite. The objective of this study was to assess the state of science concerning available measures of worksite environmental and policy supports for physical activity (PA) and healthy eating (HE).

### Methods
We searched multiple databases for instruments used to assess worksite environments and policies. Two commonly cited instruments developed by state public health departments were also included. Studies that were published from 1991 through 2013 in peer-reviewed publications and gray literature that discussed the development or use of these instruments were analyzed. Instrument administration mode and measurement properties were documented. Items were classified by general health topic, 5 domains of general worksite strategy, and 19 subdomains of worksite strategy specific to PA or HE. Characteristics of worksite measures were described including measurement properties, length, and administration mode, as well as frequencies of items by domain and subdomain.

### Results
Seventeen instruments met inclusion criteria (9 employee surveys, 5 manager surveys, 1 observational assessment, and 2 studies that used multiple administration modes). Fourteen instruments included reliability testing. More items were related to PA than HE. Most instruments (n = 10) lacked items in the internal social environment domain. The most common PA subdomains were exercise facilities and lockers/showers; the most common HE subdomain was healthy options/vending.

### Conclusion
This review highlights gaps in measurement of the worksite social environment. The findings provide a useful resource for researchers and practitioners and should inform future instrument development.

## Introduction

Overweight and obesity are major health challenges because of their high prevalence, causal relationship with serious medical complications, and economic impact (1). The risk of developing many diseases, including type 2 diabetes, increases linearly with body mass index (2–6). Obesity prevention strategies are needed that target multiple levels of the ecologic framework across multiple settings, including the worksite. Using the worksite as a venue for health promotion is promising, because most adults spend approximately half of their waking day in their work environment (6). Research suggests that environmental and policy strategies for addressing energy balance (ie, caloric intake and energy expenditure through physical activity [PA]) in the workplace are effective (7–9). Use of worksite programs to improve employee health has been recommended by the American Cancer Society, the Centers for Disease Control and Prevention, and multiple state governments. Occupational settings take advantage of a captive population and may have existing facilities, social support, convenience, and communication mechanisms in place (10).

Targeting work environments for energy balance includes using policies, programs, and organizational practices to influence behavior. Example work environments include onsite facilities such as gymnasiums, lockers, showers, accessible stairways, and healthy vending options. Policies and programs include subsidized external gymnasium memberships; incentives to bicycle, walk, or use public transportation for the commute to and from work; and group services such as onsite yoga and health fairs (11). By facilitating access to inexpensive healthy food, exercise facilities, and a culture accepting of nonsedentary work breaks, worksites can become sites for health promotion via a healthy energy balance (6). Although tools are available for assessing worksite environments and policies in place for PA and healthy eating (HE), no review has documented the content and measurement properties of these tools. Such a review of worksite energy measurement tools could serve as a guide for researchers, practitioners, and worksites in selecting among existing tools and understanding methodologic gaps to guide potential development of new instruments. The purpose of this review was to identify and assess the state of science concerning available measurement instruments related to worksite environment and policy supports for workplace energy balance.

# Methods

The literature review was completed in May 2014, using PubMed, OVID, MedLine, Web of Science, and the Registry of Measures from the National Collaborative on Childhood Obesity. We also searched sources of gray literature, including Google Scholar and state health departments. Search terms were key words for worksites, energy balance, and measurement: (work OR worksite OR workplace OR employer OR job) AND (physical activity OR physical fitness OR diet OR exercise OR obesity OR active commuting) AND (evaluation OR monitor* OR survey OR questionnaire OR data collection). Titles of applicable results were screened for their relevance to the assessment of worksite environment and policy measurement, tool development, and worksite interventions targeting PA and HE.

The search was restricted to articles published in English from 1991 through 2013. Abstracts were scanned and accepted if related to 1 or more of the following criteria designed to capture the presence or absence of worksite supports and policies associated with employee PA and HE (eg, presence of an onsite gymnasium, incentives to use public transportation to and from work): 1) studies describing measurement properties of a specific instrument, 2) descriptive studies of environmental and policy supports among a sample of employees or worksites, and 3) cross-sectional or intervention studies that used a specified instrument or explicitly stated the items used to systematically assess worksite environment and policies and their potential associations with PA and HE. Full-text articles were scanned when the information from abstracts was insufficient to make a conclusion about inclusion. Abstracts were excluded if they focused solely on the development or implementation or both of worksite health promotion programs and, thus, were not related to measuring current supports and policies. Moreover, abstracts were rejected if they did not emphasize policy or environmental supports in a nonhome-based worksite. Finally, full-text articles and their reference lists were scanned for references that cited the development of a specific worksite tool, survey, or checklist on policies and environmental supports related to PA and HE. The instruments used among articles that met inclusion criteria were abstracted. Each instrument was categorized on the basis of 1 of 4 administration options: employee or self-report, manager report, observational, or multiple modes. Measurement properties, including reliability and validity, were documented.

The final component of the review involved classifying each unique instrument item into an item inventory. Items were first classified by the *general health topic* they addressed: PA, HE, or both (healthy eating and physical activity [HEPA]). Next, items were classified by the general worksite strategy being assessed, referred to as the *primary domain*. These strategies are based on the ecological model, the *Guide to Community Preventive Services*, and research by Kahn et al (12,13) and include promotions and programs (eg, informational media), organizational policies and practices (eg, incentives), internal physical environment (eg, access to healthy food and PA options), internal social environment (eg, role models), and external environment (eg, worksite neighborhood options for HE and PA). Primary domains were further disaggregated into *subdomains* by using constant comparison to classify the PA (19 subdomains) and HE (19 subdomains) strategies (Table 1). Interrater agreement for classifying the instrument items was 85% among 3 raters.

# Results

Seventeen worksite instruments were identified that included items about worksite environment and policies related to PA, HE, or both and met inclusion criteria. The administration modes of the 17 instruments varied (n = 9 self-report; n = 5 manager report, n = 1 observational; and n = 2 using multiple modes) as did the total number of HE and PA items per instrument (range, 10–226) (Table 2). More items were related to PA than to HE. Nine instruments included both PA and HE items, 7 instruments had only PA items, and only 1 included solely HE items related to worksite environment and policy supports. Of the 17 instruments, 14 reported reliability, of which 8 reported generally high interrater results (Table 2). Five instruments reported various validity measures including content, face, predictive, and construct validity results. Health promotion experts provided substantial guidance in development of the instruments, and significant correlations were found for workplace environmental sections within the instruments. The item inventory indicated that the most common health topic was PA (PA and HEPA) (64% of all items [n = 669]). HE (HE and HEPA) consisted of 369 items, or 36%.

### Physical activity

Two instruments, the Environmental Assessment Tool (EAT) (29) and the Checklist of Health Promotion Environments at Worksites (CHEW) (34), had the highest number of PA items (151 and 107, respectively) and used multiple modes of administration. Of the 17 instruments, only 1, Working Well Trial (WWT) (33), did not contain items related to PA. Of the surveys with PA items, most (14 of 16) included at least 1 item related to the external environment relevant for PA (Figure 1). The domain that was represented by the fewest number of instruments was the internal social environment, with only 7 total instruments containing at least 1 PA item for that domain. In terms of subdomains, only 1 instrument contained an item related to community partnerships, workplace challenges, or office connectivity, whereas 12 covered the subdomains counseling/classes/education, access to PA equipment, and lockers and showers.

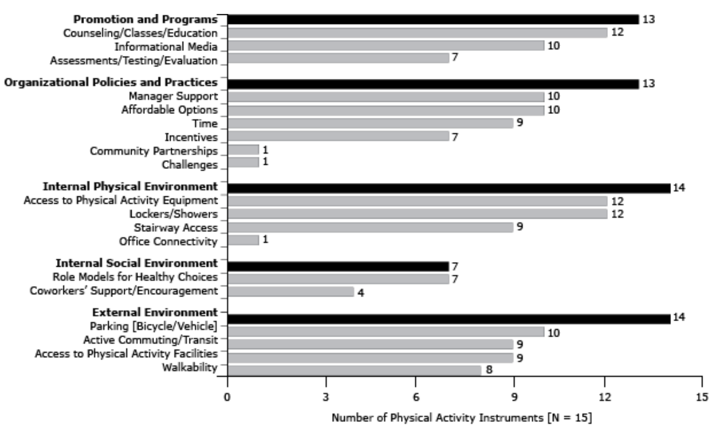


Figure 1. Number of instruments containing at least 1 item from each physical activity domain and subdomain (N = 15), review of measures of worksite environmental and policy supports for physical activity and healthy eating, United States, 1991–2013.

Specific results for each instrument were also explored. Of the 19 subdomains for PA-related items, the California Worksite Assessment Checklist (CA) instrument included items covering the most subdomains (16 of 19 subdomains). The Workplace Walkability Audit Tool (WWAT) instrument covered the fewest subdomains (1 of 17 subdomains).

### Healthy eating

Of the 5 primary domains, 3 (promotion and programs, organizational policies and practices, and internal physical environment) had the greatest coverage, with 9 of the 10 healthy eating instruments containing at least 1 item for each respective primary domain (Figure 2). Similar to the findings for PA domain coverage, the primary domain with the least coverage was the internal social environment; 5 of the 10 HE instruments covered that topic. Additionally, a noticeable gap is indicated through the external environment primary domain; only 6 instruments covered HE items related to the external food environment of worksites. The California Worksite Assessment Checklist (CA) instrument (21) spanned the greatest number of HE subdomains (15 of 19 subdomains). The HE instrument with the least coverage, Workplace Nutrition and Exercise Climate Scale (WNECS) (25), included items across 5 of the 19 subdomains.

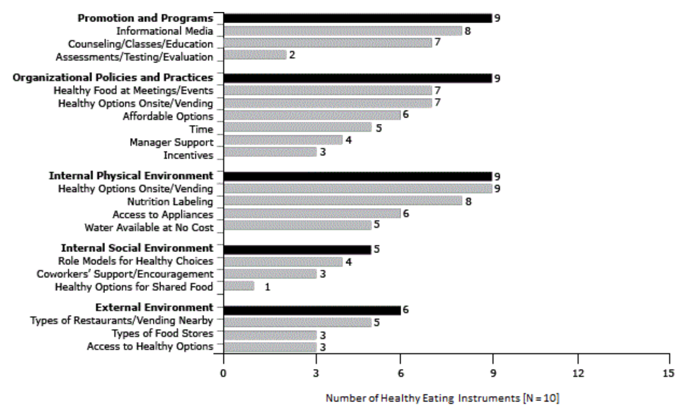


Figure 2. Number of instruments containing at least 1 item from each healthy eating domain and subdomain (N = 10), review of measures of worksite environmental and policy supports for physical activity and healthy eating, United States, 1991–2013.

## Discussion

As a venue for delivering HE and PA efforts, worksites provide a channel for reaching the large segment of the population that is employed (147 million as of November 2014, according to the US Bureau of Labor Statistics) (6,10). Moreover, measuring environmental and policy supports for PA and HE in the workplace is an important component in assessing and addressing the factors related to overweight and obesity (14). This review of worksite measures identified various data collection instruments and highlights several matters that require further consideration and attention for future research.

The results of the item inventory highlight both extensive and deficient domain coverage for both PA- and HE-related items. Overall, the primary domains of promotion and programs, organizational policies and practices, and internal physical environment had the greatest coverage among HE and PA items. The primary domain of internal social environment had few items for either HE or PA. We also found several administration modes used, most instruments being self-report. Only 1 instrument was observational (WWAT), although several used multiple methods. With 14 of the 17 instruments relying on either employee or manager self-report, the state of worksite PA and HE measurement is susceptible to respondent and social desirability bias. Regarding measurement properties, most instruments (14 of 17) reported high reliability results, mostly interrater measures. Validity was assessed for 5 instruments, with emphasis on content validation.

There was variety in the content gaps of the measures reviewed. Overall, there were few documented measures about HE in and around the workplace. Most HE measures focused on onsite cafeteria and vending options but neglected external environments (eg, healthy options within a 10-minute walk), organizational policies (eg, healthy snacks at meetings and events), and the social environment. The promotion and programs domain contains 8 measures with items related to informational media and 7 with classes or education (both subdomains); however, only 2 of 10 instruments included any items on assessments, testing, evaluation, and HE. Provided that a full-time employee spends at least 8 hours per day at the worksite — therefore, at least 1 meal is consumed at or near work during most working days — the gaps in HE measures is an important finding that deserves further attention. Exploring the diverse aspects of food environments near workplaces, rather than solely assessing onsite cafeteria and vending options, would be beneficial.

Of the 5 domains, internal social environment was included in the fewest HE- and PA-related instruments. Social environments, including role models, champions, and support, are highly associated with PA and obesity (15,16). Among the subdomains, specialized instruments (ie, Office Environment and Sitting Scale [20], Kaczynski et al [22], and the WWAT [30]) had minimal, if any, coverage. Also, despite including more than 100 unique items, CHEW had minimal coverage for the HE subdomains (only 9 of 19 subdomains covered) (Appendix).

Performing this review did have challenges and limitations. Forcing instrument items into domains and especially subdomains presented some difficulties in operationalizing the specific items. Items could also fit into more than 1 subdomain. The process of developing the subdomains was iterative; new items forced ever greater specificity in the naming and operationalization of the 38 subdomains. However, the specificity of selected subdomains — such as walkability, which can include land use mix, aesthetics, and sidewalks, compared with stairway access, which only refers to the presence of stairs — still varies greatly. We were systematic and prescriptive in our literature search for worksite measures, but this may not be an exhaustive list of worksite instruments, especially those present in the gray literature. Finally, Carnethon and colleagues (17) suggest that efforts moving forward must not only focus on PA but also reduce sedentary behaviors at worksites, and this can be accomplished via policies and designs. Future worksite measurements must do a better job of including sedentary behaviors in their instruments.

This review provides a concise guide for employers to existing worksite measures on PA and HE, both for selecting appropriate assessment instruments for the worksite and as a means to introduce new policies and programs to support healthy workers. For example, employers can administer health risk appraisals in combination with organizational health promotion checklists that have been developed. This approach would provide information to the employee and employer where there may be overlap or gaps between worksite supports and health risks and benefits. Social and physical environments in and around the workplace should be designed to be conducive to recommended healthy behaviors (18). In addition, optimal environmental modifications should promote healthy behaviors while simultaneously minimizing the physical, organizational, and occupational risk in the work environment.

