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Behavioral and Mental Health Risk Factor Profiles among Diverse Primary Care Patients

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Abstract

Behavioral and mental health risk factors are prevalent among primary care patients and contribute substantially to premature morbidity and mortality and increased health care utilization and costs. Although prior studies have found most adults screen positive for multiple risk factors, limited research has attempted to identify factors that most commonly co-occur, which may guide future interventions. The purpose of this study was to identify subgroups of primary care patients with co-occurring risk factors and to examine sociodemographic characteristics associated with these subgroups. We assessed 12 behavioral health risk factors in a sample of adults (n = 1628) receiving care from nine primary care practices across six U.S. states in 2013. Using latent class analysis, we identified four distinct patient subgroups: a 'Mental Health Risk' class (prevalence = 14%; low physical activity, high stress, depressive symptoms, anxiety, and sleepiness), a 'Substance Use Risk' class (29%; highest tobacco, drug, alcohol use), a 'Dietary Risk' class (29%; high BMI, poor diet), and a 'Lower Risk' class (27%). Compared to the Lower Risk class, patients in the Mental Health Risk class were younger and less likely to be Latino/Hispanic, married, college educated, or employed. Patients in the Substance Use class tended to be younger, male, African American, unmarried, and less educated. African Americans were over 7 times more likely to be in the Dietary Risk versus Lower Risk class (OR 7.7, 95% CI 4.0–14.8). Given the heavy burden of behavioral health issues in primary care, efficiently addressing co-occurring risk factors in this setting is critical.

Keywords

behavioral health; multiple risk factors; primary care; latent class analysis

Introduction

Poor health behaviors, in particular tobacco use, poor diet, and physical inactivity, are major causes of morbidity and mortality.[1,2] Alcohol misuse, drug use, sleep disorders, depression, and stress also significantly contribute to poor health and are associated with high health care utilization and health care costs.[3] These health risks have been shown to co-occur, [4–6] potentially acting synergistically, resulting in greater negative health consequences including higher chronic disease incidence and severity.[7–9] Thus, research is needed to understand the interrelationship between risk factors.

Primary care represents a key setting for addressing unhealthy behaviors and mental health risk factors, but methods for routinely assessing these factors are underdeveloped. The majority of the adult population in the U.S. has received primary care services in the past year, and prior research has demonstrated that primary care providers can play a critical role in addressing behavioral issues.[10] Nevertheless, few practices systematically assess health risks. Among practices that do, most do not comprehensively assess these risks.[11] Instead, many routinely assess only isolated risk factors (e.g., tobacco) or assess risks only in subpopulations (e.g., diabetics). Additionally, assessments are often not pragmatic, yielding results that are not actionable.[12]

Further, many existing interventions focus solely on one health risk. However, interventions targeting multiple behavioral health risks have been increasingly recognized as integral to efforts to improve population health.[5,6,11,13] Emerging evidence suggests interventions may be as effective when they address co-occurring behavioral health risk factors as when addressing single risk factors.[14–16] A number of multiple risk factor interventions have addressed secondary prevention among patients with existing disease, but few have focused on primary prevention.[11,13] In primary care, addressing each risk factor separately may not be as practical or efficient as multiple risk factor interventions given time and resource constraints. Gaining a better understanding of the types of patients who typically present with co-occurring behavioral risk factors and identifying which risk factors tend to cluster is important for the development of interventions targeting multiple behavioral health needs.

The purpose of this study is to identify subgroups of primary care patients with co-occurring behavioral health risk factors, to ascertain sociodemographic characteristics associated with these subgroups, and to explore clustering of patient subgroups by clinic type. We anticipated that study results could be used to guide population-level interventions addressing commonly co-occurring risk factors. The study sample comprised adults receiving care from nine primary care practices that participated in the My Own Health Report (MOHR) project, funded by the National Cancer Institute (NCI) and the Agency for Healthcare Research and Quality (AHRQ).[17–19] While several studies have examined the co-occurrence of health risk factors in primary care, [20–22] these studies assessed a limited number of domains. The present study assessed a wider range of health domains. Furthermore, the study sample, which includes patients recruited from urban, rural, suburban, and safety net clinics across the country, is more diverse than prior studies.

