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REGULAR ARTICLE

Trends in Health Behavior Patterns Among U.S. Adults, 2003–2015

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Abstract

Background Over the last two decades, considerable resources from U.S. federal and philanthropic entities were dedicated to improving preventive and reducing chronic disease risk behaviors.

Purpose Given the population health efforts to improve health behaviors in adults, this study explored how health behavior patterns shifted over the years by exploring multiple health behavior patterns.

Methods Data were obtained from the odd years between 2002 and 2016 Behavioral Risk Factor Surveillance System. Latent class analyses including fruit and vegetables, physical activity, cigarette smoking, and heavy and binge drinking were conducted for each year.

Results Three-class models best fit the data and were most interpretable. Each year included Healthy or Physically Active (preventive behaviors, no risk behaviors), Apathetic (no preventive/risk behaviors), and Binge-drinking groups. Gender and age consistently distinguished the Healthy/Physically Active groups from the Apathetic and Binge-drinking groups across the years.

Conclusions This study confirms health behavior clusters exist and have been stable across time. This is encouraging as trends have not gotten worse, but there is room for improvement. Repetition of the groups across years suggests that despite population-level interventions, a large segment of the U.S. population at risk for chronic diseases are not engaging in preventive health.

Keywords: Alcohol • BRFSS • Cigarette smoking • Fruits and vegetables • Latent class analysis • Physical activity

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Introduction

Cancer, diabetes, and cardiovascular disease remain among the leading causes of death in the United States [1], undermining health, shortening life expectancy, and leading to a high economic burden [2, 3]. This is especially true in minority populations [4]. Smoking, inactivity, excessive intake of energy-dense food, red meat, salt, and alcohol are associated with an increased risk for these chronic diseases [5]. Past research has shown that physical activity (PA) and diets high in nonstarchy vegetables are protective [6]. Given the controllable and modifiable nature of these behaviors, the progression and promotion of behavioral science will likely improve the prevention of these chronic diseases.

Common health behaviors cluster or co-occur [7–10], leading to lifestyle patterns influencing the risk of preventable diseases [7, 11–21]. A majority of U.S. adults meet the criteria for two or more health risk behaviors [8–10, 22, 23]. When unhealthy behaviors cluster, the negative health outcomes multiply [24, 25], leading to increased health care and disability costs [26–28]. This burden can be minimized by replacing risky health behaviors with healthy lifestyle behaviors [24, 29]. Given the public health importance, recent health promotion efforts have targeted multiple health behavior change.

Intervention research supports the likely success of comprehensive lifestyle promotion by clustering health behaviors. For example, individuals progressing toward smoking cessation also increased PA [30, 31] and decreased alcohol use [32]. A randomized controlled trial found that individuals who adopted one healthy behavior were up to five times more likely to adopt an additional healthy behavior [33]. Research also suggests "gateway behaviors" or behaviors that, when intervened upon, have a positive influence on additional healthy changes [34, 35]. Given the natural pattern of healthy behaviors, interventions targeting a healthy lifestyle change may be more effective and affect public health.

However, there is a lack of research addressing how behavior clusters evolve across the U.S. population as federal and foundation agencies invest in population-level behavior change efforts. This can inform if major national efforts like Let's Move (www.letsmove.gov) and the 5-a-day [36] have had a population impact, if the status quo is maintained or if the clustering implicates a worsening of the situation. Therefore, the purpose of this study is to investigate health behavior cluster patterns in the U.S. population in the last 13 years.

METHODS

Study Population and Design

Data were obtained from the 2003, 2005, 2007, 2009, 2011, 2013, and 2015 Behavioral Risk Factor Surveillance System (BRFSS; N > 225,000/year). The BRFSS is a telephone-administered, national epidemiological survey developed by the Center for Disease Control and Prevention (CDC) to examine the state-level prevalence of health risk behaviors in adults related to premature mortality and morbidity. The odd year BRFSS data were used in this analysis due to consistency in measurement of variables of interest. Note that surveys administered after 2010 underwent data collection methodology changes, including Cell Phone Surveys and new weighting methodology, and a change in the structure of diet and PA questions. For 2003–2009, a final weight is assigned to each respondent in the sample and this weight accounts for probability of selection among strata (subsets of area code/prefix combinations), number of residential telephone numbers in respondent's household, number of adults in respondent's household, and distribution of age-by-sex or age-by-race/ethnicity-by-sex in a region or state. For 2011–2015, the weighting protocol focused on population representativeness in sex, age, race, education, marital status, home ownership, phone ownership, and substate region. The inclusion of cell phones improved the representativeness of the sample. However, the CDC also notes that common risk behaviors in younger adults and "certain racial or ethnic or minority groups" will likely be higher in the 2011 dataset as well as small increases in tobacco use and binge drinking are expected with the change in methodology [37, 38]. Additional information about the survey instrument, study procedures, sampling, and study population are provided elsewhere [39].

Measures

Demographics

Participants self-reported their age, sex, race/ethnicity, education, and income. Age was categorized into 5-year intervals for a total of 14 categories ranging from 18–24 to 80+ years. Sex was dichotomized into (0) female and (1) male. Race/ethnicity was determined by *Are you Hispanic or Latino*? (yes/no) and *Which of the following would you say is your race?* Participants were categorized into non-Hispanic White, Hispanic, non-Hispanic Black, non-Hispanic Multiracial, and Other (combination of Asian, Alaskan Native, Native American, Native Hawaiian, and Other Pacific Islander). Regarding education, participants were asked *What is the highest grade or year of school you completed?* and answer choices were presented on a continuum: (i) never attended school or only kindergarten, (ii) grades 1–8, (iii) grades 9–11, (iv) grade 12 or GED, (v) college 1–3 years, and (vi) college 4 years or more. For income, participants were asked *Is your annual income from all sources:* (i) *less than 10,000*; (ii) *less than 15,000*; (iii) *less than 20,000*; (iv) *less than 25,000*; (v) *less than 35,000*; (vi) *less than 50,000*; (vii) *less than 75,000*; and (viii) *75,000 or more*.