## Acknowledgments

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# Tables

**Table 1. Physical Activity and Healthy Eating Domain Details, Review of Measures of Worksite Environmental and Policy Supports for Physical Activity and Healthy Eating, United States, 1991–2013**

| Subdomain | Description |
|---|---|
| **Physical Activity** | |
| **I. Promotion and programs** | **Key words: promote, posters, program, distribute** |
| Assessments/testing/evaluation | Employee fitness testing, measurements of employee PA, health screening |
| Counseling/classes/education | Informational support for participation in programs related to PA, organized PA activities (classes, clubs, long-term programs), and educational informative sessions (seminars, classes, meetings) that promote PA |
| Informational media | Worksite media sources or signage (posters, flyers, bulletin boards, maps) that encourage, promote, or direct employees to participate in active behaviors; sharing of information |
| **II. Organizational policies and practices** | **Key words: policy, guidelines, manager, worksite requirements** |
| Affordable options | Subsidies, worksite contributes financial assistance, free gymnasium access, insurance discounts |
| Time | Flex-time, specific policy where employees can participate in PA during work hours |
| Incentives | Worksite sponsors financial, material, or other types of prizes, incentives, and gifts for PA |
| Challenges | Worksite supports PA challenge (eg, steps per day) |
| Manager support | General statement about worksite, manager, or employer support or participation in PA initiatives |
| Community partnerships | Employer engages with entities outside of work environment; affiliating or collaborating with community organizations to improve health |
| **III. Internal physical environment** | **Key words: access, interior, facilities — anything indoors** |
| Access to PA equipment | Fitness centers, machines (ellipticals, treadmills), free weights, areas designated for PA |
| Stairway access | Access, visible, safe; general qualities about stairs |
| Lockers/showers | Access and availability; qualities about lockers/showers |
| Office connectivity | Hallways, passages, route, intersect, room, workstation |
| **IV. Internal social environment** | **Key words: coworker, support, values** |
| Role models for healthy choices | Peer modeling, coworkers as guides and good examples, coworker PA behavior |
| Coworkers' support/encouragement | Positive interaction between employee and coworkers in favor of PA or healthy activities |
| **V. External physical and social environment** | **Key words: worksite neighborhood, outdoor, access** |
| Walkability | Land use mix, sidewalks/paths/trails, traffic, aesthetics, crime, safety, access to public transit |
| Parking (bicycle/vehicle) | Vehicle and bicycle outdoor parking, safe areas for bicycles, carpool parking spots, parking a vehicle farther away to increase walking distance to work |
| Active commuting/transit | Bicycle lanes, lockers, and showers only in reference to active commuting |
| Access to PA facilities | Walking distance to areas dedicated to PA, recreational facilities, parks, open space |
| **Healthy Eating** | |
| **I. Promotion and programs** | **Key words: promote, posters, program, distribute** |

Abbreviations: HE, healthy eating; PA, Physical activity.

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**Table 1. Physical Activity and Healthy Eating Domain Details, Review of Measures of Worksite Environmental and Policy Supports for Physical Activity and Healthy Eating, United States, 1991–2013**

| Subdomain | Description |
|---|---|
| Assessments/testing/evaluation | Employee fitness testing, measurements of employee HE, health screening |
| Counseling/classes/education | Informational support for participation in programs related to HE, organized HE activities (classes, clubs, long-term programs), educational informative sessions (seminars, classes, meetings) that promote HE |
| Informational media | Worksite media sources or signage (posters, flyers, bulletin boards) that encourage, promote, or direct employees to participate in HE; sharing of information |
| **II. Organizational policies and practices** | **Key words: policy, written guidelines, manager, requirements** |
| Affordable options | Cafeteria has discounts for healthy food |
| Time | Flexible lunch breaks, sufficient time to eat properly, ability to leave work to access healthy food store, lunch is enforced at worksite |
| Incentives | Worksite sponsors financial, material, or other types of prizes, incentives, and gifts for HE |
| Healthy food at meetings/events | Specific to catered food, worksite contracts with healthy food service, provides fruits and vegetables and healthy beverages |
| Healthy options onsite/vending | Not presence of healthy food, but a policy for healthy alternatives in worksite cafeteria/vending; this includes specific polices that distinguish healthy items from nonhealthy items (ie, requirements for nutrition labeling) or those concerning food preparation and serving size. Or, manager/employer initiatives and efforts to offer healthy options |
| Manager support | General statement about worksite, manager, or employer support or participation in HE initiatives |
| **III. Internal physical environment** | **Key words: access, interior, facilities — anything indoors** |
| No-cost water | Water dispensers/coolers, drinking fountains, contracts with water company, available and free to employees at any time |
| Nutrition labeling | Presence of nutrition labeling in cafeteria or vending machines |
| Healthy options onsite/vending | Statement that healthy and nutritious options are available or offered onsite in both cafeteria and vending machines |
| Access to appliances | Worksite environment has access to refrigerator, microwave, toaster, or other appliances that make it possible for employees to bring food from home or cook during work |
| **IV. Internal social environment** | **Key words: coworker, support, values** |
| Healthy options for shared food | Birthdays, seminars, or activities where employees who bring food to share for social settings (not catered) are encouraged to be healthy or provide options for healthy treats/snacks |
| Role models for healthy choices | Peer modeling, coworkers as guides and good examples, coworker HE behavior, noticing that coworkers bring healthy lunches |
| Coworkers' support/encouragement | Positive interaction between employee and coworkers in favor of HE or healthy activities |
| **V. External physical and social environment** | **Key words: neighborhood, restaurant, store, outdoor, access** |
| Access to healthy options | Not referencing a specific vendor (restaurant/store), but the availability of healthy foods not associated with a store/restaurant (eg, low-fat items, fruits and vegetables) |
| Types of food stores | Grocery stores, farmers market; stores where employees can shop for food |
| Types of restaurants/vending nearby | Fast food, convenience stores that sell food for immediate consumption |

Abbreviations: HE, healthy eating; PA, Physical activity.

Table 2. Worksite Questionnaire Details, Review of Measures of Worksite Environmental and Policy Supports for Physical Activity and Healthy Eating, United States, 1991–2013

| Survey Name | Administration Mode | Year | Survey Details (No. of Items, Time Required) | Sample (a. Sample Size, b. Location, c. Type of Worksite) | Reliability | Validity | Health Topic |
|---|---|---|---|---|---|---|---|
| Worksite and Energy Balance Survey (WEBS) (19) | Self-report | 2013 | 72, NR | a. 104<br>b. Missouri<br>c. Variety | Test–retest by total population and by obesity status and size of worksite | NR | PA/HE |
| Office Environment and Sitting Scale (OFFESS) (20) | Self-report | 2013 | 12, NR | a. 307<br>b. Australia<br>c. Higher education campus | Internal consistency<br>Test-retest<br>% agreement overall and by office type | NR | PA |
| California Worksite Assessment Checklist (CA) (21) | Self-report | 2010 | 31, NR | a. NA<br>b. NA<br>c. NA | NR | NR | PA/HE |
| (No Name) Kaczynski et al (22) | Self-report | 2010 | 11, NR | a. 375 Full-time workers<br>b. Manhattan, KS<br>c. Variety | NR | NR | PA |
| Worksite Supportive Environments for Active Living Survey (SEALS) (23) | Self-report | 2010 | 28, <30 min | a. 1,250 Working adults<br>b. Mid-South United States<br>c. Higher education campus | Internal consistency<br>Test-retest<br>Construct | Face<br>Content<br>Discriminant | PA |
| Check for Health (WI) (24) | Manager report | 2010 | 68, NR | a. NA<br>b. NA<br>c. NA | NR | NR | PA/HE |
| Workplace Nutrition and Exercise Climate Scale (WNECS) (25) | Self-report | 2010 | 119, NR | a. 156 Full-time workers<br>b. Florida<br>c. Variety | Internal consistency<br>Interrater | NR | PA/HE |
| Environmental Perception Measure (EPM) (26) | Self-report | 2009 | 10, <30 min | a. 23 Studies in literature review<br>b. NA<br>c. NA | Test–retest<br>Internal consistency<br>% Agreement | Predictive | PA |
| Community Healthy Living Index (CHLI) (27) | Manager report | 2008 | 75, NR | a. Task force of 20 experts<br>b. NA<br>c. NA | Interrater | NR | PA/HE |
| Worksite Environmental Measure (WEM) (28) | Manager report | 2007 | 105, >30 min | a. 4 Bus garages<br>b. Minneapolis/St Paul<br>c. Bus garage (indoor/outdoor) | Interrater | NR | PA/HE |
| Environmental Assessment Tool (EAT) (29) | Multiple | 2006 | 105, >30 min | a. 12 Worksites<br>b. Not reported<br>c. Chemical | Interrater | Predictive<br>Concurrent | PA/HE |

Abbreviations: HE, healthy eating; NA, not applicable; NR, not reported; PA, physical activity.

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**Table 2. Worksite Questionnaire Details, Review of Measures of Worksite Environmental and Policy Supports for Physical Activity and Healthy Eating, United States, 1991–2013**

| Survey Name | Administration Mode | Year | Survey Details (No. of Items, Time Required) | Sample (a. Sample Size, b. Location, c. Type of Worksite) | Reliability | Validity | Health Topic |
|---|---|---|---|---|---|---|---|
| | | | | companies | | | |
| Workplace Walkability Audit Tool (WWAT) (30) | Observational | 2005 | 14, NR | a. 10 University campuses<br>b. NA<br>c. Higher education | Interrater | NR | PA |
| Neighborhood Quality of Life Survey (NQLS) (31) | Self-report | 2004 | 32, NR | a. 1,313 Working adults<br>b. Seattle, Baltimore, DC regions<br>c. Not reported | Internal consistency | NR | PA |
| Workplace Physical Activity Framework (WPAF) (32) | Manager report | 2003 | 45, 30 min | a. 15 Employees<br>b. Alberta, Canada<br>c. Education, municipality, hospital | Interrater | Content | PA |
| Working Well Trial (WWT) (33) | Self-report | 1999 | 12, NR | a. 114 Worksites<br>b. Massachusetts, Florida, National Cancer Institute | Internal consistency | NR | HE |
| Checklist of Health Promotion Environments at Worksites (CHEW) (34) | Multiple | 1995 | 112, >30 min | a. 20 Worksites<br>b. Australia<br>c. Variety | Interrater | NR | PA/HE |
| Heart Check (HRTCHK) (35) | Manager report | 1993 | 226, >30 min | a. >10,000 Employees<br>b. New York<br>c. Variety | Interrater internal consistency | Content face construct criterion | PA/HE |

Abbreviations: HE, healthy eating; NA, not applicable; NR, not reported; PA, physical activity.

# Appendix

A. Supplemental figure. Breakdown of Worksite Instrument by Administration Mode, Review of Measures of Worksite Environmental and Policy Supports for Physical Activity and Healthy Eating, United States, 1991–2013. This file is available for download as a Microsoft Word document [DOCX — 19 KB].

B. Supplemental figure. Subdomain Coverage by Instrument, Review of Measures of Worksite Environmental and Policy Supports for Physical Activity and Healthy Eating, United States, 1991–2013. This file is available for download as a Microsoft Word document [DOC — 108 KB].

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ORIGINAL RESEARCH

# Impact of the Affordable Care Act on Access to Care for US Adults With Diabetes, 2011–2012

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PEER REVIEWED

## Abstract

### Introduction

Lack of health insurance is a barrier to medical care, which may increase the risk of diabetes complications and costs. The objective of this study was to assess the potential of the Affordable Care Act (ACA) of 2010 to improve diabetes care through increased health care access by comparing health care and health outcomes of insured and uninsured people with diabetes.

### Methods

We examined demographics, access to care, health care use, and health care expenditures of adults aged 19 to 64 years with diabetes by using the 2011 and 2012 Medical Expenditure Panel Survey. Bivariate descriptive statistics comparing insured and uninsured persons were evaluated separately by income above and below 138% of the federal poverty level (FPL), (a threshold for expanded Medicaid eligibility in select states under the ACA) using the *t* test and proportion and median tests.

### Results

Uninsured adults reported poorer access to care than insured adults, such as having a usual source of health care (69.0% vs 89.5% [≤138% FPL], 77.1% vs 94.6% [>138% FPL], both $P < .001$) and having lower rates of 6 key diabetes preventive care services ($P \leq .05$). Insured adults with diabetes had significantly higher health care expenditures than uninsured adults ($13,706 vs $4,367, $10,838 vs $4,419, respectively, both $P < .001$).

### Conclusion

Uninsured adults with diabetes had less access to health care and lower levels of preventive care, health care use, and expenditures than insured adults. To the extent that the ACA increases access and coverage, uninsured people with diabetes are likely to significantly increase their health care use, which may lead to reduced incidence of diabetes complications and improved health.

## Introduction

In 2012, more than 29 million Americans were living with diagnosed diabetes (1). The serious health challenges facing people with diabetes include heart disease, stroke, hypertension, kidney disease, neuropathy, and blindness (2). Researchers estimate that the economic burden to society of diagnosed diabetes reached $245 billion in 2012 (3). Although private and public health insurance programs provide important access to health care for some people with diabetes, millions of working-age adults with diabetes lack health insurance (4). This suggests that a high proportion of the population with diabetes faces significant challenges in access to health care, which may lead to suboptimal care, increased rates of long-term complications, and greater health care expenditures.

The Affordable Care Act (ACA) of 2010 is designed to provide access to coverage for previously uninsured Americans. Adults with incomes below 138% of the federal poverty level (FPL) will gain access to Medicaid coverage in states that expand coverage (5) (28 states including the District of Columbia as of January 24, 2015). People with incomes above the poverty level in all states can obtain access to private insurance plans in health insurance "marketplaces." In addition, premiums in these marketplaces are subsidized for people with household incomes between 100% and 399% of the FPL (6). An estimated 60% of the uninsured will obtain health insurance through one or the other of these 2 methods by 2019 (7). As of September 2014, ACA had reduced the number of uninsured by more than 9 million (8), although a separate breakdown for people with diabetes was not available.

Previous published work has shown that the uninsured face significant barriers to obtaining health care and face higher out-of-pocket health care costs than the insured (9). In addition, the uninsured can experience health problems as a result of the lack of access to medical care. Although much research has focused on the general uninsured population, few studies have focused on the population with diabetes. A study similar to ours focused on Medicaid and diabetes, although the authors used older data and did not include people with higher incomes (10), who are also affected by ACA. In addition, because health care reform, one of the most important social policy changes in the United States in decades, is now nearly fully implemented, no studies have taken a snapshot of the uninsured US population with diabetes and considered how their medical care may be changing under full implementation of ACA in 2014 and beyond.

The objective of this study was to gauge the potential impact of ACA on improving diabetes care through improved health care access by comparing health care and health outcomes of a large national sample of insured and uninsured adults with diabetes. Our results provide a straightforward comparison of the gap between the insured and uninsured before health care reform and insights about how indicators for these 2 groups may converge in coming years.

# Methods

To obtain the latest pre-ACA snapshot of the US population with diabetes, we pooled data from the 2 most recent years of the Medical Expenditure Panel Survey (MEPS), the 2011 and 2012 household component full-year consolidated data files (11,12). (This period is "pre-ACA" because major provisions were not effective until 2014, although limited features such as expanded coverage for young adults began in 2010.) MEPS is an ongoing set of surveys sponsored by the Agency for Healthcare Research and Quality (AHRQ) that collects nationally representative data on health services and expenditures of the noninstitutionalized civilian population. MEPS is constructed from a subsample of households participating in the National Health Interview Survey and uses a stratified random sample design and computer-assisted in-person interviews (13). MEPS is well suited for this analysis because it provides detailed information on health care use and expenditures and also includes survey responses, capturing data on items such as health care access. Other national surveys and claims data provide one or the other type of data but rarely both.

MEPS respondents are interviewed 3 times during a calendar year and asked several questions about health care use, insurance, expenditures, access to care, preventive care services, and chronic diseases. People with diabetes are asked about health outcomes and health care specific to diabetes. For many measures on the full-year consolidated file, MEPS combines data from each respondent's multiple interviews to create 1 calendar year variable.