Methods

Study Design and Setting

A detailed description of the MOHR study has been previously published.[17–19,23] The study was a pragmatic cluster randomized trial to evaluate the effect of the MOHR feedback system on goal setting in nine primary care practices including five AHRQ-funded Practice

Based Research Network and four Federally Qualified Health Centers sites. The MOHR assessment was administered to patients electronically to patients presenting for chronic disease management and wellness visits as part of routine care and data were used to generate individualized feedback reports for patients and providers. The assessment was completed by 1,707 patients between March and December of 2013.[18] We excluded 79 patients (<5%) due to missing data on sociodemographics, resulting in a final analytic sample of 1,628. The study was approved by the Institutional Review Boards of participating sites.

Measures

The MOHR assessment consisted of 20 items measuring 13 domains. Items were selected through a national consensus building process.[12] Respondents were considered to have scored "positive" for a domain/risk factor based on the following thresholds: *Overweight/Obese*: self-reported height and weight corresponding to a BMI value > 25 kg/m^2; *Inadequate physical activity*: < 150 minutes of physical activity per week; *Inadequate fruit and vegetable consumption*: < 5 servings of fruits and vegetables per day; *Excessive fast food consumption*: 1 or more times per week; *Excessive sugar-sweetened beverage consumption*: 1 or more times per day; *Sleep disturbance*: "sometimes/often/always" experiencing daytime sleepiness; *Tobacco use*: use of tobacco or smokeless tobacco in the past 30 days; *Excessive alcohol intake*: 1 or more binge episodes in the past year (≥4 drinks/day for women, ≥5 drinks/day for men); *Illicit drug use/inappropriate prescription use*: 1 or more times in the past year; *Anxiety:* score of 4 or more on two PHQ items; *Depression*: score of 4 or more on two PHQ items; *Stress*: stress level of > 5 out of 10 in the past week.[18] These definitions resulted in binary indicator variables for 12 factors. Nine sociodemographic characteristics were assessed: gender, age, race, ethnicity, English proficiency, employment status, marital status, nativity, and education. A one-item measure of perceived health was omitted from the present analysis.

Statistical Analysis

We conducted latent class analysis (LCA) using the LCA procedure in SAS 9.4 (SAS Institute, Cary, NC).[24] LCA is a statistical method used to identify subgroups of individuals in a population who share important characteristics or behaviors, as indicated by their responses to a set of observed categorical variables.[25] The subgroups are unobserved and are therefore considered latent classes. For our analyses, the observed variables characterizing the latent classes included the 12 behavioral and mental health risk factor indicators. LCA differs from cluster analysis in that it fits a statistical model to the data rather than finding clusters based on an arbitrary distance measure. Because LCA is based on a statistical model, model selection and goodness of fit procedures are available, and the model can be extended to include covariates to predict individuals' latent class membership.[26]

To fit a LCA model, one specifies the number of latent classes, k. Then, using maximum likelihood, the procedure finds the best k-class solution and estimates the response probability on each indicator for each class, and the probability that each individual in the sample belongs to each class. Typically, models specifying an increasing number of latent classes (e.g., k = 2, 3, 4, 5) are fit and compared with the goal of identifying the best k.

Selection of the number of latent classes is made by taking into account both model fit and interpretability. Following recommendations for LCA models,[27,28] we used the Bayesian Information Criterion (BIC) and adjusted BIC to compare models with different k on model fit, where lower values indicate a better fit. For model interpretability, we were guided by the following considerations: each class should be distinguishable from the others based on the item response probabilities, no class should be trivial in size, and it should be possible to give each class a meaningful label.[24]

After identifying the best k, we assessed whether model fit could be improved by allowing different class solutions by sex and/or racial/ethnic groups and confirmed that this modification was unnecessary. We then assigned each individual to a latent class based on their class of highest posterior probability and tabulated the frequencies of the 12 health risk behaviors within each class.

Next, we extended the model to include demographic covariates to predict class membership. This extension, also performed using the LCA procedure, involved fitting a multinomial logistic regression model in which the multinomial outcome variable was latent class membership. These analyses resulted in odds ratios for membership in one class compared to a reference class based on covariates. We also tabulated demographic characteristics by latent class.

Results

Comparing Class Solutions

Table 1 displays model fit indices for LCA models specifying 2, 3, 4 or 5 latent classes. BIC favored the three-class solution while adjusted BIC favored the four-class solution. In terms of interpretability, the three-class solution had a normative class, a dietary risk class, and a class for mental health and substance abuse risk. The four-class solution separated the last class into two more clearly delineated classes. By comparison, the five-class solution resulted in worse fit indices and was less interpretable. Consequently, the four-class solution was selected. Using posterior probabilities of class membership, individuals were then assigned to one of the four latent classes.