Physical Activity 2003–2009

For moderate PA, participants were asked *Now thinking about the moderate PA you do in a usual week, do moderate activities for at least 10 minutes at a time, such as brisk walking, bicycling, vacuuming, gardening, or anything else that causes small increases in breathing or heart rate? How many days per week do you do these moderate activities for at least 10 minutes at a time? On days when you do moderate activities for at least 10 minutes at a time, how much total time per day do you spend doing these activities?* For vigorous PA, participants were asked *Now thinking about the vigorous PA you do in a week, do you do vigorous PA for at least 10 minutes at a time, such as running, aerobics, heavy yard work, or anything else that causes large increases in breathing or heart rate? How many days per week do you do these vigorous activities for at least 10 minutes at a time? On days when you do vigorous activities for at least 10 minutes at a time, how much total time per day do you spend doing these activities?* Minutes were summed across activities and categorized into (i) met objectives—≥150 min of PA per week and (ii) insufficient or no activity—<150 min of PA per week.

Physical Activity 2011–2015

Participants were asked *During the past month, other than your regular job, did you participate in any physical* *activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise?* Participants identified the activities they participated in and for two activities that gave them the most exercise, they disclosed how many minutes per week they engaged in each activity. Minutes were summed across activities and categorized into (i) met objectives—≥150 min of PA per week and (ii) insufficient or no activity—<150 min of PA per week. These categorizations are consistent with CDC guidelines [40] and are consistent with the advice provided to individuals in population-level efforts including Let's Move and other physical activity media campaigns.

Fruit and Vegetable Intake 2003–2009

This variable was based on several questions including *Not counting juice, how often do you eat fruit?; How often do you eat green salad?; How often do you eat carrots?; Not counting carrots, potatoes, or salad, how many servings of vegetables do you usually eat?* Note that, for the last question, carrots and green salad are excluded because they were asked about specifically, whereas potatoes were excluded because it is usually consumed as a starch and paired with unhealthy additives, rapidly absorbed, and has a high glycemic index [41, 42]. Juice is not counted as a serving of fruit as it lacks fiber, has a high sugar content, and increases the risk of chronic conditions such as Type II diabetes [43]. All responses were converted to daily consumption and combined servings of fruits and vegetables per day were calculated and categorized as follows: (i) met objectives—consuming fruits and vegetables five or more times per day and (ii) insufficient fruits and vegetables—less than five times per day.

Fruit and Vegetable Intake 2011–2015

This was assessed by the following questions: *During the past month, not counting juice, how many times per day, week, or month did you eat fruit? During the past month, how many times per day, week, or month did you eat dark green vegetables for example broccoli or dark leafy greens including romaine, chard, collard greens or spinach? During the past month, how many times per day, week, or month did you eat orange-colored vegetables such as sweet potatoes, pumpkin, winter squash, or carrots? Not counting what you just told me about, during the past month, about how many times per day, week, or month did you eat OTHER vegetables?* All responses were converted to daily consumption and combined servings of fruits and vegetables per day were calculated and categorized as follows: (i) met objectives—consuming fruits and vegetables five or more times per day and (ii) insufficient fruits and vegetables—less than five times per day.

Cigarette Smoking

Participants were asked *Have you smoked at least 100 cigarettes in your life? Do you smoke cigarettes every day, some days, or not at all?* These questions classified participants into two categories: (i) current smoker (every day)—respondents who smoked ≥100 cigarettes in their lifetime and now smoke every day or some days and (ii) never or former smoker—respondents who smoked ≥100 cigarettes in lifetime and currently do not smoke or who had not smoked at least 100 cigarettes in their lifetime.

Alcohol Use

Two alcohol variables were included binge drinking and heavy drinking. Participants were asked *During the past 30 days, how many days per week or per month did you have at least one drink or any alcoholic beverage?* To get drink-occasions-per-day, this number was divided by 7 days/week or 30 days/month based on participants' unit of response. Participants were asked *Considering all types of alcoholic beverages, how many times during the past 30 days did you have 5 or more drinks on an occasion?* Binge drinkers were defined as adults having five or more drinks on one occasion. Participants who reported at least one drink-occasion-per-day in the last 30 days and having five or more drinks on one or more occasion in the past month were categorized as binge drinkers. Participants were also asked *On the days when you drank, during the past 30 days, about how many drinks did you drink on average?* Total number of alcoholic drinks per day was calculated by multiplying the average number of drinks per occasion by drink-occasions-per-day and this number was used to identify heavy drinkers (average of more than one and more than two drinks per day for women and men, respectively).

Statistical Analyses

All analyses were conducted using Mplus Version 7.3 [44]. Weighted percentages and unweighted frequencies are displayed in Table 1. Latent class analysis (LCA) is a statistical method that assumes underlying groupings of individuals exist within heterogeneous populations. Five health behavior indicators were entered into a series of complex mixture LCA models to examine the underlying health behavior patterns of U.S. adults for each analyzed year. To compute LCAs, Mplus performs several iterations of model fit using random start values for parameter estimates to ensure identification of the maximum likelihood solutions. For this study, each model was estimated at least three times with increased number of starts and iterations. If the log-likelihood was not replicated three times, the number of starts and iterations were increased until replication was achieved. To account for error in class membership and avoid predictor variables

Table 1 Frequencies of Participants' Health Behaviors[a] and Demographic Characteristics