We restricted the study sample to adults aged 19 to 64 years who reported that they had been diagnosed with diabetes (most people over age 65 with diabetes are unaffected by ACA coverage provisions, because they are eligible for Medicare.) We stratified analysis by household income at less than 138% of the FPL (hereafter, low income) and greater than 138% of the FPL (hereafter, high income), because these are the eligibility limits for Medicaid in states choosing to expand coverage.

We used edited variables when possible, which are cleaned for consistency by AHRQ across the multiple survey rounds in MEPS. These variables included age, sex, race/ethnicity, education, census region, and health insurance status. We collapsed the level of detail on variables such as employment, because these measures serve only as controls intended to identify systematic differences between the sample groups and are not primary aspects of diabetes care or outcomes. All outcomes, which are measured over a period of time (employment, insurance, access to care, diabetes care, health care use, and health care expenditures), were limited to the current year, 2011 or 2012, for the corresponding MEPS sample. For ease of exposition, we created the following mutually exclusive groups for the previous 12 months out of the monthly MEPS insurance indicators in the following order: dual eligible (Medicaid and Medicare), Medicaid, Medicare, private insurance, TRICARE and Civilian Health and Medical Program of the Department of Veterans Affairs (CHAMPVA), and other public insurance. People with more than 1 insurance type were grouped into the first applicable type in the insurance indicator list.

Diabetes-specific measures were from the MEPS Diabetes Care Survey (DCS), a paper-and-pencil survey module administered to those reporting that they had ever been diagnosed with diabetes. The DCS includes self-report of the year of diagnosis, of ever having had diabetes complications of the eye or kidney, and of receiving 6 preventive care measures in the past year (hemoglobin A1c blood test, feet checked for sores or irritations, dilated eye examination, blood cholesterol check, influenza vaccination, and blood pressure checks). We calculated the years since diabetes was first diagnosed as the difference between the respondent's age at interview and the age at diagnosis. We used the DCS-specific survey weight when reporting DCS measures.

For physical health and comorbidities, we analyzed self-reported body mass index (BMI) (kg in weight/$m^2$ in height) and the prevalence of all adult priority conditions, as defined by AHRQ (14).

In addition to diabetes, the conditions are hypertension, heart disease (coronary heart disease, angina, myocardial infarction, other unspecified heart disease), stroke, emphysema, chronic bronchitis, high cholesterol, cancer, joint pain, arthritis, and asthma. Several of these are either linked to diabetes as complications associated with diabetes management and duration; others are risk factors that present additional challenges to proper diabetes care.

We included 3 broad measures of access, measured as binary indicators. All respondents were asked if they had a usual source of medical care in the past year. Respondents were also asked if they were ever unable to access necessary medical care in the past year and if they were unable to get necessary prescription medications. For health care use in the past year, we studied the number of physician or clinic office visits and total number of prescriptions. We included binary indicators for any emergency department visit and any inpatient hospital nights, because these services are used infrequently and their statistical distribution is skewed. We examined total health care expenditures, out-of-pocket health care expenditures, and prescription drug expenditures, which included diabetes supplies.

Survey-specific procedures in Stata 13.1 (StataCorp LP) with weighted analyses and analytic subpopulations were used. To pool the 2011–12 data, we halved the survey weights so that the results equally represented people with diabetes for 2011 and 2012. Differences between insured and uninsured people were examined separately by income group using means, proportions, and crosstabs. Tests of significance were computed using survey-specific *t* tests, proportions, and $\chi^2$ tests. We also computed medians of health care expenditure and use data and tested differences by using the nonparametric k-sample test on equality of medians.

## Results

We estimated from MEPS that from 2011 through 2012, more than 13 million adults in the United States aged 19 to 64 years were living with diagnosed diabetes, and nearly 2 million of them lacked health insurance (Table 1). The prevalence of diabetes ranged from 4.8% among the uninsured with incomes above 138% of the FPL to 10.5% among the insured with incomes at or below 138% of the FPL (Table 1); in both income groups, insured persons were more likely to have diabetes than uninsured persons ($P < .001$).

Differences by insurance status suggest some patterns that may be related to both the likelihood of having insurance and the prevalence of diabetes. In both income groups, uninsured persons were more likely to be nonwhite ($P = .007$, low income; $P < .001$, high income). Among the low-income groups, uninsured people with diabetes (42.7%) were more likely than the insured to be employed (26.5%) ($P < .001$). Significant regional differences by insurance status were also apparent among the low-income groups ($P = .002$); more than 55% of low-income uninsured adults and only 39% of insured adults resided in states in the southern census region.

High-income, insured adults with diabetes had a higher average BMI than uninsured adults (33.5 vs 31.5, $P = .002$); this was also the case with overweight adults ($P = .02$) and those with high levels of morbid obesity (class II/III, $P = .01$). Low-income insured adults had significantly higher rates of 7 chronic conditions (heart disease, stroke, emphysema, bronchitis, joint pain, arthritis, asthma) than those without insurance (all $P < .01$ or smaller), and high-income people had higher rates of 2 conditions (high cholesterol and arthritis) (both $P < .05$).

Significant differences in health care access were seen in both income groups, both in having a usual source of care ($P < .001$) and being unable to access necessary health care ($P < .001$). Low-income people were also much more likely to report that they were unable to get necessary prescription medications ($P = .002$). Significant differences by insurance status for all 6 recommended diabetes preventive care services (ie, Hemoglobin A1c [HbA1c] test, foot examination, eye examination, blood cholesterol check, influenza vaccine, and blood pressure check) were found across income groups ($P \leq .05$).

In both income groups, insured adults with diabetes were much more likely to have used medical services in the past year than those without health insurance (Table 2). For instance, in the low-income group, the mean number of annual office visits among the insured was nearly triple the mean number among the uninsured ($P < .001$) and nearly double that among the high-income group ($P < .001$). The mean number and the median number of prescriptions were also substantially higher among the insured in both income groups ($P < .001$). The likelihood of using emergency department services ($P = .001$) or having inpatient hospital nights ($P < .001$) in the past year was significantly greater ($P < .001$) among the low-income group than the high-income group.

Differences in health care use and differences in expenditures between the insured and uninsured in both income groups were large. Mean total expenditures were much greater among the insured, which probably reflects greater access to health care: nearly $6,400 higher for those with incomes above 138% of the FPL ($P < .001$) and more than $9,300 higher for those with incomes at or below138% FPL ($P < .001$). Median differences were slightly smaller but still significant for both groups ($P < .001$). Out-of-pocket expenditures were higher among the uninsured only in the low-income group. Prescription drug expenditures were a significant driver of total expenses and were much greater among the insured than uninsured for both income groups ($P < .001$).

# Discussion

Our findings showed that from 2011 through 2012, shortly after passage of ACA, nearly 2 million working-age adults with diabetes lacked health insurance. We also showed that access to care was a significant barrier among this population and that proper diabetes care lagged among the insured on all indicators. Thus, the potential of ACA to improve health and health care for people with diabetes appears to be large. If the health care patterns of the uninsured in 2011–12 move toward those of the insured, our results suggest that expanded insurance coverage will likely increase health care costs in the short-term for people with diabetes. Although long-term effects were beyond the scope of our research, it is possible that these may be more favorable for health outcomes and expenditures. For example, a recent study found that weight loss among people with diabetes reduced health expenditures over 10 years (15), and other health care interventions have also been shown to reduce the burden of diabetes (16). Counterbalancing these findings are the findings from the Oregon Health Insurance Experiment (17), in which newly acquired Medicaid did not significantly reduce average HbA1c during the first 2 years of coverage. Our findings are consistent with that study in that we found higher rates of diagnosed diabetes and greater use of prescription medications among the insured than the uninsured samples.

Our findings showed that uninsured adults with diabetes undergo different patterns of care than those with health insurance. For instance, in our study the uninsured were much less likely to obtain prescriptions, make office visits to physicians, and to have a usual source of care. Rates of current multiple disorders, several of which are associated with diabetes, were greater among the insured than the uninsured in both income groups; differences were significant for 6 conditions among the low-income sample and for 2 conditions among the high-income sample. Possible explanations include self-selection, in which those who have a greater need for care seek insurance voluntarily, or improved access, in which the insured are diagnosed for these conditions at higher rates (4). The percentage of respondents reporting fair or poor health was nearly 10 points higher among the high-income uninsured group ($P = .02$), possibly supporting an access theory, although no significant differences were seen among the low-income group.

The observed disconnect between patterns of care provided and need for care suggests that as uninsured adults with diabetes obtain new health insurance under full implementation of ACA in 2014 and beyond, we should expect their use of medical care to increase significantly — more office visits, prescriptions, and use of inpatient care. Our results distinguish between people with incomes below 138% of the FPL who will become eligible for Medicaid (in states expanding Medicaid) and those people with incomes above 138% of the FPL; results also demonstrate that health care use should increase for both groups, although the gap in services is larger among low-income persons, suggesting greater potential demand among low-income persons. However, many other barriers to good diabetes care exist, besides health insurance, that are not directly targeted by ACA, including education, literacy, language, attitudes, beliefs, and social support (18).

Given the longstanding finding (19) that the uninsured face difficulties obtaining access to a usual source of health care, it is not surprising that uninsured adults with diabetes in both the high- and low-income groups we studied were significantly less likely to report having a usual source of care ($P < .001$). Greater total expenditures among the insured probably reflect access, or the ease of obtaining necessary medical care. Early observations in the Oregon studies indicate similar trends (20). The fact that our findings show that inpatient and emergency department services were greater among the insured parallels findings in Oregon (21) and recent qualitative evidence (22). Furthermore, among those with Medicaid, access to primary care providers may be limited in some areas, given low provider reimbursement rates.

Our results should be interpreted with caution. First, our study compares descriptive results. A more detailed comparison could use multivariate analysis to control for associations between variables presented here. The descriptive findings here serve as a starting point and guide for future research.

Second, our results are based on cross-sectional data, so we cannot assign causation to the differences in health status, outcomes, and health care use, access, or expenditures between uninsured and insured people. People with health insurance are likely to be different from those without health insurance in some important ways, both observable and unobservable. Multivariate models can control for the observables, although some of the differences we found probably reflect both observable and unobservable factors. Our goal with this analysis was not to estimate causal inference. Rather, we sought to address the research gap in the literature on differences between the uninsured and insured population of people with diabetes, above and below the average Medicaid eligibility cutoff of 138% FPL, by assessing numerous health outcomes and health care access and use measures. The fact that our demographic indicators show a high level of Medicaid use by the income group at or below 138% FPL and a high level of private insurance by the over-138% FPL group supports the value of such a comparison. That is, the uninsured in each group who become insured after ACA are likely to receive most of their coverage through the dominant form of insurance for that income group (Medicaid for low income, private insurance for high income). Although we expect some changes in patterns of health care and health care use to result from changes in coverage, measurement of the actual effects will need to be conducted in future research studies after additional years of post-ACA implementation data are available. We also see relatively few differences in demographics between the insured and uninsured, except for nonwhite race/ethnicity and region, which is probably due to the more restrictive Medicaid income criteria for low-income adults in Southern states.

Third, the study is limited to adults aged 19 to 64 years, so the findings here cannot be extended to children or the elderly, although they are less directly targeted by ACA. Fourth, the MEPS measure of the diabetes population reflects currently diagnosed adults. The population with undiagnosed diabetes is sizable (4), and some of these people may be newly diagnosed under ACA as a result of improved health care access. On the one hand, the highest rate of undiagnosed diabetes is found among the uninsured (4), so our findings may be viewed as underestimates of the potential number of uninsured people with diabetes who could be assisted by implementation of ACA. We could not identify adults in the diabetes population who may or will not be eligible for coverage under ACA (noncitizens or persons living in states that will not expand Medicaid); this nonidentification would overstate the number of uninsured people with diabetes who could be assisted by implementation of the ACA.

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# Tables

**Table 1. Health and Demographic Characteristics of US Adults With Diabetes Aged 19 to 64 Years, Medical Expenditure Panel Survey 2011 and 2012**

| Characteristic[a] | ≤138% Federal Poverty Level | | | >138% Federal Poverty Level | | |
|---|---|---|---|---|---|---|
| | Uninsured[b] (95% CI) | Insured[b] (95% CI) | *P* Value[c] | Uninsured[b] (95% CI) | Insured[b] (95% CI) | *P* Value[c] |
| Diabetes prevalence | 5.6 (4.8–6.6) | 10.5 (9.3–11.6) | <.001 | 4.8 (4.0–5.6) | 6.7 (6.1–7.2) | <.001 |
| Unweighted sample (n = 1,568) | 325 | 774 | — | 318 | 1791 | — |
| Weighted sample (n = 13,084,968) | 770,404 | 2,529,894 | — | 1,024,650 | 8,704,030 | — |
| **Demographic characteristic** | | | | | | |
| Age (mean), y | 49.8 (48.4–51.1) | 50.8 (49.8–51.9) | .19 | 51.8 (50.2–53.5) | 52.3 (51.6–53.0) | .62 |
| Female | 51.1 (43.6–58.6) | 53.9 (49.2–58.7) | .52 | 43.6 (35.0–52.2) | .464 | .57 |
| Race/ethnicity nonwhite | 68.1 (58.9–77.3) | 53.2 (46.3–60.1) | .007 | 54.7 (45.2–64.3) | 35.4 (31.8–39.0) | <.001 |
| Years of education, mean | 11.3 (10.7–11.9) | 11.6 (11.3–12.0) | .28 | 11.7(11.1–12.3) | 13.5(13.4–13.7) | <.001 |
| Ever employed in calendar year 2011 or 2012 | 42.7 (35.1–50.3) | 26.6 (21.8–31.5) | <.001 | 69.6 (61.7–77.6) | 73.8 (71.0–76.5) | .33 |
| Census region: Northeast | 8.1 (4.4–14.7) | 20.8 (15.7–27.0) | .002 | 14.4 (8.7–22.7) | 14.6 (12.0–17.7) | .22 |
| Census region: Midwest | 18.7 (12.7–26.6) | 18.4 (14.6–22.8) | | 16.7 (11.2–24.1) | 23.8 (19.5–28.7) | |
| Census region: South | 55.8 (46.7–64.5) | 38.7 (33.0–44.7) | | 44.0 (35.5–53.0) | 43.2 (39.2–47.3) | |
| Census region: West | 17.4 (11.4–25.7) | 22.1 (17.3–27.9) | | 24.9 (18.3–32.9) | 18.4 (15.6–21.4) | |
| Urban/metropolitan statistical area | 82.8 (76.3–89.2) | 76.7 (70.1–83.4) | .15 | 87.7 (81.6–93.7) | 83.0 (79.3–86.6) | .16 |
| **Type of health insurance in 2011 or 2012** | | | | | | |
| Medicaid | — | 47.8 (41.4–54.4) | <.001 | — | 6.9 (5.6–8.6) | <.001 |
| Medicare | — | 12.9 (10.1–16.4) | | — | 9.0 (7.2–11.2) | |
| Both Medicaid and Medicare | — | 17.1 | | — | 2.6 (1.8–3.8) | |

Abbreviations: BMI, body mass index; CI, confidence interval.
[a] Values are percentages unless otherwise noted.
[b] Tests of insurance status are between >138% federal poverty level insured and ≤138% federal poverty level. All other tests are by insurance status within income groups. All results were weighted to be nationally representative.
[c] Tests of significance were computed by using survey-specific *t* tests for continuous variables, proportions tests for binary variables, and $\chi^2$ tests for proportions.
[d] TRICARE/CHAMPVA is coverage for military families and dependents through the TRICARE system and Civilian Health and Medical Program of the Department of Veterans Affairs (CHAMPVA).
[e] Obese class II = BMI 35.0–39.9; obese class III = BMI ≥40.