Four Latent Class Model

Table 2 and Figure 1 present the proportion of the sample assigned to each of the four classes and the prevalence of the 12 risk factors within each class. Class 1 had the highest rates of stress, anxiety, and worry of the four clusters and was consequently labeled “Mental Health Risk.” This class comprised 14% of the sample. Class 1 also had the highest rates of physical inactivity and daytime sleepiness among all classes. Class 2 had the highest rates of tobacco use, binge drinking, and drug use and was subsequently labeled the “Substance Use Risk” class. This group, which comprised 29% of the sample, also had high rates of inadequate fruit/vegetable intake and sugar sweetened beverage intake. Class 3, which also encompassed 29% of the sample had the highest rates of overweight/obese BMI, fast food intake, sugary beverage intake, and nearly the highest rate of inadequate fruit and vegetable intake and was therefore labeled the “Dietary Risk” class. This group also had among the lowest rates of anxiety, depression, tobacco, binge drinking, and drug use, which is underscored by Figure 1. Class 4 had the lowest rates of 8 of the 12 risk factors and did not have the highest rate of any risk factor, as illustrated in Figure 1, and was given the label of "Lower Risk." This class comprised 27% of the sample. Close to three-quarters of Lower Risk class patients were overweight/obese. However, consumption of fast food and sugar-sweetened beverages was relatively infrequent, and tobacco and drug use was non-existent in this group.

Relationship between Demographic Characteristics and Class Membership

Table 3 shows the sociodemographic characteristics of each class. Table 4 displays the results from the multinomial logistic regression model predicting class membership based on sociodemographic characteristics. The odds ratios in Table 4 compare the Lower Risk class (Class 4) to all other classes. Compared to individuals in the Lower Risk class, patients in the Mental Health Risk class were significantly less likely to be older (≥ 65 years), Latino/Hispanic, married, college educated, or employed full time. Patients in the Substance Use Risk class had over 2 times greater odds of being male (OR 2.8, 95% CI: 1.9, 4.2), African American (OR 2.3, 95% CI: 1.2, 4.3), and speaking English well (OR 2.7, 95% CI: 1.4, 5.2). They were also more likely to be younger and less likely to be Latino/Hispanic, married, or college-educated compared to the Lower Risk class. Patients in the Dietary Risk class had 7.7 times greater odds of being African American (95% CI: 4.0, 14.8) and were less likely to be married (OR 0.6, 95% CI: 0.4, 0.9) or have a college education (OR 0.3, 95% CI: 0.2, 0.5) compared to the Lower Risk class.

Clinic Characteristics by Class Membership

The multinomial logistic regression model including clinic as a predictor was significant ($p<0.001$), indicating that the proportions of patients in each class varied by clinic. We examined class distribution by clinic location (urban, n = 3; suburban, n = 1; rural, n = 5) and type (FQHC, n = 6; non-FQHC, n = 3). The suburban clinic had a larger Lower Risk class (67% of sample), relative to urban (27% of sample) and rural clinics (22% of sample). The Dietary Risk class was larger in the FQHC clinics (36%) compared to non-FQHC clinics (16%). The Lower Risk class was larger in non-FQHC clinics (37%) compared to FQHC clinics (23%). We attempted to fit a multivariable model to examine the effect of clinic characteristics on class membership after controlling for individual sociodemographics. However, the model would not converge due to high collinearity between patient and clinic characteristics. For example, 93% of Latino/Hispanic patients were from three of the nine clinics. Thus, it was not possible to determine whether the variation in class size by clinic was due to clinic-level practices or sociodemographic differences in clinic populations.

Discussion

The LCA identified four meaningful latent subgroups of patients, each with distinct clusters of behavioral risks. No class represented more than 30% of the sample. By contrast, two prior studies that conducted LCA to examine the co-occurrence of behavioral risk factors identified solutions where classes represented substantially larger proportions. One study conducted among primary care patients in the VA study identified only three classes and found that 89% could be classified into a “healthier” class.[20] Another conducted with National Epidemiologic Survey of Alcohol and Related Conditions (NESARC) data identified five classes and found 50% of the sample belonged to the “inactive, non-substance abuser” class.[22] The results of these prior studies may differ from ours due to their assessment of fewer behavioral risk factor domains or their relatively more homogenous populations.