	Weighted percentages (unweighted frequencies)						
	2003	2005	2007	2009	2011	2013	2015
	N = 226,802	N = 303,770	N = 367,312	N = 369,193	N = 426,509	N = 412,336	N = 355,418
Behaviors[a]							
Met F&V Recs	11.69 (27,949)	12.95 (40,912)	13.80 (52,248)	13.09 (50,589)	11.77 (51,715)	11.59 (48,286)	11.49 (41,280)
Met PA Recs	44.72 (101,309)	48.40 (13,6761)	46.31 (163,879)	61.15 (214,586)	48.36 (211,364)	45.36 (197,398)	45.70 (173,285)
Smoker	22.76 (49,849)	20.86 (61,178)	19.57 (69,136)	18.06 (61,330)	20.22 (73,204)	17.82 (66,449)	16.56 (51,908)
Binge drinker	16.51 (30,886)	14.91 (34,648)	15.92 (44,365)	15.34 (41,306)	17.59 (55,047)	16.52 (53,441)	16.62 (45,171)
Heavy drinker	5.76 (12,151)	5.28 (14,326)	5.31 (18,325)	5.17 (17,725)	6.31 (14,052)	5.98 (23,029)	5.86 (19,525)
Covariates							
Gender							
Male	49.64 (92,421)	49.81 (120,518)	49.73 (142,505)	49.65 (145,285)	49.89 (173,858)	49.56 (174,457)	49.85 (156,025)
Female	50.36 134,381)	50.19 (183,252)	50.27 (224,807)	50.35 (223,908)	50.11 (252,651)	50.44 (237,879)	50.15 (199,393)
Race							
White	70.40 (178,613)	69.52 (240,342)	68.70 (292,062)	67.98 (293,011)	66.08 (333,621)	64.50 (321,571)	64.04 (275,491)
Black	9.62 (17,740)	9.44 (23,927)	9.44 (28,452)	10.12 (29,651)	11.29 (34,479)	11.55 (33,091)	11.61 (27,805)
Other	4.89 (9,803)	4.78 (12,172)	5.63 (14,056)	5.28 (14,581)	5.66 (17,670)	6.11 (18,176)	6.29 (15,986)
Multiracial	1.56 (3,711)	1.47 (5,640)	1.49 (6,268)	1.55 (6,275)	1.49 (7,808)	1.38 (7,962)	1.41 (6,848)
Hispanic	13.52 (16,935)	14.78 (21,689)	14.75 (26,474)	15.07 (25,675)	15.49 (32,931)	16.47 (31,536)	16.65 (29,288)
Income							
<$15,000	11.54 (28,582)	11.24 (37,342)	9.79 (40,532)	10.59 (42,198)	13.69 (54,207)	13.42 (50,839)	11.55 (37,132)
$15,000–$24,999	17.89 (42,479)	17.05 (55,751)	15.20 (63,432)	15.97 (65,239)	18.75 (78,050)	18.11 (74,854)	17.06 (57,935)
$25,000–$34,999	13.90 (32,713)	12.70 (41,664)	11.57 (46,840)	10.62 (44,831)	11.48 (50,943)	11.05 (47,914)	10.54 (38,504)
$35,000–$50,000	17.16 (40,465)	16.16 (51,492)	15.23 (59,876)	14.38 (57,101)	13.87 (63,614)	13.90 (60,465)	13.62 (51,153)
≥$50,000	39.51 (82,563)	42.85 (117,521)	48.20 (156,632)	48.44 (159,824)	42.21 (179,695)	43.52 (178,264)	47.23 (170,694)
Education							
<HS graduate	11.17 (22,679)	11.42 (29,494)	10.69 (34,346)	10.17 (32,075)	14.45 (35,529)	14.42 (32,351)	13.41 (25,043)
HS graduate	29.94 (67,968)	29.27 (91,821)	27.78 (109,410)	27.26 (107,608)	28.53 (122,678)	27.74 (116,578)	27.37 (95,763)
Some college	27.25 (62,579)	26.63 (81,315)	26.57 (97,970)	26.74 (100,350)	30.44 (116,521)	31.05 (114,115)	31.54 (98,235)
College graduate	31.64 (73,576)	32.68 (101,140)	34.97 (125,586)	35.82 (129,160)	26.58 (151,781)	26.79 (149,292)	27.68 (136,377)
Age (year)							
18–24	12.15 (14,874)	11.82 (14,261)	9.84 (12,042)	9.87 (9,671)	11.22 (16,982)	11.44 (20,443)	11.15 (17,076)
25–29	8.91 (16,636)	8.43 (18,714)	8.30 (17,293)	8.04 (13,617)	8.76 (19,571)	8.32 (20,195)	8.42 (16,674)
30–34	10.12 (20,316)	10.71 (23,949)	10.98 (23,563)	11.08 (20,417)	9.80 (25,085)	9.65 (24,569)	9.84 (20,003)
35–39	10.13 (22,133)	10.10 (27,460)	10.16 (29,289)	9.42 (25,851)	8.52 (27,332)	8.04 (25,427)	8.41 (21,580)
40–44	11.41 (25,272)	10.98 (30,505)	11.51 (32,850)	11.14 (29,195)	10.06 (31,736)	9.32 (28,453)	8.95 (22,759)
45–49	10.05 (24,906)	10.10 (32,846)	9.57 (38,013)	9.45 (36,270)	9.16 (36,833)	8.46 (32,404)	7.89 (26,398)
50–54	9.10 (23,602)	9.32 (33,130)	10.12 (41,806)	10.46 (42,246)	10.62 (44,972)	10.49 (41,758)	10.05 (34,203)
55–59	7.40 (19,981)	7.77 (30,946)	7.72 (40,622)	7.82 (42,900)	7.97 (48,689)	8.77 (46,164)	8.63 (39,153)
60–64	5.75 (16,088)	5.79 (24,912)	6.54 (36,535)	7.02 (40,966)	7.54 (49,167)	7.97 (46,338)	8.25 (41,484)
65–69	4.44 (13,448)	4.56 (20,792)	4.64 (29,629)	4.85 (33,827)	5.15 (39,781)	5.91 (41,597)	6.37 (39,815)
70–74	3.62 (11,421)	3.53 (17,200)	3.65 (23,962)	3.79 (26,953)	3.97 (31,359)	4.34 (32,047)	4.71 (29,788)
75–79	3.76 (9,174)	3.60 (14,283)	3.51 (19,651)	3.34 (21,365)	3.40 (24,476)	3.43 (23,344)	3.54 (21,092)
80 and older	3.18 (8,951)	3.30 (14,772)	3.47 (22,057)	3.71 (25,915)	3.83 (30,526)	3.86 (29,597)	3.77 (25,393)

[a]Percentages and frequencies are for the presence of behaviors. *Met F&V Recs* met fruit and vegetable recommendations; *Met PA Recs* met physical activity recommendations.

influencing the latent class solution, the automatic three-step method (R3Step in Mplus) was used to determine the relationship between the latent class variable and predictor variable [45]. The three-step method first estimates a latent class model with only the latent class indicators. The second step involves creating a most likely class variable from the latent class posterior distribution obtained in step 1 and determining the measurement error for class membership. Finally, the third step re-estimates the model with covariates added, the most likely class variable from step 2 remains constant and measurement error is fixed and prespecified to the error values computed in step 2. Two main advantages of this method are that the latent class model structure is not altered by the inclusion of covariates and the inclusion of measurement error for the most likely class variable acknowledges that latent classes are not perfect. The covariates are estimated using binomial logistic regressions and Healthy or Physically Active served as the reference group each year.