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(continued)

**Table 1. Health and Demographic Characteristics of US Adults With Diabetes Aged 19 to 64 Years, Medical Expenditure Panel Survey 2011 and 2012**

| Characteristic[a] | ≤138% Federal Poverty Level | | | >138% Federal Poverty Level | | |
|---|---|---|---|---|---|---|
| | Uninsured[b] (95% CI) | Insured[b] (95% CI) | *P* Value[c] | Uninsured[b] (95% CI) | Insured[b] (95% CI) | *P* Value[c] |
| | | (13.2–21.8) | | | | |
| Private insurance | — | 18.1 (13.7–23.5) | | — | 78.8 (75.8–81.4) | |
| TRICARE/CHAMPVA[d] | — | 3.1 (15.1–6.2) | | — | 1.9 (1.3–2.9) | |
| Other public insurance | — | 1.0 (0.4–2.4) | | — | 0.8 (0.4–1.7) | |
| **Diabetes and associated conditions** | | | | | | |
| Age of onset, y | 40.3 (38.0–42.6) | 39.6 (37.9–41.2) | .58 | 41.8 (39.4–44.1) | 41.9 (40.8–42.9) | .95 |
| Years since diagnosis | 9.5 (7.6–11.5) | 11.1 (9.8–12.3) | .14 | 10.2 (8.2–12.2) | 10.5 (9.6–11.4) | .82 |
| Kidney problems | 12.9 (7.4–18.3) | 15.0 (11.2–18.8) | .48 | 12.5 (6.8–18.2) | 7.9 (6.2–9.7) | .12 |
| Eye problems | 24.9 (17.6–32.2) | 28.8 (24.1–33.5) | .38 | 20.8 (13.8–27.8) | 16.7 (14.0–19.3) | .26 |
| **Physical health and comorbidities** | | | | | | |
| BMI (kg/m$^2$) | 32.7 (31.4–33.9) | 33.8 (33.0–34.7) | .14 | 31.5 (30.4–32.6) | 33.5 (32.8–34.2) | .002 |
| BMI overweight (25.0–29.9) | 28.5 (21.7–36.3) | 22.4 (18.3–27.1) | .17 | 33.8 (26.8–41.5) | 24.7 (21.8–28.0) | .02 |
| BMI obese I (30–34.9) | 26.5 (20.5–33.5) | 26.9 (22.5–31.9) | .91 | 29.7 (23.5–36.8) | 28.7 (25.9–31.7) | .78 |
| BMI obese II/III[e] (≥35.0)) | 34.4 (27.0–42.5) | 38.9 (33.4–44.8) | .34 | 24.3 (17.8–32.4) | 35.4 (31.7–39.3) | .01 |
| High blood pressure/hypertension | 72.0 (65.1–78.9) | 76.3 (71.8–80.7) | .31 | 72.9 (65.8–80.0) | 68.7 (65.4–71.9) | .27 |
| Coronary heart disease, angina, acute myocardial infarction, other heart disease | 20.0 (12.9–27.1) | 32.2 (26.9–37.4) | .007 | 22.0 (15.0–29.0) | 21.9 (18.8–25.0) | .99 |
| Stroke | 4.5 (0.6–9.7) | 13.0 (9.6–16.4) | .007 | 7.7 (2.5–12.8) | 6.2 (4.7–7.7) | .60 |
| Emphysema | 1.2 (0.0–2.6) | 6.2 (4.7–7.7) | .002 | 1.8 (0.0–4.1) | 1.8 (1.0–2.6) | .97 |
| Chronic bronchitis | 4.5 (1.5–7.6) | 12.4 | .004 | 8.0 | 5.5 (3.7–7.2) | .36 |

Abbreviations: BMI, body mass index; CI, confidence interval.
[a] Values are percentages unless otherwise noted.
[b] Tests of insurance status are between >138% federal poverty level insured and ≤138% federal poverty level. All other tests are by insurance status within income groups. All results were weighted to be nationally representative.
[c] Tests of significance were computed by using survey-specific *t* tests for continuous variables, proportions tests for binary variables, and $\chi^2$ tests for proportions.
[d] TRICARE/CHAMPVA is coverage for military families and dependents through the TRICARE system and Civilian Health and Medical Program of the Department of Veterans Affairs (CHAMPVA).
[e] Obese class II = BMI 35.0–39.9; obese class III = BMI ≥40.

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**Table 1. Health and Demographic Characteristics of US Adults With Diabetes Aged 19 to 64 Years, Medical Expenditure Panel Survey 2011 and 2012**

| Characteristic[a] | ≤138% Federal Poverty Level | | | >138% Federal Poverty Level | | |
|---|---|---|---|---|---|---|
| | Uninsured[b] (95% CI) | Insured[b] (95% CI) | *P* Value[c] | Uninsured[b] (95% CI) | Insured[b] (95% CI) | *P* Value[c] |
| | | (8.1–16.7) | | (2.9–13.1) | | |
| High blood cholesterol | 60.5 (52.1–69.0) | 68.8 (64.3–73.3) | .09 | 53.8 (44.5–63.1) | 67.3 (64.3–70.4) | .008 |
| Cancer | 7.5 (3.5–11.4) | 11.6 (8.6–14.6) | .10 | 9.5 (2.4–16.6) | 13.0 (10.3–15.7) | .39 |
| Joint pain | 57.2 (49.6–64.9) | 71.7 (67.4–75.9) | .001 | 60.0 (51.6–68.3) | 64.2 (60.7–67.6) | .36 |
| Arthritis | 36.5 (29.0–44.0) | 54.6 (48.7–60.5) | .001 | 30.0 (21.9–38.2) | 39.8 (36.1–43.4) | .04 |
| Asthma | 9.9 (5.3–14.5) | 26.5 (21.3–31.7) | <.001 | 10.1 (4.4–15.8) | 11.6 (9.7–13.6) | .62 |
| Self-rated general health as fair or poor versus excellent, very good, or good | 56.9 (48.9–64.8) | 59.2 (53.8–64.6) | .64 | 40.0 (32.5–47.6) | 30.2 (27.2–33.2) | .02 |

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

[a] Values are percentages unless otherwise noted.

[b] Tests of insurance status are between >138% federal poverty level insured and ≤138% federal poverty level. All other tests are by insurance status within income groups. All results were weighted to be nationally representative.

[c] Tests of significance were computed by using survey-specific *t* tests for continuous variables, proportions tests for binary variables, and $\chi^2$ tests for proportions.

[d] TRICARE/CHAMPVA is coverage for military families and dependents through the TRICARE system and Civilian Health and Medical Program of the Department of Veterans Affairs (CHAMPVA).

[e] Obese class II = BMI 35.0–39.9; obese class III = BMI ≥40.

Table 2. Health Care Access, Use, and Expenditures of US Adults Aged 19 to 64 Years With Diabetes, Medical Expenditure Panel Survey 2011 and 2012

| Measure[a] | ≤138% Federal Poverty Level | | | >138% Federal Poverty Level | | |
|---|---|---|---|---|---|---|
| | Uninsured (95% CI) | Insured (95% CI) | *P* Value[b] | Uninsured (95% CI) | Insured (95% CI) | *P* Value[b] |
| **Access to and use of health care in 2011 or 2012** | | | | | | |
| Had a usual source of care | 69.0 (60.6–77.5) | 89.5 (86.3–92.7) | <.001 | 77.1 (71.0–83.1) | 94.6 (93.1–96.1) | <.001 |
| Unable to access necessary medical care | 18.5 (12.7–24.4) | 6.5 (4.1–8.8) | <.001 | 13.8 (7.9–19.6) | 2.5 (1.6–3.5) | <.001 |
| Unable to get necessary prescription medications | 17.6 (11.1–24.2) | 6.4 (3.9–8.9) | .002 | 9.0 (3.9–14.1) | 4.0 (2.7–5.3) | .06 |
| HbA1c test | 83.4 (76.4–91.3) | 95.6 (93.2–98.0) | .003 | 86.6 (79.2–94.0) | 97.5 (96.5–98.6) | .004 |
| Feet checked | 48.5 (38.9–58.0) | 67.0 (62.7–71.3) | <.001 | 49.9 (40.1–59.7) | 69.6 (66.6–72.7) | <.001 |
| Eye examination | 35.9 (27.5–44.2) | 58.1 (52.7–63.3) | <.001 | 38.8 (30.2–47.4) | 65.6 (62.1–69.1) | <.001 |
| Cholesterol check | 66.2 (58.5–73.9) | 77.4 (73.2–81.6) | .015 | 69.5 (62.4–76.6) | 88.1 (85.8–90.2) | <.001 |
| Influenza vaccine | 32.4 (25.3–39.6) | 57.2 (51.4–62.9) | <.001 | 37.8 (28.1–47.5) | 61.8 (58.6–64.9) | <.001 |
| Blood pressure check | 84.4 (79.3–89.4) | 96.5 (94.4–98.6) | <.001 | 90.3( 86.7–94.0) | 98.1 (97.4–98.8) | <.001 |
| Office visits, mean no. | 4.1 (3.0–5.2) | 11.0 (8.8–13.1) | <.001 | 4.6 (3.5–5.6) | 8.8 (7.9–9.7) | <.001 |
| Office visits, median no. | 2 | 5 | <.001 | 3 | 5 | <.001 |
| Total prescription fills in year, mean | 23.4 (18.7–28.0) | 51.3 (43.9–58.7) | <.001 | 23.5 (18.4–28.6) | 36.2 (34.0–38.6) | <.001 |
| Total prescription fills in year, median | 17 | 37 | <.001 | 15 | 25 | <.001 |
| Any emergency department visit | 19.3 (14.7–24.0) | 33.3 (28.3–38.2) | <.001 | 22.9 (16.4–29.4) | 21.9 (19.3–24.6) | .79 |
| Any inpatient nights | 8.9 (5.2–12.6) | 25.6 (20.8–30.3) | <.001 | 10.9 (5.7–16.1) | 14.7 (12.3–17.1) | .22 |
| **Expenditures in 2011 or 2012, $[c]** | | | | | | |
| Total, mean | 4,367 (2,558–6,176) | 13,706 (11,514–15,897) | <.001 | 4,419 (2,891–5,946) | 10,838 (9,796–11,879) | <.001 |
| Total, median | 1,297 | 6,382 | <.001 | 1,483 | 4,767 | <.001 |
| Out-of-pocket, mean | 1,177 (837–1,516) | 755 (620–889) | .021 | 1,490 (994–1,985) | 1,288 (1,175–1,401) | .43 |
| Out-of-pocket, median | 432 | 225 | .005 | 795 | 808 | .09 |

Abbreviation: CI, confidence interval.
[a] Values are percentages unless otherwise stated.
[b] Tests of significance were computed using survey-specific *t* tests for continuous variables, proportions tests for binary variables, and nonparametric *k*-sample tests for medians. All results were weighted to be nationally representative.
[c] Expenditures are as reported in current-year dollars. Measures refer to the full calendar year for respondents in either the 2011 or 2012 household component full-year consolidated Medical Expenditure Panel Survey data files. Samples were pooled as described in the methods section.

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**Table 2. Health Care Access, Use, and Expenditures of US Adults Aged 19 to 64 Years With Diabetes, Medical Expenditure Panel Survey 2011 and 2012**

| Measure[a] | ≤138% Federal Poverty Level | | | >138% Federal Poverty Level | | |
|---|---|---|---|---|---|---|
| | Uninsured (95% CI) | Insured (95% CI) | *P* Value[b] | Uninsured (95% CI) | Insured (95% CI) | *P* Value[b] |
| Prescription drugs and diabetes supplies, mean | 1,194 (857–1,530) | 4,296 (3,295–5,298) | <.001 | 1,492 (946–2,037) | 3,414 (3,056–3,771) | <.001 |
| Prescription drugs and diabetes supplies, median | 355 | 1,894 | <.001 | 346 | 1,744 | <.001 |

Abbreviation: CI, confidence interval.
[a] Values are percentages unless otherwise stated.
[b] Tests of significance were computed using survey-specific *t* tests for continuous variables, proportions tests for binary variables, and nonparametric *k*-sample tests for medians. All results were weighted to be nationally representative.
[c] Expenditures are as reported in current-year dollars. Measures refer to the full calendar year for respondents in either the 2011 or 2012 household component full-year consolidated Medical Expenditure Panel Survey data files. Samples were pooled as described in the methods section.

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SPECIAL TOPIC

# Outside the Exam Room: Policies for Connecting Clinic to Community in Diabetes Prevention and Treatment

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PEER REVIEWED

## Abstract

The public health burden and racial/ethnic, sex, and socioeconomic disparities in obesity and in diabetes require a population-level approach that goes beyond provision of high-quality clinical care. The Robert Wood Johnson Foundation's Commission to Build a Healthier America recommended 3 strategies for improving the nation's health: 1) invest in the foundations of lifelong physical and mental well-being in our youngest children; 2) create communities that foster health-promoting behaviors; and 3) broaden health care to promote health outside the medical system. We present an overview of evidence supporting these approaches in the context of diabetes and suggest policies to increase investments in 1) adequate nutrition through breastfeeding and other supports in early childhood, 2) community and economic development that includes health-promoting features of the physical, food, and social environments, and 3) evidence-based interventions that reach beyond the clinical setting to enlist community members in diabetes prevention and management.

## Introduction

Preventing and treating diabetes are major public health priorities in light of the increased risk for disability and premature death associated with the disease. Diabetes is the seventh leading cause of death in the United States, contributes to cardiovascular, renal, vision, and other complications, and results in $245 billion in total costs (1). In 2005 through 2010, an estimated 21 million adults aged 20 or older in the United States had diabetes, a 9.3% prevalence (vs 5.5% in 1988–1994 and 7.6% in 1999–2004) (2). Trends suggest that diabetes prevalence has been increasing over the past several decades in conjunction with a sharp increase in the prevalence of obesity. Racial/ethnic disparities have increased over the same period; in 2005 through 2010, prevalence among African Americans (15.4%) and Mexican Americans (11.6%) was significantly higher than prevalence among non-Hispanic whites (8.6%) (2). In 2011 through 2012, the prevalence of obesity was 8.1% among infants and toddlers, 16.9% among children and youths aged 2 to 19 years, and 34.9% among adults aged 20 years or older, with prevalence higher among adult women than men and higher among non-Hispanic blacks and Hispanics than non-Hispanic whites and non-Hispanic Asians (3). Both the considerable public health burden and the significant racial/ethnic and sex disparities in obesity and in diabetes prevalence, control, and mortality require a population-level approach that goes beyond reliance on what clinical interventions can address to reduce the burden of these conditions (4).