We found a low proportion of primary care patients fit into the lower risk class, which is consistent with prior descriptive research from the MOHR study.[18] Prior analyses of MOHR data found that patients on average screened positive for six risk factors. Even though the group labeled “Lower Risk” given they had the lowest prevalence for most risk factors compared to the other three classes, it is important use caution when interpreting this group. No members used tobacco or drugs and few consumed sugar-sweetened beverages, consistent with healthy behavior. However, most “lower risk” patents were still overweight/obese, consumed inadequate servings of fruits and vegetables per day, and reported low physical activity levels, likely putting them at elevated risk for metabolic syndrome and chronic disease. These findings confirm the importance of population-wide efforts to support healthier eating, increased physical activity, and weight management, given the ubiquity of these issues in the population.

The Dietary Risk and Substance Use risk classes were the largest, each accounting for 29% of the sample. The size of the Dietary Risk class is not surprising; substantial prior research has documented the high prevalence of obesity and poor dietary and physical activity levels among primary care populations in the U.S.[29–31] Although the link between overweight/obesity and negative health consequences is well documented,[32] given the potential for misclassification,[33] the value of BMI in predicting risk for chronic disease is enhanced when considered in combination with other measures such as blood pressure, triglycerides, and insulin resistance, when available. Perhaps more surprising was the equivalent size of the Substance Use Risk and Dietary Risk classes, despite relatively lower prevalence of substance abuse risk factors in the general population.[34] The inclusion of prescription drug misuse as well as illicit drug use in our “substance use” measure may have contributed to this finding. Among patients in the Substance Use Risk class, tobacco was the most common risk factor, followed by binge drinking and drug use. It should be noted that reported illicit drug use/prescription drug misuse was relatively low in our sample compared to rates observed in other primary care samples.[35,36] Although at present addressing tobacco use is strongly emphasized in primary care, binge drinking and illicit drug use are infrequently addressed in this setting.[37] Co-occurrence of these risk factors in our primary care sample suggests a bundled intervention approach may be warranted. This type of approach may be more feasible if clinics’ existing infrastructure for tobacco control can be leveraged to address binge drinking and drug use. Despite well-documented associations between mental health conditions and substance use,[38] few patients in the substance use class screened positive for anxiety or depressive symptoms. This could suggest underreporting of mental health symptoms in this group or that the substance use class is currently experiencing less anxiety and depressive symptoms, potentially due to self-medicating.[39,40]

The Mental Health Risk class was the smallest, accounting for 14% of the sample. In addition to high rates of the risk factors that earned it the label of "Mental Health Risk" (e.g., stress, anxiety, depression), this class also showed the highest rates of sleeplessness and inadequate physical activity, plus very low levels of fruit and vegetable intake. Prior research has found that interventions aimed at promoting physical activity may be effective in reducing depressive symptoms.[41,42] Studies have also documented the importance of addressing sleep disorders simultaneously with depression and anxiety. Our findings further underscore the potential value of goal-setting for physical activity and sleep habits with primary care patients who are experiencing depression, stress, or anxiety.

Examples of prior multiple risk factor interventions include those that simultaneously target nutrition and physical inactivity, smoking cessation and weight gain, and various, multiple substance abuse behaviors.[11,13,43,44] Such interventions have often targeted populations with specific chronic conditions such as cardiovascular disease,[11,13,45] diabetes,[11] and cancer.[13,46–48] Although more research is needed, there is some evidence to support that implementing interventions that simultaneously address multiple risk factors may be as or more effective than interventions targeting single risk factors or behaviors.[14,15,49,50] Our results underscore the potential value of bundled approaches and provide guidance for the direction such interventions. Adaptive interventions applying the Multiphase Optimization Strategy (MOST) or Sequential Multiple Assignment Randomized Trial (SMART) designs emphasize tailoring intervention types, intensity, and sequence at multiple stages based on individual progress, which offers a promising approach to increasing efficiency and effectiveness of interventions.[51] For example, Strecher and colleagues (2008) evaluated the effect of a web-based smoking cessation program that used a MOST design to compare the results of varying five intervention aspects. Study results revealed that a higher level of tailoring for two aspects resulted in greater tobacco abstinence at 6-month follow-up compared to less tailoring.[52] "SMART" electronic health record-based interventions may present opportunities for providers to monitor patient progress over time (e.g., blood pressure, BMI, etc.) and develop customized treatment plans designed to give a patient the right type and dose of an intervention at the right time.