Mplus provides multiple fit statistics to determine the best-fitting, most parsimonious model, including the Akaike information criteria (AIC) [46], Bayesian information criteria (BIC) [47], and the Vuong–Lo–Mendell–Rubin adjusted likelihood ratio test [48]. Lower AIC and BIC are preferred; however, with large datasets, the AIC and BIC may continue to decrease even after the best-fitting model has been found. Due to our large datasets, we used scree plots of the AIC and BIC to help us determine the number of factors to retain. The Vuong–Lo–Mendell–Rubin adjusted likelihood ratio test compares the model with K classes to a model with $K - 1$ classes to determine how many classes are needed to represent the data and a parsimonious p value < .001 suggests that the model with K classes best represents the data. Given that large sample sizes have the potential for Type I errors, we decided it would be parsimonious to use an alpha level of $p < .01$ rather than $p < .05$ for interpretation of significant covariates. class interpretability was also considered in addition to fit statistics. Specifically, class size in relation to sample size and class homogeneity (item response probabilities > 0.60 and < 0.30 indicated class members similar to each other) were considered in choosing the best models. Note that entropy, a measure of class separation, was calculated and presented in the tables. However, it is not a measure of model fit and not advisable to be used in model selection [49]. Extremely low entropy suggests that the model is not useful for finding homogenous classes; conversely, high entropy does not prove homogeneity of clusters in all situations [50].

RESULTS

Sample sizes ranged from 226,902 to 426,509. The majority of the sample for each year were female (50.11%–50.36%), White (64.04%–70.40%), college graduates (26.58%–35.82%), and with household incomes $50,000 or greater (39.51%–48.44%). Regarding behaviors, 11.49%–13.80% met fruit and vegetable recommendations, 44.72%–61.15% met PA recommendations, 16.56%–22.76% smoked cigarettes, 14.91%–17.59% engaged in binge drinking, and 5.17%–6.31% engaged in heavy drinking.

Latent Class Profiles

Model fit indices are presented in Table 2. Figure 1 is an example of a comparison of the three-class and four-class model solutions. Note that the Binge drinking and PA/Binge drinking in the four-class model is a splitting of the Binge-drinking class in the three-class model. This splitting of the smallest class was typical across the years and was a consideration when choosing the most conservative and informative models for interpretation (Table 3).

2003

The Vuong–Lo–Mendell–Rubin adjusted likelihood ratio test supported a four-class model. However, the scree plot of the AIC and BIC supported a three-class model. The four-class model had a group with only 2% of participants, whereas the three-class model had better interpretability, homogeneity, and was more parsimonious. We chose the three-class model with the following groups: Healthy (11%; high probability of meeting fruit and vegetable and PA recommendations, low probability of smoking and drinking), Apathetic (80%; low probability of smoking, drinking, and meeting fruit and vegetable recommendations), and Binge drinking (9%; high probability of binge drinking). When compared to the Healthy group, individuals in the Apathetic group were younger (odds ratio [OR] = 0.92), male (OR = 2.89), lower income (OR = 0.87), less educated (OR = 0.74), more likely to be Black (OR = 1.30), and less likely to be Other (OR = 0.79) versus White. The Binge-drinking group was younger (OR = 0.72), male (OR = 7.38), lower income (OR = 0.85), less educated (OR = 0.57), and less likely to be Hispanic (OR = 0.76) versus White than the Healthy group.

2005

The Vuong–Lo–Mendell–Rubin adjusted likelihood ratio test and the scree plots of the AIC and BIC supported a three-class model with good interpretability and homogeneity: Physically Active (12%; high-probability meeting PA recommendations, low-probability smoking and drinking), Apathetic (80%; low-probability smoking, drinking, meeting fruit and vegetable recommendations), and Binge drinking (8%; high-probability binge drinking). When compared to the Physically Active

Table 2 Latent Class Analyses Model Fit Indices for R3Step Data Analysis Procedures