In January of 2014, the Robert Wood Johnson Foundation's Commission to Build a Healthier America (hereafter referred to as the Commission) recommended 3 broad strategies for improving the nation's health: 1) invest in the foundations of lifelong physical and mental well-being in our youngest children, 2) create communities that foster health-promoting behaviors, and 3) broaden health care to promote health outside the medical system (5). These recommendations, although not specific to any particular condition, frame the approach to diabetes prevention and treatment described in this article. Specifically, we argue that efforts to prevent obesity and diabetes must begin in the earliest years of life and should be integrated into high-quality early childhood programs. Such programs necessarily include evidence-based interventions to address nutrition in young children as the foundation for a health-promoting behavior they will continue into adolescence and adulthood. To the extent that early intervention increases educational attainment (6) and higher levels of education predict better health behaviors (7), supporting early childhood development should also have indirect effects on obesity and diabetes. Cardiovascular and metabolic disease risks were lower for individuals in their mid-30s who had received high-quality early intervention as children than for those who had not received this intervention (8).

Within neighborhoods and communities, features of the built environment (eg, community design conducive to walking), the food environment (eg, access to healthful foods), and other aspects of community and economic development (eg, jobs, housing, transportation) should support behaviors that promote obesity and diabetes prevention (9–11). As the Commission notes, "efforts should be made to improve the health of all communities, [but] we must prioritize communities where low-income Americans lack opportunities to make healthy choices" (p. 22) (5). Health care access within communities is also a necessary condition for obesity and diabetes prevention and treatment, and includes not only physical proximity but also affordability and culturally appropriate care. Although necessary, access alone is not sufficient for prevention and treatment.

In the clinical setting and at its interface with the community, there are multiple opportunities to address diabetes prevention and treatment. The emphasis on high-quality treatment and the coordination of patient care (eg, patient-centered medical homes [PCMHs]) within the Affordable Care Act has prompted a reassessment of health care delivery in the United States. Prevention and treatment of diabetes, particularly in socially disadvantaged and traditionally underserved populations, will require far greater coordination than exists now among providers and between health care systems and community-based partners. The Commission calls for an expansion of the concept of "vital signs" in clinical and public health settings to include nonmedical factors such employment, education, health literacy, and safe housing. The Commission also envisions "prescriptions" for behaviors such as healthful eating that can be "filled" with community-based programs (5).

We provide an overview of the evidence for each of these approaches. We also present a model for how policies can be enacted that will bridge the clinic and the community in diabetes prevention and treatment efforts, while noting examples of best practices. Finally, we will highlight future directions for research, practice, and policy in this area.

## Invest in the Foundations of Lifelong Physical and Mental Well-Being in Our Youngest Children

Poor early childhood nutrition can negatively affect children's physical and emotional development; it can increase their risk for obesity and diabetes and limit their adult achievement and productivity (12). There are many factors that affect children's nutrition, including those related to social, familial, cultural, and community influences. Research shows that the first 3 years of life are a period of rapid brain development and physical growth (13). Consequently, without proper nutrition, young children are uniquely at risk for development delays or impairments (12,13). Breastfeeding protects against childhood overweight and obesity, which are common causes of early onset of type 2 diabetes, but only 13% of babies are exclusively breastfed at the end of 6 months (14). The success rate among mothers who want to breastfeed can be improved through interpersonal, institutional, and policy support. Early child care providers also are in a unique position to support breastfeeding by ensuring that staff members at early child care centers are well-trained to meet national recommendations set by the American Academy of Pediatrics and outlined in *Caring for Our Children: National Health and Safety Performance Standards* (15) for supporting breastfeeding mothers. Support may include allowing mothers to breastfeed at the facility, feeding a mother's pumped breast milk to her baby, thawing and preparing bottles of pumped milk as needed and keeping extra breast milk in a freezer. State and local jurisdictions can also set and enforce standards for early childhood care to ensure that standards are implemented (15). As of December 2011, only 6 states' (Arizona, California, Delaware, Mississippi, North Carolina, and Vermont) licensing regulations contained language that met national recommendations for supporting breastfeeding (16).

Early child development and nutrition programs, such as the Special Supplemental Nutrition Program for Women, Infants, and Children (WIC) and the Child and Adult Care Food Program (CACFP), are federally funded food programs aimed at ensuring infants and children have access to nutritious food. WIC provides funds for buying healthful supplemental foods from WIC-authorized vendors, nutrition education, and help locating health care and other community services. CACFP provides meals and snacks to children and adults in day care facilities and in after-school programs. Although these federal programs help meet the daily nutritional needs of millions of young, low-income children during a critical period of growth and development, the dietary guidelines, structure, and reimbursements are outdated and complex, leaving many children without the benefits of these programs (17).

Evidence-based interventions that target young children are essential in ensuring healthy growth and development, including obesity prevention. *Healthy People 2020* (18) outlines several objectives and strategies to increase the proportion of persons aged 2 years or older whose diets are consistent with the US Department of Agriculture's *Dietary Guidelines for Americans* (19). Many of these objectives could be achieved by enhancing the nutritional quality of food and beverages supported and supplied by federal nutrition assistance programs (20).

Several states, (eg, Delaware, North Carolina, Missouri, and Colorado) have implemented efforts to encourage improvement of meal standards associated with federal programs (21); however, effectiveness of these efforts are not well-defined and documentation of success from these programs is scant.

## Create Communities That Foster Health-Promoting Behaviors

Policy-level changes that influence the built environment can have a positive effect on the health of residents, particularly in low-resource communities. Environments with ample opportunities for residents to be physically active can enable adherence to physicians' recommendations for exercise, and aspects of the built environment that affect physical activity and food behaviors are associated with obesity prevalence (22). According to the *Community Guide* (23), there is evidence to support the recommendation of community-scale and street-scale urban design and land-use policies to promote physical activity and overall health. These policies include community planning and development policies such as zoning codes that facilitate active transportation, connectivity of sidewalks and streets, and the provision for aesthetic and safety aspects of the physical environment (23). Improved access to public transportation is also a recommended strategy to increase physical activity within communities.

According to the Recommended Community Strategies and Measurements to Prevent Obesity in the United States from the Centers for Disease Control and Prevention (CDC) (24), promoting the availability of, and access to, affordable healthful food and beverages is recommended to improve community health. Of the 24 CDC recommendations, 7 are related to increasing the availability of healthful food in public venues and underserved areas (24). Food access policies such as those that provide incentives to food retailers to locate in underserved areas or to offer healthful food and beverage choices in those areas can reduce the barriers to improved nutrition as clinically recommended for health promotion and disease prevention. And although evidence of impact is emerging in adult populations (9), a systematic review reported that there is moderate evidence of the relationship between community and consumer nutrition environments and dietary intake of children and adolescents up to age 18 years (25). Other policies that can create sustainable nutrition improvements include provisions for farmers markets or farm-to-table initiatives and zoning laws that reduce the number of retail businesses or restaurants selling unhealthful foods within communities. Although there is a growing body of research on these policies, behavioral and disease prevention outcomes are often difficult to compare because of differences in assessment methods (9).

Both the built environment and food access depend on community and economic development policies within communities that determine zoning for residential, industrial, and commercial space, business activities, and resources such as schools and health centers. Considering health as a key component of policy decisions regarding community and economic development is consistent with the principles of "health in all policies" and the Health Impact Assessment (26). Informed by research on the social determinants of health, the Federal Reserve System and the Robert Wood Johnson Foundation have partnered to develop the Healthy Communities Initiative to highlight the need for closer coordination between the community development and health sectors, particularly in low-income communities (10).

## Broaden Health Care to Promote Health Outside the Medical System

Diabetes is a chronic disease that requires ongoing patient education, self-management, and clinical care to achieve desired outcomes. It is critical to understand how the patient's ability to manage diabetes is affected by the Commission's nonclinical vital signs such as employment, healthful food access, safe housing, and health literacy.

The PCMH is a mechanism for the redesign of health care delivery promoted through the Affordable Care Act. The PCMH model seeks to provide comprehensive, patient-centered, coordinated care that is accessible and has a consistent focus on quality improvement and patient safety.

The PCMH model incorporates some of the most successful strategies for improving glucose control, such as promotion of self-management, changes in the health care team, and case management, all documented in a meta-analysis to lower hemoglobin A1c (HbA1c) by approximately 0.5% to 0.6% (27). Numerous PCMH demonstration projects have been evaluated regarding cost, use, and quality metrics in diabetes care over the short term. Most have shown some reductions in cost, hospitalizations, and emergency department visits, although these may not be sustained and may not apply equally to those with type 1 diabetes and those with type 2 diabetes (28). PCMH demonstrations have also reported improvements in quality metrics such as HbA1c, low-density lipoprotein cholesterol, and blood pressure with improved patient and provider satisfaction; however, behavioral and psychosocial outcomes in these models are not well studied (29,30).

Although patients with low income and low education from racial/ethnic minority populations may benefit from the coordinated approach in a PCMH, many of these demonstrations have not targeted these groups. In a retrospective cohort study of 1,457 patients with diabetes receiving care in a PCMH academic practice, black patients were less likely to receive HbA1c testing, receive an influenza vaccination, or meet low-density lipoprotein cholesterol or blood pressure targets than non-Hispanic whites, after adjusting for other demographic, health, and socioeconomic factors (31). Black patients were also less likely to see their primary care provider during visits, less likely to see an endocrinologist, and more likely to be seen in the emergency department; however, there was no apparent difference in treatment intensity.

As part of the team-based approach that promotes patient self-management, community health workers (CHWs) are a key resource for connecting clinic to community, particularly in disadvantaged, underserved populations. CHWs are typically lay people from the community who are trained to serve as liaisons between patients and the health care community. They may work in teams with health care providers, provide group education in the community or clinical setting, or conduct home visits to follow up and address barriers to care. Regarding their role in diabetes care, interventions using nurse–CHW teams and CHWs trained as certified diabetes educators have been associated with mean HbA1c reductions of about 0.5% in numerous evaluations (32).

The Chronic Disease Self-Management Program (CDSMP) trains patients with chronic diseases as lay leaders in community settings to promote self-confidence in symptom control, decision-making, and patient–provider communication. A longitudinal study of the program among 1,170 participants demonstrated reductions in emergency department visits at 12 months and hospitalizations at 6 months as well as improved self-reported health, patient–physician communication, and medication compliance (33). Among patients with diabetes, results have been more variable. A trial with 196 participants recruited from 2009 through 2011 in a health care system in Texas found no significant differences between groups in HbA1c reduction over 12 months, although both groups saw HbA1c reductions from baseline of approximately 0.6% (34). This study also found no benefit to the CDSMP in diabetes self-care activities (34). However, in a separate analysis, patients in the CDSMP arm of this trial did have reduced odds of diabetes-related hospitalization or emergency department visits and longer times before hospitalization than the control arm (35). An uncontrolled longitudinal study of 114 patients found significant improvement in HbA1c at 6 months among patients with baseline HbA1c greater than 7% after participation in a CDSMP (36).

We highlight 2 successful interventions targeting underserved populations. These interventions seek to connect clinic to community.

## Project Sugar 2

Project Sugar 2, conducted in Baltimore, Maryland, randomized 542 African Americans in an urban managed-care organization during 2001 through 2003 to either biannual telephone counseling with a lay health educator and educational mailings or to an intensive intervention involving a nurse case manager and CHW visits. CHWs and case managers used clinical algorithms and intervention action plans, addressing topics ranging from nutrition and medication adherence to socioeconomic issues, to determine the frequency and intensity of follow-up and to maintain patient communication with health care providers. There was no significant difference in HbA1c between groups at 24 months after adjusting for age, baseline HbA1c level, and duration of follow-up. However, emergency department visits were significantly reduced in the intensive intervention arm by 23% at 24 months. At 24 and 36 months, those receiving the higher-intensity care (at least 2 visits from nurse case manager, or 4 visits from CHW, or both) saw the most benefit in reduction of emergency department visits (37).

## The South Side Diabetes Initiative

The South Side Diabetes Initiative in Chicago is an intervention, started in 2009, involving 6 health centers in a quality-improvement collaborative, patient activation, provider training, and community partnerships and outreach (38). The 6 health centers collectively serve just over 7,200 patients with diabetes annually. The quality-improvement collaborative shares best practices among health centers (eg, diabetes registries, case management, CHW interventions, and group medical visits). Patient activation tailors self-management education to literacy level and income restrictions. Providers are trained on cultural competency, behavioral counseling, and shared decision making. Finally, community outreach involves collaboration with local farmers markets, grocery stores, and food pantries to discount healthful food and provides education as well as medical home referrals. Although components have not been studied in aggregate, the quality-improvement collaborative enhanced perceived chronic care delivery, patient activation improved self-management behaviors and HbA1c levels, and provider training increased confidence in communication. Among 21 patients surveyed after receiving culturally tailored diabetes education and shared decision-making training, significant improvements were seen in self-reported dietary adherence, glucose monitoring, and foot care, and HbA1c declined from 8.24% at baseline to 7.33% at 3 months ($P = .02$) (39).

## Conclusion

Successful prevention and management of diabetes will require efforts that go beyond traditional clinical care, particularly in underserved and socially disadvantaged populations. There are evidence-based and promising strategies for intervening in early life, in the community, and at the nexus between the community and clinical settings. More research is needed to further establish the effectiveness of these approaches, particularly to determine the specific pathways through which clinical–community connections help to improve diabetes prevention and treatment outcomes. Identifying opportunities to intervene outside the examination room will be critical to effectively prevent and manage both obesity and diabetes. The Commission recommendations for health promotion offer a useful guide for areas to target. Policies are needed that support increased investments in 1) adequate nutrition through breastfeeding and other supports in early childhood, 2) community and economic development that includes health-promoting features of the physical, food, and social environments, and 3) evidence-based interventions that reach beyond the clinical setting to enlist community members in diabetes prevention and management.

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ORIGINAL RESEARCH

# Diabetes Topics Associated With Engagement on Twitter

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## Abstract

### Introduction

Social media are widely used by the general public and by public health and health care professionals. Emerging evidence suggests engagement with public health information on social media may influence health behavior. However, the volume of data accumulating daily on Twitter and other social media is a challenge for researchers with limited resources to further examine how social media influence health. To address this challenge, we used crowdsourcing to facilitate the examination of topics associated with engagement with diabetes information on Twitter.

### Methods

We took a random sample of 100 tweets that included the hashtag "#diabetes" from each day during a constructed week in May and June 2014. Crowdsourcing through Amazon's Mechanical Turk platform was used to classify tweets into 9 topic categories and their senders into 3 Twitter user categories. Descriptive statistics and Tweedie regression were used to identify tweet and Twitter user characteristics associated with 2 measures of engagement, "favoriting" and "retweeting."

### Results

Classification was reliable for tweet topics and Twitter user type. The most common tweet topics were medical and nonmedical resources for diabetes. Tweets that included information about diabetes-related health problems were positively and significantly associated with engagement. Tweets about diabetes prevalence, nonmedical resources for diabetes, and jokes or sarcasm about diabetes were significantly negatively associated with engagement.

### Conclusion

Crowdsourcing is a reliable, quick, and economical option for classifying tweets. Public health practitioners aiming to engage constituents around diabetes may want to focus on topics positively associated with engagement.

## Introduction

Diabetes is a major public health problem projected to reach rates as high as 1 in 3 adults in the United States by 2050 (1). Behavior changes, including adopting a healthy diet and increasing physical activity, can decrease the risk of type 2 diabetes and the severity of diabetes-related complications (2,3). There are many online sources for diabetes information, and recent research suggests that a significant proportion of people with diabetes seek health information online (2).

Social media have emerged as popular channels for health information-seeking and sharing; approximately 80% of US adult Internet users have searched online for health information (4,5). Social media are increasingly used by health care providers (5,6) and public health practitioners (7–9) to find and share health information, conduct surveillance, and manage emergency situations.