Examining the relationship between demographics and class membership may be useful when choosing among intervention strategies. The Mental Health Risk class tended to be younger, less ethnically-diverse, unmarried, and less educated compared to other classes. However, these associations may be reflective of demographic differences in who is willing to report symptoms of mental illness, rather than the prevalence of those symptoms. Prior research has found greater mental health-related stigma among ethnic minorities compared to whites.[53,54] The Dietary Risk class included a substantially greater proportion of African Americans, unmarried patients, and less educated patients compared to patients in the Lower Risk class. The Substance Use class tended to be younger, male, African American, and were less likely to be married or have a college education compared to the Lower Risk class. Prior research has observed higher rates of tobacco use, binge drinking, and illicit drug use among younger males with low levels of education, compared to other segments of the population, which is consistent with our findings.[55–57] It should be noted that our substance use results may not reflect the growing opioid epidemic among non-Latino whites, given few participating clinic sites were located in high burden areas.[58]

The study has limitations. We are only able to classify people based on risk factors measured. Sun exposure, non-aerobic physical activity, and more nuanced aspects of diet, although relevant were not measured. The MOHR assessment relied on self-report, which could lead to under-reporting, particularly for sensitive behaviors. The tool was designed to screen for risk factors, not to estimate the proportion of patients with diagnosable mental health or substance use conditions. Although we sought to engage a diverse set of primary care clinics, we did not intend to recruit a nationally representative sample, which limits generalizability of findings. Nevertheless, strengths of the study include a large and diverse sample, assessment of a wider variety of domains than prior studies, and use of LCA methods.[20–22,59,60]

Although it is important to understand the co-occurrence of risk factors among primary care patients, it remains a tremendous challenge to address these risk factors within a primary care setting.[61–63] Addressing multiple risk factors simultaneously may seem even more challenging than addressing risk factors one-by-one. Providers are unlikely to be able to address more than one risk factor in any single visit. Given this context, significant attention has focused on integration of technology that may reduce provider burden.

Prior studies conducted in the VA have demonstrated the feasibility of assessing multiple risk factors using electronic health records (EHRs), which may translate to other settings.[20,59] There is also considerable interest in wearable health technology. To be most useful, data from wearable technologies could be automatically synced to the EHR and used to trigger EHR-guided interventions such as clinical decision prompts, patient-directed text messages, or patient portal alerts. However, to date these technologies have primarily been used to address physical activity. Additional research is needed to better understand how these technologies could be used to address other risk factors (e.g., diet, sleep, alcohol use, mood), perhaps by integrating self-report data. Given the heavy burden posed by behavioral health issues in primary care, effectively and efficiently addressing co-occurring risk factors in this setting is critical.

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Study Highlights

- Using latent class analysis, we identified four distinct patient subgroups (i.e., classes)
- The classes included Mental Health Risk, Substance Use Risk, Dietary Risk, and a Lower Risk class
- Substance use and dietary risk classes were the largest, each representing 29% of the sample
- The mental health risk was the smallest class, encompassing 14% of the sample
- A number of demographic factors differentiated the lower risk class from the other three classes

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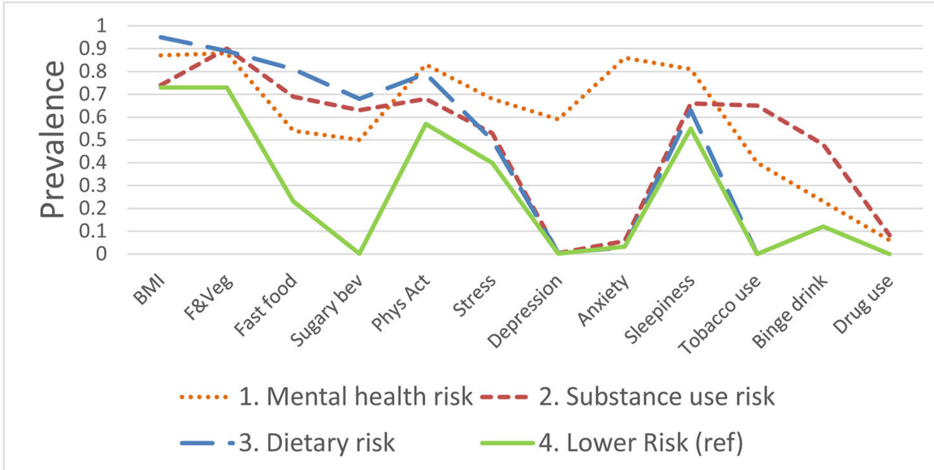

Figure 1.