	Number of classes			
	2	3	4	5
2003				
Pearson chi-square	423.020	164.500	19.450	4.661
df/*p* value	20 (p = .0000)	14 (p = .0000)	8 (p = .0126)	2 (p = .0973)
AIC	969,530.393	966,154.155	965,521.533	965,489.564
BIC	969,644.043	966,329.796	965,759.165	965,789.187
Sample-adjusted BIC	969,609.085	966,275.770	965,686.070	965,697.024
Entropy	0.838	0.666	0.716	0.745
Lo, Mendell, Rubin	36,868.963 (p = .0000)	3,343.056 (p = .0000)	716.86 (p = .0000)	43.382 (p = .3818)
N of each class				
Class 1	205,932 (90.80)	25,220 (11.12)	181,907 (80.21)	218 (0.10)
Class 2	20,869 (9.20)	21,072 (9.29)	4,776 (2.11)	17,476 (7.71)
Class 3		180,509 (79.59)	22,642 (9.98)	12,865 (5.67)
Class 4			17,476 (7.71)	226,42 (9.98)
Class 5				173,601 (76.54)
2005				
Pearson chi-square	321.355	138.586	38.282	3.464
df/*p* value	20 (p < .0001)	14 (p = .0000)	8 (p = .0000)	2 (p = .1769)
AIC	1,278,182.594	1,272,619.170	1,272,027.176	1,271,850.763
BIC	1,278,299.458	1,272,799.778	1,272,271.529	1,272,158.860
Sample-adjusted BIC	1,278,264.499	1,272,745.752	1,272,198.434	1,272,066.697
Entropy	0.842	0.623	0.664	0.506
Lo, Mendell, Rubin	40,573.992 (p = .0000)	5,502.774 (p = .0000)	596.124 (p = .2674)	201.779 (p = .2146)
N of each class				
Class 1	269,326 (88.66)	24,280 (7.99)	3,152 (1.04)	11,043 (3.64)
Class 2	34,441 (11.34)	37,414 (12.32)	22,568 (7.43)	90,885 (29.92)
Class 3		242,073 (79.69)	242,158 (79.72)	12,623 (4.16)
Class 4			35,980 (11.82)	62,473 (20.57)
Class 5				126,743 (41.72)
2007				
Pearson chi-square	344.809	134.617	36.443	3.934
df/*p* value	20 (p = .0000)	14 (p = .0000)	8 (p = .0000)	2 (p = .1399)
AIC	1,550,744.152	1,544,899.081	1,544,328.651	1,544,210.118
BIC	1,550,863.105	1,545,082.917	1,544,577.371	1,544,523.722
Sample-adjusted BIC	1,550,828.147	1,545,028.890	1,544,504.276	1,544,431.559
Entropy	0.836	0.588	0.677	0.699
Lo, Mendell, Rubin	53,367.885 (p = .0000)	5,781.869 (p = .0000)	574.951 (p = .0860)	131.336 (p = .5604)
N of each class				
Class 1	321,988 (87.67)	45,657 (12.43)	5,522 (1.50)	525 (0.14)
Class 2	45,306 (12.34)	47,931 (13.05)	45,470 (12.38)	54,310 (14.79)
Class 3		273,706 (74.52)	28,8433 (78.53)	44,486 (12.11)

Table 2 Continued

	Number of classes			
	2	3	4	5
Class 4			27,869 (7.59)	4,947 (1.35)
Class 5				263,027 (71.61)
2009				
Pearson chi-square	360.747	153.112	17.431	2.664
df/*p* value	20 ($p < .0000$)	14 ($p < .0000$)	8 ($p = .0259$)	2 ($p = .2640$)
AIC	1,479,756.557	1,474,485.291	1,473,705.806	1,473,657.761
BIC	1,479,875.559	1,474,669.203	1,473,954.628	1,473,971.493
Sample-adjusted BIC	1,479,840.601	1,474,615.176	1,473,881.533	1,473,879.330
Entropy	0.834	0.562	0.645	0.627
Lo, Mendell, Rubin	51,913.905 ($p < .0000$)	5,215.454 ($p = .0003$)	781.326 ($p = .0011$)	84.117 ($p = .7617$)
N of each class				
Class 1	51,212 (13.88)	269,697 (73.10)	25,129 (6.81)	30,862 (8.37)
Class 2	317,717 (86.12)	54,499 (14.77)	275,322 (74.63)	266,923 (72.35)
Class 3		44,733 (12.13)	26,878 (7.29)	21,005 (5.69)
Class 4			41,600 (11.28)	8,467 (2.30)
Class 5				41,672 (11.30)
2011				
Pearson chi-square	454.552	156.388	13.225	1.553
df/*p* value	20 ($p < .0000$)	14 ($p < .0000$)	8 ($p = .1043$)	2 ($p = .4601$)
AIC	1,797,731.150	1,789,435.329	1,788,588.095	1,788,555.003
BIC	1,797,851.746	1,789,621.704	1,788,840.250	1,788,872.938
Sample-adjusted BIC	1,797,816.788	1,789,567.677	1,788,767.155	1,788,780.774
Entropy	0.808	0.439	0.515	0.541
Lo, Mendell, Rubin	66,494.623 ($p = .3333$)	8,202.365 ($p < .0000$)	848.327 ($p = .0003$)	44.519 ($p = .6959$)
N of each class				
Class 1	387,359 (90.83)	72,359 (16.97)	34,454 (8.08)	18,675 (4.38)
Class 2	39,093 (9.17)	162,992 (38.22)	23,457 (5.50)	21,475 (5.04)
Class 3		191,100 (44.81)	163,297 (38.29)	17,377 (4.08)
Class 4			205,244 (48.13)	205,574 (48.21)
Class 5				163,351 (38.31)
2013				
Pearson chi-square	377.356	116.038	31.924	3.405
df/*p* value	20 ($p < .0000$)	14 ($p < .0000$)	8 ($p = .0001$)	2 ($p = .1822$)
AIC	1,683,709.404	1,676,221.566	1,675,672.639	1,675,567.068
BIC	1,683,829.415	1,676,407.037	1,675,923.572	1,675,883.461
Sample-adjusted BIC	1,683,794.456	1,676,353.011	1,675,850.476	1,675,791.298
Entropy	0.841	0.480	0.554	0.520
Lo, Mendell, Rubin	60,322.295 ($p < .0000$)	7,404.251 ($p < .0000$)	553.777 ($p = .0143$)	116.073 ($p = .3151$)

Table 2 Continued

	Number of classes			
	2	3	4	5
N of each class				
Class 1	34,538 (8.54)	305,758 (75.61)	19,369 (4.79)	9,426 (2.33)
Class 2	369,834 (91.46)	53,752 (13.29)	39,641 (9.80)	95,773 (23.68)
Class 3		44,862 (11.09)	33,887 (8.38)	12,259 (3.03)
Class 4			311,475 (77.03)	127,858 (31.62)
Class 5				159,056 (39.33)
2015				
Pearson chi-square	315.192	95.226	15.287	3.576
df/*p* value	20 ($p < .0001$)	14 ($p < .0001$)	8 ($p = .0538$)	2 ($p = .1673$)
AIC	1,432,230.858	1,426,579.915	1,426,104.840	1,426,056.804
BIC	1,432,349.230	1,426,762.854	1,426,352.346	1,426,368.877
Sample-adjusted BIC	1,432,314.272	1,426,708.827	1,426,279.251	1,426,276.714
Entropy	0.831	0.447	0.543	0.529
Lo, Mendell, Rubin	48,565.056 ($p < .0001$)	5,589.936 ($p < .0001$)	480.795 ($p = .0014$)	201.023 ($p = .2850$)
N of each class				
Class 1	28,339 (8.13)	45,154 (12.96)	30,272 (8.69)	14,310 (4.11)
Class 2	320,069 (91.87)	134,546 (38.62)	12,331 (3.54)	8,810 (2.53)
Class 3		168,708 (48.42)	171,835 (49.32)	150,370 (43.16)
Class 4			133,970 (38.45)	38,642 (11.09)
Class 5				136,277 (39.11)

AIC Akaike information criterion; *BIC* Bayesian information criterion.