Social media are unique communication and dissemination tools with interaction, or audience engagement, being a central feature. Social media engagement has been defined as "establishing a connection with others to contribute to a common good" (10). Recent studies suggest public health social media interventions that include opportunities for engagement may have success in prompting small behavior changes (11,12). For example, an intervention linking pedometer use to Facebook encouraged competition among friends for increasing steps taken at work and resulted in a significant increase in steps compared with a control group (13). Engagement with messages sent on Twitter, or "tweets," is associated with characteristics of both the tweet itself and the sender of the tweet. Specifically, including a hashtag or link in a tweet increases engagement (14). In addition, Twitter user characteristics that include the number of followers, the number of followees (Twitter users being followed), and the age of a Twitter account are also associated with engagement (14). Features of tweets and their senders associated with engagement have been well-studied, but little has been done to identify tweet topics associated with engagement.

Twitter is one of the top 3 social media applications and is used by 19% of all adults and 23% of online adults in the United States (15). Duggan et al (15) found that Twitter was used by more men than women and by more young adults (18 y–49 y) than older adults (50 y–≥65 y). Twitter use rates are higher for non-Hispanic blacks and Hispanics than for non-Hispanic whites. Because diabetes rates are high for men and for Hispanic and non-Hispanic black Americans (1), Twitter may be useful in reaching several groups with high rates of diabetes.

Twitter is an application for "microblogging," or sending and receiving brief (140 characters or fewer), direct messages (ie, "tweets") (16). Twitter accounts can be followed by other Twitter users, allowing individuals or organizations to receive and share ("retweet") messages to their followers, reply to tweets, and mark tweets as a "favorite." As of October 2013, Twitter estimated that 500 million tweets are sent each day (17). The large volume of tweets presents a challenge for scientists with limited resources in collecting, managing, and analyzing this so-called big data.

Applications such as Amazon's Mechanical Turk allow the crowdsourcing of small online tasks, also known as Human Intelligence Tasks (HITs). Crowdsourcing is the use of large groups of people, often on the Internet, to do a specific task. HITs are tasks a computer is unable to perform alone; HITs are performed through the use of an open network of workers, also known as "turkers." A researcher can post HITs that include classification, transcribing, image tagging, and other tasks, which are then completed by turkers, who earn anywhere from half a cent to tens of dollars per HIT completed.

Turkers can work from anywhere in the world; a 2010 study found most turkers reside in the United States (47%) or India (34%). As of April 2014, the percentage of turkers in the United States was 51.5%, and 33% were in India (18). Within the United States, most turkers are male (57%) with a mean age of 32.7 years and are more educated than the general population (73% of the US public has completed at least some college compared with 88% of US turkers) (19). In India, 65% of turkers are male, the average age is 30.5 years, and 81% have a college education (19). Making money is the top motivation for using Mechanical Turk, ahead of other factors such as enjoyment and killing time (20). Evidence regarding the influence of compensation rates is conflicting; early work suggested that low compensation rates (on average $1.60/h) did not affect the quality of completed tasks. However, a recent study found that although compensation did not influence quality for US turkers, turkers from India produced higher quality data for higher compensation (20). Turkers have been used in health-related studies and can be useful in research given their low pricing and speed of service (21).

The widespread use of social media to find health information, including diabetes information, and the potential for social media engagement to influence health behavior presents an opportunity to better understand engagement with diabetes information online. However, the volume of Twitter data accumulating daily presents a challenge for social scientists with limitations on human and financial resources. To address the opportunity and challenge, we sought to 1) examine engagement with diabetes information on Twitter and 2) examine the Amazon Mechanical Turk as a new tool to aid public health researchers working with social media data.

# Methods

## Data collection and classification

As with traditional news sources, Twitter use varies by day of the week (22). To account for this variation, we used a constructed week sampling procedure (23). Specifically, we selected 1 week of randomly selected days (eg, 1 randomly selected Monday, 1 Tuesday) from May and June 2014. We downloaded all tweets that included the hashtag "#diabetes" from each selected day by using the twitteR software package from R (24). The twitteR package allows download of the tweet text and several associated characteristics: screen name of tweet sender, date and time tweet was sent, how many times the tweet was retweeted or favorited (designated a favorite by the reader), and whether the tweet was a "native retweet," which is a retweet sent by using the Twitter retweet function. We removed native retweets and selected a random sample of 100 tweets from each day. Numerous metrics to capture engagement have been proposed in past research (10,25); we selected 2: favoriting and retweeting. Favoriting is a low-level type of engagement demonstrating agreement with tweet content, whereas retweeting indicates a moderate level of engagement because the retweeter is sharing content with others (12,25).We also collected Twitter user descriptions for each user in the sample who sent a tweet by using the NodeXL Twitter list search function (26).

Three authors (J.K.H., A.M., S.M.R.) reviewed the tweets about diabetes and worked together to develop a classification scheme for each tweet and tweet sender. The classification scheme has 9 topic statements and 3 Twitter user types (Table 1). We entered the classification scheme into the Amazon Mechanical Turk requester system (https://requester.mturk.com/). The topics were entered as a list with checkboxes that allowed turkers to select all topics that applied to each tweet. Twitter user type was entered as a list with radio buttons allowing only 1 type of Twitter user to be selected. The Figure is an example of a HIT from the Saturday data as it would appear to a turker. A HIT included a single tweet for classification.

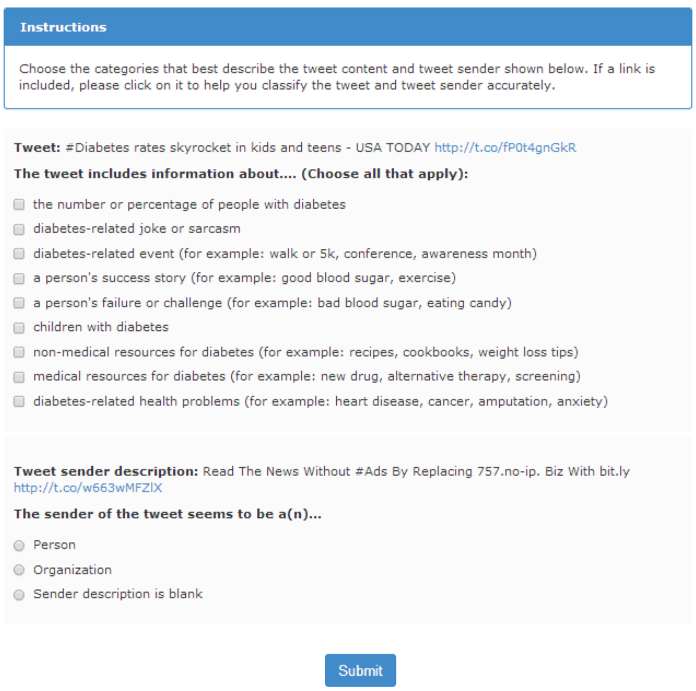


**Figure.** A screen capture of an example tweet and the description of the Twitter user who sent the tweet along with the instructions for classifying the tweet into topic and user categories. At the bottom is the submit button.

To ensure reliable classification, we followed Hipp et al (27) and requested that each HIT be completed by 4 different turkers. We limited eligibility to turkers who had completed 50 or more HITs with an approval rate of 95% or higher. The classification of 700 tweets 4 times each at $.07 per tweet resulted in a total cost of $196. Amazon charges a fee for use of the Mechanical Turk system. In this case, the settings we selected resulted in a 10% fee, or $19.60, costing a total of $215.60 to classify 700 tweets 4 times each.

## Data management and analysis

To examine reliability of the classification system we used a 1-way random model for absolute agreement (28) to calculate the intraclass correlation coefficient for each topic and user type. Once we determined that the topics and user types were classified reliably, any topic and user type classification selected by 2 or more turkers for a tweet was assigned to the tweet. Finally, although we had a large number of tweets from which to select our daily samples, 66 Twitter users appeared in the data more than once. We examined associations between the number of tweets a user contributed to the data set and the mean number of favorites and retweets per tweet and found no significant association. We also found no significant correlation between the number of tweets a user contributed and the proportion of a user's tweets in any topic category. In addition, the mean number of tweets in the data set did not differ by user type (ie, organization or individual). To ensure observations were independent, we selected one tweet at random from each of the Twitter users who contributed multiple tweets to the data set. The final sample size was 447 tweets from 447 Twitter users with unique screen names. The final set of tweets was classified by 192 turkers who each coded a median of 5 tweets each (range, 1–86). On average, it took a turker 3 minutes, 26 seconds, to code a single tweet.

We used descriptive statistics and Tweedie regression to examine tweet and Twitter user characteristics associated with engagement. The 2 indicators of engagement, number of favorites and number of retweets, are count variables. Poisson models are often used to model count variables; however, each tweet was favorited a mean of 0.74 times (variance, 52.23), and each tweet was retweeted 0.74 times (variance, 32.03). The magnitude of the variance in relation to the mean violates the Poisson regression assumption that the mean and variance are equal. Having a very large variance in relation to the mean indicates the data are overdispersed. In addition, these data included many zeros for both favoriting (n = 363) and retweeting (n = 367). Tweedie regression accounts for overdispersed count data with a large number of zeros.

We built the regression models in 2 steps. We started with reduced models that included only predictors shown in prior studies to be associated with engagement. Specifically, reduced models included presence of a link in the tweet, the number of followers of the tweet sender, the number of followees of the tweet sender, and the age of the sender's Twitter account. Although demonstrated as important to engagement, we did not include hashtags as a predictor because all tweets included the hashtag #diabetes as a result of the data collection process. To develop the full model, we then added topic and type of Twitter user to the reduced model.

We used the Aikake Information Criterion (AIC) to determine whether model fit improved from the reduced to the full model. A lower AIC indicates a better-fitting model. In addition, we examined leverage and Cook's D values to identify and assess outlying and influential values. Analyses were conducted using IBM SPSS version 22 (IBM Corp).

## Results

Tweets were sent by Twitter users with a median of 631.5 followers (range, 7–242,646), and following a median of 613.5 others (followees range, 0–76,742), with accounts open a mean of 1,132 days (standard deviation [SD], 645). The most common diabetes tweet topics were medical resources for diabetes (n = 130, 29.0%) and nonmedical resources for diabetes (n = 124, 27.7%). The least common tweet topic was children with diabetes (n = 24, 5.4%). Tweets about events were most likely to be favorited and retweeted. The percentage of tweets favorited had a small range across tweet topics. The least favorited topic, medical resources for diabetes, was favorited 17.7% of the time, whereas the most favorited topic, diabetes-related event, was favorited 28.3% of the time. The range was much wider for retweeting, ranging from retweets of just 6.8% of tweets about a person's failure or challenge and 5.2% of a diabetes-related joke or sarcasm to 43.4% of tweets regarding a diabetes-related event. Just over half the tweets were sent by a person (54.9%), 40.2% were sent by an organization, and 4.9% had a blank user description. Interrater reliability was good (0.60–0.74) for half the measures and excellent (0.75–1.00) for the other half. Table 1 shows frequency and reliability for topics,Twitter user type, and example tweets for each category.

There was 1 extreme outlying case for both outcomes and 1 additional outlier for the number of favorites model. The extreme case was an individual with the most followers (n = 262,646) of any of the Twitter users in the data but whose tweets were not favorited and were only retweeted once. The outlier for the favoriting model had the highest value for the number of favorites outcome. Because the 2 cases appeared legitimate, we retained them in the data set.

Reduced and full models were significantly better than null models at explaining the outcomes ($P < .001$). The full models had lower AIC statistics indicating they fit better than the reduced models (Table 2). Significant coefficients indicated that 2 tweet characteristics were positively and significantly associated with being favorited. First, consistent with past research, there was a positive association between a tweet being favorited and the tweet sender having more followers. Second, tweets including information about diabetes-related health problems were positively and significantly associated with being favorited. However, topics negatively and significantly associated with a tweet being favorited were number or percentage of people with diabetes and nonmedical resources for diabetes.

Likewise, there was a positive and significant relationship between having a large number of followers and retweeting. However, there were negative associations between retweeting and the topics of number or percentage of people with diabetes, diabetes-related joke or sarcasm, and nonmedical resources for diabetes. In addition, although the proportion of tweets retweeted and favorited was highest overall for tweets about events, once other tweet characteristics were accounted for, the event topic was not significantly associated with favoriting or retweeting. Finally, contrary to the results of prior studies, the full models indicated that number of followees, account age, and including a URL did not influence engagement (Table 2).

## Discussion

Through an examination of a sample of tweets about diabetes using crowdsourcing for data classification, we learned 2 things that may aid public health researchers and practitioners working with social media: 1) the Mechanical Turk may be a reliable, quick, and economical way for researchers to code large amounts of complex social media data; and 2) tweet topics may be associated with tweet engagement in public health. Consistent with Hipp et al (27), we found that tweet classification was reliable at the good or excellent level with 4 coders. The total cost associated with tweet classification was low, and the time required to code tweets was minimal, suggesting that crowdsourcing through Amazon's Mechanical Turk system may be a viable alternative for researchers with limited financial resources to classify large amounts of social media data quickly and reliably.

Research that examined tweet characteristics associated with engagement has primarily relied on methods from computer science including data mining and machine learning. These tools are useful in identifying patterns in social media data related to tweet topic, sentiment (such as sarcasm), and parts of speech. However, the tools have 2 limitations: 1) they require specialized skills not always the purview of social scientists and 2) machine learning algorithms have some limitations in the types of classification they can accurately handle, although methods are increasingly sophisticated and able to handle complex tasks. In contrast, the Mechanical Turk system requires minimal technical skill for use by researchers and provides access to a large population of people with the ability to reliably code many complex topics.

An analysis of tweets classified through Mechanical Turk identified several tweet topics associated with 2 forms of tweet engagement, retweeting and favoriting, which may be explained by tweet topic. Specifically, the topic "nonmedical resources for diabetes" had a negative significant relationship with both favoriting and retweeting. An examination of tweets classified as nonmedical resources indicated that some of these tweets may lack credibility or appear to be spam. For example, this tweet was not favorited or retweeted a single time despite the Twitter user sending the tweet having more than 20,000 followers: "*Learn a Little-Known But 100% Scientifically Proven Way To ERASE Your #Diabetes in 3 SHORT weeks #wellness #health* http://t.co/CbaarqLuPu."

In addition, retweeting and favoriting were significantly lower for tweets about the number or percentage of people with diabetes, whereas favoriting was higher for tweets about health problems associated with diabetes. This may indicate that Twitter users are engaging with health information specific to their personal health situation but not with general information. Finally, retweeting was significantly lower for tweets that included a diabetes-related joke or sarcasm.

Public health professionals working in diabetes and other areas may wish to consider how Twitter topics influence engagement. Tweet strategies often include guidance on features (eg, hashtags, URLs) to include in a tweet, tweet timing, and other nontopical strategies for increasing engagement. However, our results demonstrated that, controlling for tweet and tweet sender characteristics, tweet topic is influential in whether a tweet is favorited or retweeted.