Table 1

Model fit criteria for latent class models with varying numbers of latent classes

Number of latent classes specified	BIC	Adjusted BIC
2	1956	1877
3	1775 *	1654
4	1787	1625 *
5	1847	1643

BIC and adjusted BIC are criteria for selecting the best model from among a set of possible models; lower values indicate better models.

*Lowest value

Table 2

Prevalence of behavioral health risk factor for the overall sample and by latent class

	Class 1 Mental Health Risk (n=232)	Class 2 Substance Use Risk (n=474)	Class 3 Dietary Risk (n=480)	Class 4 Lower Risk (n=442)	Overall (n=1628)
	%	**%**	**%**	**%**	**%**
Class prevalence	14	29	29	27	100
Risk Factors					
Body mass index (≥25 kg/m^2)	87	74	95	73	82
Fruits and vegetables (<5 servings/week)	88	90	89	73	85
Fast food (≥1 time/week)	54	69	81	23	58
Sugary beverages (≥1 time per day)	50	63	68	0.2	46
Physical activity (<150 minutes/week)	83	68	79	57	70
Stress (>4 stress/week)	68	53	50	40	51
Depression (Score ≥4)	59	<1	<1	<1	9
Anxiety or worry (Score ≥4)	86	6	3	3	16
Sleepiness (Sometimes/Often/Always)	81	66	63	55	64
Tobacco use (Use in past 30 days)	40	65	0.0	0.0	25
Binge drinking (≥1 binge episode/year)	23	48	12	12	24
Drug use (≥1 time/year)	6	8	0	0	3

Shading is provided for interpretation and indicates risk factors that have high prevalence within each class.

* Reference group

Table 3

Demographic characteristics of the overall sample and by latent class

Demographic Characteristic	Class 1 Mental Health Risk (n=232)	Class 2 Substance Use Risk (n=474)	Class 3 Dietary Risk (n=480)	Class 4 Lower Risk (n=442)	Overall (n=1628)
	%	%	%	%	%
Mean age, years (sd)	47.2 (12.8)	43.8 (14.9)	51.3 (14.0)	54.3 (14.8)	49.3 (14.9)
< 30	9	26	7	7	13
30 to < 50	45	32	35	27	33
50 to < 65	39	35	40	38	38
≥ 65	7	7	18	28	16
Male	21	53	19	35	34
Race/ethnicity					
White	62	53	27	53	46
Latino/Hispanic	21	16	28	35	25
African American	13	25	44	5	24
Other	4	6	1	8	5
Married	41	39	56	70	53
At least some college	34	36	30	65	44
Employed	25	50	47	44	44
Speaks English very well/well	89	97	79	80	86

Table 4

Association between demographic characteristics and class membership based on results of multinomial logistic regression

Demographic Characteristic	Class 1 vs Class 4 (Mental Health Risk vs. Lower Risk)	Class 2 vs Class 4 (Substance Use Risk vs. Lower Risk)	Class 3 vs Class 4 (Dietary Risk vs. Lower Risk)
	OR (95% CI)	OR (95% CI)	OR (95% CI)
Age (years)			
< 30 (Ref)	1.0	1.0	1.0
30 to < 50	1.5 (0.7, 3.1)	0.4 (0.2, 0.7)	0.9 (0.4, 1.8)
50 to < 65	0.6 (0.3, 1.4)	0.2 (0.1, 0.4)	0.7 (0.3, 1.4)
≥ 65	0.1 (0.1, 0.4)	0.1 (0.0, 0.1)	0.6 (0.3, 1.3)
Male	0.8 (0.5, 1.2)	2.8 (1.9, 4.2)	0.7 (0.5, 1.1)
Race/ethnicity			
White (Ref)	1.0	1.0	1.0
Latino/Hispanic	0.3 (0.1, 0.5)	0.3 (0.2, 0.5)	0.8 (0.5, 1.5)
African American	0.9 (0.4, 1.9)	2.3 (1.2, 4.3)	7.7 (4.0, 14.8)
Other	0.4 (0.2, 1.0)	0.8 (0.4, 1.4)	0.5 (0.2, 1.2)
Married	0.3 (0.2, 0.5)	0.4 (0.2, 0.5)	0.6 (0.4, 0.9)
At least some college	0.2 (0.1, 0.4)	0.2 (0.1, 0.3)	0.3 (0.2, 0.5)
Employed	0.4 (0.3, 0.7)	1.2 (0.8, 1.7)	1.4 (0.9, 2.0)
Speaks English very well/well	1.8 (0.9, 3.7)	2.7 (1.4, 5.2)	1.0 (0.5, 1.8)