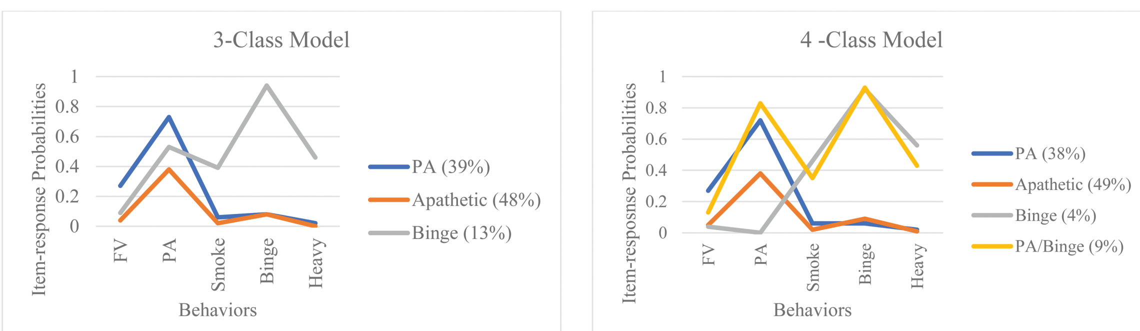

Fig. 1. Comparison of three-class and four-class solutions for 2015. Percentages noted in legend are latent class prevalences for the respective classes. *Binge* binge drinking; *FV* fruits and vegetables; *Heavy* heavy drinking; *PA* physical activity.

group, the Apathetic group was younger (OR = 0.93), male (OR = 2.38), lower income (OR = 0.89), less educated (OR = 0.73), and more likely to be Black versus White (OR = 1.24). The Binge-drinking group was younger (OR = 0.74), male (OR = 6.27), lower income (OR = 0.88), less educated (OR = 0.56), more likely to be Multiracial (OR = 1.61), and less likely to be Other (OR = 0.59) versus White when compared to the Physically Active group.

2007

The Vuong–Lo–Mendell–Rubin adjusted likelihood ratio test and the scree plots of the AIC and BIC supported a three-class model with good interpretability and homogeneity: Physically Active (13%; high-probability meeting PA recommendations, low-probability smoking and drinking), Apathetic (75%; low-probability smoking, drinking, meeting fruit and vegetable recommendations), and Binge drinking (12%; high-probability binge

Table 3 Item Response Probabilities and Demographic Differences Among Latent Classes

	2003			2005			2007				2009	
	Healthy	Apathetic	Binge drinking	Physically active	Apathetic	Binge drinking	Physically active	Apathetic	Binge drinking	Physically active	Apathetic	PA/Binge drinking
Latent class prevalences	**11**	**80**	**9**	**12**	**80**	**8**	**13**	**75**	**12**	**12**	**73**	**15**
Average latent class probabilities	**.87**	**.88**	**.85**	**.98**	**.82**	**.85**	**.90**	**.83**	**.78**	**.71**	**.84**	**.77**
Item response probabilities[a]												
Met F&V Rec	**.61**	**.02**	**.07**	.54	**.00**	**.09**	.53	**.01**	**.09**	.46	**.05**	**.08**
Met PA Rec	**.62**	.42	.56	**.62**	.43	.57	**.64**	.42	.58	**.84**	.59	**.77**
Smoker	**.10**	**.21**	.54	**.10**	**.20**	.50	**.10**	**.18**	.45	.06	**.18**	.39
Binge drinker	**.05**	**.07**	**.93**	**.04**	**.07**	**.92**	**.06**	**.06**	**.93**	.06	**.04**	**.92**
Heavy drinker	**.02**	**.01**	.57	**.02**	**.01**	.42	**.02**	**.00**	.38	.02	**.01**	.36
Covariates[b,c]												
Male	Ref	**2.89**	**7.38**	Ref	**2.38**	**6.27**	Ref	**2.47**	**6.12**	Ref	**3.71**	**8.59**
		2.67, 3.13	**6.65, 8.19**		**2.23, 2.53**	**5.69, 6.92**		**2.31, 2.65**	**5.58, 6.71**		**3.38, 4.08**	**7.73, 9.55**
Age	Ref	**0.92**	**0.72**	Ref	**0.93**	**0.74**	Ref	**0.97**	**0.75**	Ref	**0.94**	**0.74**
		0.91, 0.93	**0.70, 0.73**		**0.92, 0.94**	**0.73, 0.75**		**0.96, 0.97**	**0.73, 0.76**		**0.93, 0.96**	**0.72, 0.75**
Income	Ref	**0.87**	**0.85**	Ref	**0.89**	**0.88**	Ref	**0.88**	0.99	Ref	**0.82**	0.98
		0.85, 0.90	**0.82, 0.88**		**0.88, 0.91**	**0.85, 0.92**		**0.86, 0.90**	0.95, 1.02		**0.79, 0.85**	0.94, 1.02
Education	Ref	**0.74**	**0.57**	Ref	**0.73**	**0.56**	Ref	1.01	**0.65**	Ref	**0.56**	**0.58**
		0.71, 0.77	**0.54, 0.60**		**0.71, 0.76**	**0.55, 0.61**		0.98, 1.05	**0.61, 0.68**		**0.53, 0.59**	**0.55, 0.62**
Race (ref = white)												
Black	Ref	**1.30**	0.96	Ref	**1.24**	0.85	Ref	**1.38**	1.05	Ref	**1.33**	0.86
		1.15, 1.46	0.81, 1.14		**1.11, 1.38**	0.72, 1.01		**1.24, 1.52**	0.88, 1.25		**1.14, 1.55**	0.70, 1.05
Hispanic	Ref	1.04	**0.76**	Ref	0.97	0.81*	Ref	0.87	**0.78**	Ref	0.90	1.14
		0.90, 1.19	**0.64, 0.94**		0.86, 1.09	0.68, 0.96		0.78, 0.98	**0.67, 0.92**		0.77, 1.05	0.96, 1.36
Multiracial	Ref	0.84	1.04	Ref	0.84	**1.61**	Ref	0.77	1.08	Ref	0.90	1.09
		0.66, 1.05	0.78, 1.39		0.67, 1.05	**1.20, 2.15**		0.63, 0.94	0.81, 1.43		0.70, 1.14	0.79, 1.50
Other	Ref	**0.79**	0.78	Ref	0.84	**0.59**	Ref	0.95	**0.70**	Ref	0.85	**0.54**
		0.68, 0.92	0.62, 0.97		0.72, 0.96	**0.47, 0.73**		0.83, 1.09	**0.57, 0.86**		0.71, 1.00	**0.43, 0.67**