Our study has several limitations, including the use of a hashtag for data collection. Tweets about diabetes may not contain #diabetes, so we may have missed some important tweets or patterns of relationships. An emerging body of work on hashtag use on Twitter (29) indicates some topics are more likely to be included with a hashtag than others, so use of a hashtag for data collection may have influenced the topics in the tweets we collected. The tweets were collected within 1 to 3 days of being sent. Because Wisemetrics reports that the half-life of tweets is 24 minutes (30), and others report the half life as between 5 minutes and 2.8 hours, it is unlikely the tweets would have accrued a large number of additional favorites or retweets over time. However we cannot rule out that additional favorites or retweets may have occurred given more time. Despite its limitations, our process and findings may be useful to public health researchers studying social media and to public health professionals and organizations that use social media as a way to communicate with constituents about diabetes and other topics.

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# Tables

**Table 1. Diabetes Topics Associated With Engagement on Twitter: Reliability, Frequency, and Examples of Tweets in Each Tweet Category**

| Topic and User Characteristic | Example Tweet | ICC (95% CI) | Total Tweets, n (%) | Tweets Favorited, n (%) | Tweets Retweeted, n (%) |
|---|---|---|---|---|---|
| **Topic** | | | | | |
| Number or percentage of people with diabetes | @CDCgov estimates that 1 in 3 US adults will have #diabetes by 2050. There's hope. | .82 (.80–.84) | 37 (8.3) | 7 (18.9) | 7 (18.9) |
| Diabetes-related joke or sarcasm | My crack dealer #wcw #littledebbie #diabetes @LittleDebbie | .82 (.80–.84) | 58 (12.9) | 16 (27.6) | 3 (5.2) |
| Diabetes-related event (for example: walk or 5k, conference, awareness month) | This goofy bunch raised over $2,500 to help find a cure for #diabetes. Way to go #TeamReasonRiders! #TourDeCureIndy | .82 (.80–.84) | 53 (11.8) | 15 (28.3) | 23 (43.4) |
| A person's success story (for example: good blood glucose, exercise) | Holy Crap!! My blood glucose hasn't been at my goal of 130 in years!! Woo go me:p #diabetes #diabetic | .62 (.57–.67) | 37 (8.3) | 9 (24.3) | 8 (21.6) |
| A person's failure or challenge (for example: bad blood glucose, eating candy) | That moment when u eat lunch then realize you forgot to bolus! DOH!! #diabetes #type1 #type2 #organic . . . | .67 (.63–.71) | 44 (9.8) | 9 (20.5) | 3 (6.8) |
| Children with diabetes | #Diabetes among kids is on the rise #GLV | .83 (.81–.85) | 24 (5.4) | 6 (25.0) | 4 (16.7) |
| Nonmedical resources for diabetes (eg, recipes, cookbooks, weight loss tips) | Everyone, especially those with #diabetes, need to avoid these 10 processed foods | .70 (.66–.74) | 124 (27.7) | 26 (21.0) | 18 (14.5) |
| Medical resources for diabetes (eg, new drug, alternative therapy, screening) | Gastric banding: new ammunition in the fight against type 2 diabetes | .72 (.68–.75) | 130 (29.0) | 23 (17.7) | 24 (18.5) |
| Diabetes-related health problems (eg, heart disease, cancer, amputation, anxiety) | Dr Lane on #diabetes complications: microalbuminuria is a marker for cardiovascular disease risk #APCU2014 | .66 (.61–.70) | 57 (12.7) | 11 (19.3) | 10 (17.5) |
| **Twitter user type** | Example user description | .84 (.81–.86) | NA | NA | NA |
| Person | Type1 Diabetic, organic enthusiast, stay-at-home dad, blogger | NA | 246 (54.9) | 54 (22.0) | 39 (15.9) |
| Organization | Therapeutics initiative: providing physicians and pharmacists with up-to-date, evidence-based, practical information on prescription drug therapy | NA | 180 (40.2) | 37 (20.6) | 43 (23.9) |
| Sender description is blank | | NA | 22 (4.9) | 3 (13.6) | 2 (9.1) |

Abbreviations: ICC, intraclass correlation coefficient; CI, confidence interval; #, Twitter hashtag; NA, not applicable.

**Table 2. Tweedie Model Results Predicting the Number of Favorites and Number of Retweets for 448 Tweets Including the Hashtag, "#Diabetes," Randomly Selected From May Through June 2014**

| Characteristic | Number of Favorites | | Number of Retweets | |
|---|---|---|---|---|
| | Reduced Model b (SE) | Full Model b (SE) | Reduced Model b (SE) | Full Model b (SE) |
| **Constant** | −.174 (.379) | −518 (0.588) | −.677 (.426) | −.003 (.590) |
| **Controls** | | | | |
| **Followers (100s)** | .002 (.001)[a] | .001 (.001)[b] | .002 (.001)[a] | .001 (.001)[a] |
| **Followees (100s)** | .003 (.002) | .001 (.003) | .001 (.002) | .001 (.002) |
| **Account age (100s of days)** | −.072 (.022)[a] | −.026 (.023) | −.049 (.023)[a] | −.019 (.025) |
| **URL included** | .382 (.379) | .466 (.358) | .771 (.380)[a] | .558 (.400) |
| **Twitter user type** | | | | |
| Organization | — | 1 [Reference] | — | 1 [Reference] |
| Person | — | .393 (.333) | — | .052 (.322) |
| No user description | — | −1.286 (1.043) | — | -.085 (.866) |
| **Tweet topic** | | | | |
| Prevalence | — | −1.344 (.672)[a] | — | −1.259 (.699)[b] |
| Sarcasm/joke | — | −.037 (.518) | — | −2.964 (.828)[a] |
| Event | — | −.454 (.556) | — | −.098 (.506) |
| Success | — | −.084 (.587) | — | −.416 (.636) |
| Failure | — | −.948 (.589) | — | −1.153 (.768) |
| Children | — | −.204 (.749) | — | −.864 (.819) |
| Nonmedical resources | — | −.839 (.433)[b] | — | −1.441 (.465)[a] |
| Medical resources | — | −.702 (.443) | — | −.576 (.453) |
| Health problems | — | 1.062 (.454)[a] | — | .388 (.483) |
| **Model significance[c]** | 31.76 ($P < .001$) | 64.56 ($P < .001$) | 25.37 ($P < .001$) | 55.38 ($P < .001$) |
| **Model fit (AIC)** | 853.49 | 842.70 | 812.16 | 804.15 |

Abbreviations: AIC, Aikake Information Criterion; SE, standard error; —, variable not included in the model.
[a] $P < .05$.
[b] $P < .10$.
[c] Significance calculated using $\chi^2$.

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SYSTEMATIC REVIEW

# Use of Culturally Focused Theoretical Frameworks for Adapting Diabetes Prevention Programs: A Qualitative Review

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PEER REVIEWED

## Abstract

### Introduction
Diabetes disproportionately affects underserved racial/ethnic groups in the United States. Diabetes prevention interventions positively influence health; however, further evaluation is necessary to determine what role culture plays in effective programming. We report on the status of research that examines cultural adaptations of diabetes prevention programs.

### Methods
We conducted database searches in March and April 2014. We included studies that were conducted in the United States and that focused on diabetes prevention among African Americans, American Indians/Alaska Natives, Asian Americans/Pacific Islanders, and Latinos.

### Results
A total of 58 studies were identified for review; 29 were excluded from evaluation. Few adaptations referenced or followed recommendations for cultural adaptation nor did they justify the content modifications by providing a rationale or evidence. Cultural elements unique to racial/ethnic populations were not assessed.

### Conclusion
Future cultural adaptations should use recommended processes to ensure that culture's role in diabetes prevention–related behavioral changes contributes to research.

## Introduction

Almost 29 million US adults have diabetes, and as many as 86 million have prediabetes (1). The high rate of diabetes among US minority populations is concerning because diabetes is a risk factor for cardiovascular disease, vision loss, end stage renal disease, disability, and mortality (2). From 2010 through 2012, African Americans (13.2%), American Indians/Alaska Natives (AI/ANs) (15.9%), Asian Americans and other Pacific Islanders (9.0%), and Latinos (12.8%) were more often diagnosed with diabetes than were non-Hispanic whites (7.6%) (1). Diabetes is preventable through lifestyle changes that may also assist in diabetes control.

The Institute of Medicine (IOM) examined the impact of social and cultural environments on health outcomes and recommends that research advance in this area (3). According to the IOM report, health behaviors and other social variables occur in a cultural context that must be understood to determine which cultural variables influence adoption of health recommendations.

There is evidence that interventions (eg, for cancer care, mental health, health education) that emphasize integration of cultural knowledge (ie, ideas, rules of etiquette, and knowledge needed in social life) improve outcomes among adults (4–6). Emerging data suggest similar effects in diabetes interventions (7). Although data on cultural adaptations for youths are equivocal (5) and concerns have been raised about the impact and consequences of constituency involvement in assessments of cultural appropriateness for public health interventions (8), further evaluation is warranted to determine the key factors affecting outcomes.

Castro et al (9) suggest that the aim of cultural adaptations should be “to generate a culturally equivalent version of a model prevention program” when elements in the original intervention produce resistance to program activities or are in conflict with cultural attitudes. Castro et al (5) identified steps to guide decisions to culturally adapt evidence-based interventions, which involves justification of the effort. Justification for adaptation may be based on previous failure to engage members of priority populations or the presence of unique cultural risk factors and symptoms, or both. Once justified, an evidence-based intervention is selected and cultural adaptations of content and delivery are completed (5).

Frameworks for cultural adaptations have emerged in 2 forms. One form involves modification within content categories (10–12), with early discussions emphasizing “surface” and “deep structures” of modification (11). “Surface structure” modifications involve inclusion of photos, symbols, and recruitment and outreach strategies (11). Resnicow et al refer to “deep structure” as recognizing, reinforcing, and building on a group’s values and behaviors to provide context and meaning to important intervention components (11). The framework proposed by Kreuter et al further specifies surface and deep cultural elements (10). Culturally sensitive programming requires changes to peripheral, evidential, linguistic, constituent-involving, and sociocultural categories (10). Peripheral approaches focus on colors, fonts, photographs, or declarative titles. Linguistic strategies assure that all intervention materials are in the preferred language of the group (12). Evidential approaches make use of testimonials, narratives, stories, and statistics specific to the group and raise awareness of perceived vulnerability to the health issue (10). Constituent-involving strategies include hiring or training group members or from the community or extensively engaging the community (10), which takes advantage of members’ insider knowledge about the community’s health perceptions and may increase acceptability and relevance (13). Sociocultural approaches discuss disease in the context of social or cultural characteristics (eg, including traditional foods and physical activities) (10).

The second form of cultural adaptation frameworks defines the steps of the intervention adaptation process (5,9,14) and offers the opportunity for a systematic process. The PEN-3 model completes cultural adaptions in 2 phases that support community input on the appropriate adaptation elements. The first phase, assessment, involves information gathering to learn about the community and its perspective (the resources that promote [ie, nurturers] or inhibit [ie, barriers] behavioral change and the roles that friends and family play in behavioral change). Once this information is gathered, the community and researchers use assessment data to critique current strategies and collaboratively develop culturally appropriate interventions (14).

Barrera et al (6) reviewed the past decade’s literature to identify elements that are common to cultural adaptations of behavioral health interventions relevant for diabetes interventions. The authors report 5 stages of cultural adaptation that are a refinement of earlier recommendations: information gathering, preliminary design, preliminary testing, refinement, and final trials (3,6). The review suggests that interventions involving the inclusion of cultural elements in an adaptation are more effective than control or usual care conditions (6). The authors recommended that studies evaluate cultural adaptations completed in these stages.

In this article, we examine the cultural adaptation of diabetes prevention programs and the extent to which the call for research advances in this area is being met. We also examine content and characteristics of cultural adaptations and the extent to which the recommended “how” and “what” of adaptation have been adopted. Recommendations for next steps are provided.

# Methods

The studies included in this review were compiled from a search of computerized databases conducted in March and April of 2014. The search performed was Academic Search Complete, and the following databases were selected: Academic Search Complete, CINAHL (*Cumulative Index to Nursing and Allied Health Literature)*, CINAHL Plus, Family and Society Studies Worldwide, Global Health, Global Health Archive, Medline, PsycINFO, and Social Work Abstracts. Research published from 2004 through 2014 was included to capture systematic research of cultural adaptations of diabetes prevention programs among ethnic minorities (3,6,10–12). Key words were used to search titles, abstracts, and subject headings in all databases. The Boolean search used key words, including “Diabetes Prevention Program” or “DPP” or “diabetes prevention” and “translation” or “translating” and “African American” or “African-American” or black or “American Indian” or “Native American” or “Latino” or “Latina” or “Hispanic” or “Asian” or “Asian American”; “Diabetes Prevention Program” or “DPP” or “diabetes prevention” and “translation” or “translating” and “sociocultural” or “cultural adaptation” or “sociocultural adaptation.” A supplemental search used the terms “PEN-3” and “deep culture” to identify additional articles.

Each study identified had to meet the following criteria for inclusion: 1) was a quantitative or qualitative research study completed in the United States; 2) had diabetes prevention as the primary focus, research question, or hypothesis of the study; 3) had diabetes education and interventions aimed at prevention activities, such as diet, exercise or physical activity, or health communication; and 4) included group-specific analyses on African Americans, AI/AN, Asian Americans/Pacific Islanders, or Latinos (although these priority populations did not have to be the only group studied). The reference lists of these articles were reviewed to identify other studies that met the inclusion criteria. Review articles, meta-analyses, dissertation abstracts, and articles in languages other than English were excluded from this evaluation. Journal articles reporting data from a single study were reported separately but evaluated as a single study.

Included studies were evaluated for 1) study population included; 2) diabetes prevention activity and program studied; 3) cultural adaptation process used; 4) formative research completed and analytic method (quantitative or qualitative) used; 5) cultural components and attributes (ie, peripheral, linguistic, evidential, sociocultural, constituent-involving) included to address values, attitudes, and behaviors; 6) inclusion of community strengths and resources in program or intervention; 7) channel or media selected or used in intervention; and 8) unique cultural elements assessed (eg, inclusion of spiritual factors, identity, rituals). Studies were coded by a graduate research assistant trained by the first author (V.L.S.). The first author then reviewed all studies and coding to resolve questions identified by the graduate research assistant or the author.

# Results

A total of 58 published manuscripts were initially identified; 29 were excluded from the evaluation. A total of 29 studies were included in the qualitative synthesis for this review (Figure).

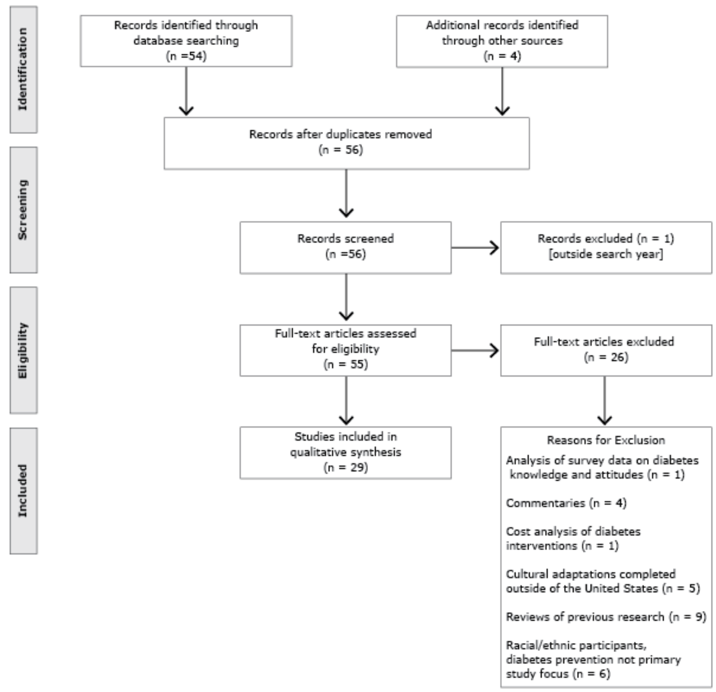


**Figure.** Number and reasons for article exclusion. Qualitative review of use of culturally focused theoretical frameworks for adaptations of diabetes prevention programs, United States, 2014.

Most studies addressed adaptation of diabetes prevention programs for Latinos (44.8%; Mexican, Puerto Rican, Dominican, and Caribbean) (15–27) and African Americans (31.0%) (28–36). Other adaptations were found for Asian Americans (2 studies: Korean, Filipino/Pacific Islanders) (37,38), AIs (4 studies: Northern Plains Indians, AI/ANs, urban southwest Indian) (39–42), and 1 study focused on a combined population (43) (Latinos/African Americans). One study focused on men (20), and 4 studies targeted women or involved mostly women (17,26,32,42) (Table 1).

The Diabetes Prevention Program (DPP) was the dominant evidence-based program subject to adaptation (84.6%). Of the 7 non-DPP adaptations, 1 was based on a program (Group Lifestyle Balance Program) (19) that was an earlier adaptation of DPP. DPP was adapted for each of the racial/ethnic categories.

Despite the availability of guidelines for completing the cultural adaptation process (3,6,9,14) and identifying potential areas for content modification (8,9), few studies referenced these approaches to cultural adaptation (15,16). The studies using cultural adaptation used Barrera et al (6), with a reference to Resnicow et al (11) and Airhihenbuwa's PEN-3 model (14). Eleven adaptations (17,20,22,23,26–28,36,37,39,43) used various other frameworks, with community-based participatory research (CBPR) most widely cited (24.1%) (Table 2).

Approximately 55.6% of studies conducted some form of information gathering or formative research in preparation for the cultural modification of an evidence-based program (15–17,23,24,28,31,36–43). Most studies collected qualitative data or used mixed methods. The primary data collection methods included focus groups for qualitative studies (n = 11) and surveys for quantitative studies (n = 4).

Four studies (25,32,34,36) focused only on surface adaptations of the intervention programs (10); an additional 7 combined surface and deep content modifications (15,21,26,37,38,40,42). Efforts included the use of community locations for meetings and organizations to assist in recruiting (21,26,34,36,38–40). Beyond churches (24.1%), the YMCA/YWCA (10.3%) was the most frequently identified community resource used in (primarily Latino) cultural adaptations. Five studies (17.2%) reported the use of racial/ethnic media for recruitment, dissemination of information, or education (21,28,31,37,38).

Of the studies completing adaptations of deep structure (n = 23), most (91.3%) used sociocultural adaptations (15,16,18–24,27–31,35–38,40,41,43), which included modifications of recipes, cooking and tasting demonstrations, recommendations for physical activity, leaders as role models and to deliver content, and the use of talking circles, storytelling, narratives, novellas, and soap opera video formats; this was followed by linguistic adaptations (61.5%), primarily for Spanish speakers (15,17–23,25,26,30,31,37,38,40,43). In all but 2 instances, language adaptations were combined with other changes. Modifications of evidential components occurred least often (19.2%) (28,36–38,40).

Approximately 52% of studies incorporated both nurturing elements of culture (promotes healthy behaviors) and cultural barriers (inhibits healthy behaviors) (15,16,18,20,22,24,28,31,35,37,39–43). Two studies (6.9%) focused solely on barriers (17,23), and 6 (20.7%) focused exclusively on nurturing elements (19,27,29,30,34,36). Nurturing elements focused on gaining support of elders and church leaders, prayer and spirituality, collectivism, and social support (14). Barriers focused on mistrust, privacy concerns, concerns about neighborhood safety and marginalization, and food traditions (14). No studies evaluated program components included as a part of a cultural modification.

Consistent with a recent review of DPP evaluations (44), 18 studies reported outcomes of cultural adaptation feasibility, pilot studies, and trials (13,18,19,22,23,25–27,29–33,37,38,40,41,43), with a primary outcome of weight loss. Seven studies from Latino communities reported weight loss (18,19,22,23,25–27) and improvement in hemoglobin A1c (23) and insulin sensitivity (27). The results of a family focused adaptation were mixed; weight loss and increased physical activity was reported among parents but not among youths (18). The church-based adaptation for Latinos and African Americans (43), 5 studies focused on African Americans (13,29–32), 2 on Asian Americans (37,38), and 1 AI/AN trial (41) reported similar weight loss findings. Two African American (29,30) and 1 Asian American study reported decreased blood glucose levels (37). Among African American studies, a family focused study (31) reported mixed findings, with changes among youths but not parents, and a youth intervention (33) resulted in changes in fat intake among boys but not girls. One AI study reporting a 3-month follow-up (40) failed to produce changes in body mass index.

# Discussion

This analysis suggests an increasing number of diabetes prevention cultural adaptations across racial/ethnic populations, reporting positive outcomes, primarily weight loss. The lack of comparisons to evidence-based interventions (no control or reliance on usual care controls) made it difficult to ascertain superior cultural adaptations. However, study data combined with the results of a recent diabetes treatment cultural adaptation (7) support the importance of continued research.

Few studies referenced recommendations for cultural adaptation processes or content. Given the recent emergence of some process recommendations, this is understandable (5,6); however, the PEN3 model (14) and content recommendations are older (10,11). Although the use of CBPR and various theoretical frameworks resulted in community input into cultural adaptations, a culturally focused approach may increase understanding of how specific cultural health beliefs vary across multiple populations and subpopulations (8) and aid in identification of key mechanisms for change (7).

Also of concern was the limited documentation of the rationale for modifications, as illustrated by Osuna et al (15) and the fact that only 52% of studies involved information gathering or a formative research phase to support the cultural modifications made to the original evidence-based diabetes prevention program. These data may have been reported as subpopulation research studies and may have been missed in our search, or authors omitted this information from study reports. However, a deliberative process should occur to avoid modifications informed by stereotypical or monolithic views of racial/ethnic communities. For example, it should not be assumed that all members of a Latino community speak Spanish as their primary language. Issues related to socioeconomics, religion, and sexual orientation should also be included.

That studies varied in their use of peripheral, linguistic, evidential, sociocultural and constituent-involving strategies is not surprising. As Osuna et al note (15), cultural adaptations should be restricted to issues and elements dictated by current research evidence and data emerging from the information-gathering phase. Although the types of modifications reported in studies seemed effective, the failure to measure participants' responses to cultural elements is a lost opportunity to understand program acceptance and behavioral change.

Future diabetes prevention cultural adaptations should use recommended processes for cultural adaptation, including justification for the adaptation, the processes of formative research and information gathering and modification, modifications in response to data, reports of refinements based on preliminary studies, and the results of final testing (6). Detailed reporting of adaptations helps researchers develop information on common cultural program modifications and makes replication of the adapted intervention easier (45). To build evidence that diabetes prevention interventions that focus on integration of culture positively influence outcomes, studies should compare cultural adaptations to the original evidence-based intervention. Researchers should also evaluate unique cultural elements included in adaptations to determine their utility. Racial/ethnic groups are not monolithic and the cultural issues that affect their responses to health programs should be examined, with the process recommended by Castro et al (5) guiding efforts.

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# Tables

**Table 1. Summary of Diabetes Prevention Program Cultural Adaptations, by Race/Ethnicity, United States, 2014[a]**

| Characteristic | Latino (n = 13) | African American (n = 10) | American Indian/ Alaska Native (n = 4) | Asian American (n = 2) |
|---|---|---|---|---|
| **Demographic** | | | | |
| Female only | 2 | 1 | 1 | 0 |
| Male only | 1 | 0 | 0 | 0 |
| Youth | 1 | 2 | 3 | 0 |
| **Program modified** | | | | |
| Diabetes Prevention Program | 8 | 6 | 4 | 2 |
| Other | 3 | 3 | 0 | 0 |
| **Cultural adaptation** | 13 | 9 | 4 | 2 |
| **Adaptation uses theory[b]** | | | | |
| Cultural | 2 | 0 | 0 | 0 |
| Other theory | 7 | 3 | 1 | 2 |
| **Study type** | | | | |
| Formative only | 4 (mean, 46.3 [range, 16–100]) | 1 (N = 25) | 1 (N = 31) | 1 (N = 127) |
| Pilot/feasibility | 5 (mean, 31.4 [range, 12–91]) | 5 (mean, 32.8 [range, 8–62]) | 1 (N = 64) | 1 (N = 48) |
| Trial | 3 (mean, 175 [range, 69–312]) | 1 (N = 604) | 1 (N = 2,553) | 0 |
| | Latino/African American, 1 (n = 183) | | | |
| **Level of adaptation[c]** | | | | |
| Surface | 4 | 3 | 2 | 2 |
| Deep | 13 | 6 | 3 | 2 |
| **Outcome** | | | | |
| Weight (eg, loss, BMI) | 7 | 5 | 1 | 2 |
| A1c, glucose, insulin sensitivity | 2 | 2 | 0 | 1 |
| Physical activity | 4 | 3 | 1 | 1 |

Abbreviations: A1c, hemoglobin A1c; BMI, body mass index.
[a] Values are whole numbers unless otherwise indicated. Values in columns may not sum to total or may exceed total value for n, because studies could adapt to accommodate more than 1 attribute or could report more than 1 outcome.
[b] Theory-driven cultural adaptation process: C, cultural (PEN-3, Castro et al, 2010 [5]); OT, other theory/model (eg, community-based participatory research, social-cognitive theory, grounded theory).
[c] Level of adaptation adapted from Resnicow et al (11).

Table 2. Detailed Summary of Diabetes Prevention Programs Evaluated for Cultural Adaptations, United States, 2014

| Author | Population | Program Modified | Cultural Adaptation | Adaptation Process | Formative Studies | Content Category[a] | Nurturer/ Barriers[b] | Community Resources |
|---|---|---|---|---|---|---|---|---|
| Atkinson et al, 2009 (28) | African American | Church-based DPP | Yes | Grounded theory | Yes | E, S, C | N, B | Church |
| Boltri et al, 2011 (30) | African American | Group lifestyle DPP | Yes | — | No | S | N | Church |
| Boltri et al, 2008 (31) | African American | DPP | Yes | — | No | L, S | N | Church |
| Brown et al, 2010 (39) | Northern Plains, AI youth | DPP | Yes | CBPR | Yes | See below | N,B | Montana reservation |
| Brown et al, 2013 (40) | Northern Plains, AI youth | DPP | Yes | — | See Brown et al, 2010 | P, L, E, S, C | N,B | Montana reservation |
| Burnet et al, 2011 (29) | African American (9-12 yrs) | Reach out | Yes | — | Yes | L, S | N, B | — |
| Chasan-Taber et al, 2014 (17) | Latina (pregnant) | Lifestyle intervention | Yes | Socio-cognitive/ TTM | Yes | L | B | — |
| Coleman et al, 2010 (18) | Latino Family | DPP | Yes | — | No | L, S | N, B | School |
| Cox et al, 2013 (32) | African American, women | DPP | Yes | — | No | C | — | — |
| Gutierrez et al, 2014 (43) | African American, Latino | DPP | Yes | CBPR | Yes | L, S | N, B | Church |
| Islam et al, 2013 (37) | Korean American | DPP | Yes | CBPR | Yes | P, E, L, S | N, B | — |
| Jiang et al, 2013 (41) | AI/AN youth | DPP | Yes | — | Yes | S | N, B | — |
| Kramer et al, 2013 (19) | Hispanic | GLB (DPP adaptation) | Yes | — | No | L, S | N | WIC |
| Mau et al, 2010 (38) | Filipino, Pacific Islander | DPP | Yes | CBPR | Yes | P,E, L, S,C | — | Gurdwara sites |
| Martinez et al, 2012 (20) | Male Mexican Immigrant | Formative | Yes | Socio-Ecological Model | Yes | L, S | N, B | — |
| Melancon et al, 2009 (16) | Mexican American and Mexican Native | Formative | Yes | PEN-3 | Yes | S, C | N, B | — |
| Merriam et | Latino | DPP | Yes | — | No | P, L, S | — | YWCA |

Abbreviations: —, information unavailable or ambiguous; AI, American Indian; AN, Alaska Native; CBPR, community-based participatory research; DPP, Diabetes Prevention Program; NDEP, National Diabetes Education Program.
[a] Content categories: P, peripheral; L, linguistic; E, evidential; S, sociocultural; C, constituent involving.
[b] N, nurturers; B, barriers. Adapted from Airhihenbuwa (14).

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Table 2. Detailed Summary of Diabetes Prevention Programs Evaluated for Cultural Adaptations, United States, 2014

| Author | Population | Program Modified | Cultural Adaptation | Adaptation Process | Formative Studies | Content Category[a] | Nurturer/ Barriers[b] | Community Resources |
|---|---|---|---|---|---|---|---|---|
| al, 2009 (see Ockene) (21) | (Caribbean) | | | | | | | |
| Millard et al, 2011 (22) | Immigrant Hispanic | Diabetes Empowerment Education Program | Yes | CBPR, TTM, Socio-Ecological Model | No | L, S, C | N, B | — |
| Ockene, et al, 2012 (23) | Dominican/Puerto Rican Spanish speakers | DPP | Yes | Socio-cognitive theory | Yes | L, S | B | YWCA |
| Osuna et al, 2011 (15) | Latino/a | Mediterranean Lifestyle Program | Yes | Castro et al, 2010 | Yes | P, L, S | N, B | — |
| Ramal et al, 2012 (24) | Latino/a, low-income | Formative | Yes | — | Yes | S | N, B | — |
| Ruggiero et al, 2007 (25) | Latino/a, | DPP | Yes | — | No | L, C | — | — |
| Ruggiero et al, 2011 (26) | Spanish speaking | DPP | Yes | CBPR | No | L, C | — | Community settings |
| Shaibi et al, 2012 (27) | Latino, adolescents | DPP | Yes | CBPR | No | S, C | N | YMCA |
| Sharma and Fleming, 2012 (33) | African American, youth | — | No | — | — | — | — | Community-based |
| Tang et al, 2014 (34) | African American | NDEP "Power to Prevent" | Yes | — | No | C | N | Church |
| Wells, 2011 (35) | African American | DPP | Yes | — | — | S | N,B | Church |
| Willging et al, 2006 (42) | American Indian, women, urban Southwest | DPP | Yes | — | Yes | P, S, C | N, B | — |
| Williams et al, 2013 (36) | African American | Fit Body and Soul | Yes | Socio-ecological | Yes | P, E, C | N | Church |

Abbreviations: —, information unavailable or ambiguous; AI, American Indian; AN, Alaska Native; CBPR, community-based participatory research; DPP, Diabetes Prevention Program; NDEP, National Diabetes Education Program.
[a] Content categories: P, peripheral; L, linguistic; E, evidential; S, sociocultural; C, constituent involving.
[b] N, nurturers; B, barriers. Adapted from Airhihenbuwa (14).