(Continued)

Table 3 Continued

	2011 Physically active	Apathetic	Binge drinking	2013 Physically active	Apathetic	Binge drinking	2015 Physically active	Apathetic	Binge drinking
Latent class prevalences	**38**	**45**	**17**	**11**	**76**	**13**	**39**	**48**	**13**
Average latent class probabilities	**.67**	**.68**	**.86**	**.76**	**.71**	**.71**	**.59**	**.77**	**.70**
Item response probabilities[a]									
Met F&V Rec	**.26**	**.03**	**.08**	**.29**	**.04**	**.10**	**.27**	**.04**	**.09**
Met PA Rec	**.73**	.36	.54	**.74**	.38	.54	**.73**	.38	.53
Smoker	**.08**	**.23**	.45	**.06**	**.21**	.40	**.06**	**.20**	.39
Binge drinker	**.09**	**.06**	**.94**	**.07**	**.07**	**.95**	**.08**	**.08**	**.94**
Heavy drinker	**.02**	**.01**	.44	**.02**	**.01**	.46	**.02**	**.00**	.46
Covariates[b,c]									
Male	Ref	**1.14**	**3.51**	Ref	**3.85**	**7.05**	Ref	**1.41**	**3.28**
		1.05, 1.23	**3.25, 3.80**		**3.45, 4.28**	**6.33, 7.85**		**1.30, 1.54**	**3.01, 3.59**
Age	Ref	**0.89**	**0.70**	Ref	0.98	**0.77**	Ref	**0.87**	**0.73**
		0.88, 0.91	**0.69, 0.71**		0.97, 1.00	**0.75, 0.78**		**0.85, 0.88**	**0.71, 0.74**
Income	Ref	**0.63**	**0.79**	Ref	**0.75**	**0.88**	Ref	**0.63**	**0.79**
		0.61, 0.65	**0.77, 0.82**		**0.72, 0.78**	**0.84, 0.91**		**0.61, 0.65**	**0.76, 0.83**
Education	Ref	**0.43**	**0.59**	Ref	**0.58**	**0.65**	Ref	**0.45**	**0.53**
		0.41, 0.45	**0.57, 0.62**		**0.55, 0.62**	**0.61, 0.69**		**0.42, 0.47**	**0.50, 0.56**
Race (ref = white)									
Black	Ref	**1.63**	1.10	Ref	**1.93**	1.13	Ref	**1.86**	**1.31**
		1.41, 1.90	0.95, 1.29		**1.60, 2.32**	0.94, 1.36		**1.58, 2.18**	**1.11, 1.54**
Hispanic	Ref	**0.62**	0.84	Ref	**0.51**	**0.58**	Ref	**0.67**	**0.70**
		0.53, 0.73	0.73, 0.97		**0.43, 0.62**	**0.49, 0.69**		**0.56, .80**	**0.59, 0.82**
Multiracial	Ref	0.81	1.10	Ref	0.68	1.19	Ref	0.74	1.13
		0.63, 1.04	0.85, 1.43		0.49, 0.95	0.89, 1.59		0.56, 0.98	0.86, 1.48
Other	Ref	1.26	**0.61**	Ref	1.01	**0.67**	Ref	1.02	**0.66**
		1.03, 1.54	**0.51, 0.74**		0.80, 1.28	**0.54, 0.84**		0.81, 1.27	**0.53, .81**

PA/Binge drinking physical activity and binge drinking; *Smoke/Binge* cigarette smoking and binge-drinking; *Met F&V Rec* met fruit and vegetable recommendations; *Met PA Rec* met physical activity recommendations; *Ref* reference group.

[a]Probabilities are for the presence of behaviors—probabilities >.6 or <.3 are bolded to indicate a high degree of class homogeneity.

[b]Odds ratio is presented with 95% confidence intervals in the second row.

[c]Due to large sample size, only covariates significant at $p \leq .01$ interpreted and bolded. $^{*}p < .05$.

drinking). When compared to the Physically Active group, the Apathetic group was younger (OR = 0.97), male (OR = 2.47), lower income (OR = 0.88), and more likely to be Black versus White (OR = 1.38). The Binge-drinking group was younger (OR = 0.75), male (OR = 6.12), less educated (OR = 0.65), and less likely to be Hispanic (OR = 0.78) or Other (OR = 0.70) versus White when compared to the Physically Active group.

2009

The Vuong–Lo–Mendell–Rubin adjusted likelihood ratio test supported a four-class model. However, the scree plots of the AIC and BIC supported a three-class model and had better interpretability and homogeneity; thus, the three-class model was retained. The classes included Physically Active (12%; high-probability meeting PA recommendations, low-probability smoking and drinking), Apathetic (73%; low-probability smoking, drinking, meeting fruit and vegetable recommendations), and PA/Binge drinking (15%; high-probability binge drinking, meeting PA recommendations). Participants in the Apathetic group were younger (OR = 0.94), male (OR = 3.71), lower income (OR = 0.82), lower education (OR = 0.56), and Black versus White (OR = 1.33) than the Physically Active group. Participants in the PA/Binge-drinking group were younger (OR = 0.74), male (OR = 8.59), less educated (OR = 0.58), and White versus Other (OR = 0.54) when compared to the Physically Active group.

2011

The Vuong–Lo-Mendell–Rubin adjusted likelihood ratio test supported a four-class model. However, the scree plots of the AIC and BIC supported a three-class model with better interpretability and class homogeneity; thus, the three-class model was retained. The classes included Physically Active (38%; high-probability meeting PA recommendations, low-probability smoking, drinking, meeting fruit and vegetable recommendations), Apathetic (45%; low-probability smoking, drinking, meeting fruit and vegetable recommendations), and Binge drinking (17%; high-probability binge drinking). When compared to the Physically Active group, participants in the Apathetic group were younger (OR = 0.89), male (OR = 1.14), lower income (OR = 0.63), less educated (OR = 0.43), Black versus White (OR = 1.63), and White versus Hispanic (OR = 0.62). Participants in the Binge-drinking group were younger (OR = 0.70), male (OR = 3.51), lower income (OR = 0.79), less educated (OR = 0.59), and White versus Other (OR = 0.61) when compared to the Physically Active group.

2013

The Vuong–Lo–Mendell–Rubin adjusted likelihood ratio test and the scree plots of the AIC and BIC supported a three-class model with good interpretability and class homogeneity: Physically Active (11%; high-probability meeting PA recommendations, low-probability smoking, drinking, meeting fruit and vegetable recommendations), Apathetic (76%; low-probability smoking, drinking, meeting fruit and vegetable recommendations), Binge drinking (13%; high-probability binge drinking). Participants in the Apathetic group were more likely to be male (OR = 3.85), lower income (OR = 0.75), less educated (OR = 0.58), Black versus White (OR = 1.93), and White versus Hispanic (OR = 0.51) than the Physically Active group. Participants in the Binge-drinking group were more likely to be younger (OR = 0.77), male (OR = 7.05), less educated (OR = 0.65), lower income (OR = 0.88), and White (vs. Other or Hispanic; OR = 0.67 and 0.58, respectively) when compared to the Physically Active group.

2015

The Vuong–Lo–Mendell–Rubin adjusted likelihood ratio and the scree plots of the AIC and BIC supported a three-class model with good class homogeneity and interpretability: Physically Active (39%; high-probability meeting PA recommendations, low-probability smoking, drinking, meeting fruit and vegetable recommendations), Apathetic (48%; low-probability smoking, drinking, meeting fruit and vegetable recommendations), and Binge drinking (13%; high-probability binge drinking). Participants in the Apathetic group were more likely to be younger (OR = 0.87), male (OR = 1.41), lower income (OR = 0.63), less educated (OR = 0.45), Black versus White (OR = 1.86), and White versus Hispanic (OR = 0.67) than the Physically Active group. Participants in the Binge-drinking group were younger (OR = 0.73), male (OR = 3.28), lower education (OR = 0.53), lower income (OR = 0.79), Black versus White (OR = 1.31), White versus Hispanic (OR = 0.70), and Other (OR = 0.66) when compared to the Physically Active group.

Discussion

This study investigated health behavior cluster patterns from 2003 to 2015 using a national dataset. Results confirm that meaningful health behavior clusters exist and were generally stable (replicated) across time in U.S. adults. Specifically, for each year, the largest group was the Apathetic group along with a smaller Physically Active/Healthy group and a Binge-drinking group with relatively consistent population distributions across the years (except 2011 and 2015). These findings support the use of multiple health behavior organizing approaches in the population. The replication and consistency of group distributions also suggest that health behavior patterns of U.S. adults are not improving, nor getting worse.

The Apathetic group was the largest group across the years. Individuals with low income and low education were more likely to be in this group than the Physically Active or Healthy groups. The Apathetic group is not engaging in risky behaviors such as smoking and drinking; however, the group is not actively engaging in preventive health behaviors such as fruit and vegetable consumption either. This group is at risk for chronic diseases [5, 6], which pose a burden to health care resources and caregivers [51–53]. Thus, it is imperative that health interventionists target adoption of health behaviors in this often-neglected group. Interventions for this group should consider the social determinants of low education and low income. For example, in addition to behavioral strategies about healthy eating and PA, interventions should also address engaging in these behaviors with limited resources, where to seek additional resources, and be delivered in a manner that is interactive and practical (for literacy and income restrictions). Interventions should also empower and encourage self-advocacy in the Apathetic group and their community around improving access to resources for health-promoting behaviors given that individuals with low income and low education are more likely to live in communities with limited access to resources for PA and health eating [54]. Given their lack of engagement in the measured health behaviors, we propose that this group will also be less likely to adopt other health behaviors such as seatbelt safety, sunscreen use, medication adherence, and routine health care visits. Therefore, interventionist targeting this group should assess and implement strategies to improve overall adoption of health behaviors.

The inability of smoking to distinguish the classes is noteworthy, whereas alcohol behavior plays a role. Smoking prevention efforts have been on the forefront during the last three decades targeting individual behavior, social norms, and imposing environmental restrictions [55]. Therefore, it is not surprising that smoking behavior is not showing up in the health behavior clusters, which only go back less than two decades. Alcohol behaviors (e.g., drinking in the past 30 days; binge drinking), however, have not changed appreciably in the past decade [56]. Given that most tobacco-dependent individuals begin smoking in adolescence [57] and with the recent increase of e-cigarettes [58], we recommend continued targeted interventions to reduce smoking initiation and avoid the re-emergence of smoking behaviors in later generations. Interventionists should take a more in-depth look at smoking cessation and prevention interventions and apply lessons learned and the most effective components of these strategies to e-cigarettes and other health behaviors. The recent Surgeon General's report on tobacco [55] describes in depth the efforts contributing to the lower smoking rates, which, in brief, include policy (nonsmoking policies, cigarette taxes, etc.), system changes (incentivizing smoking cessation through insurance, advertising restrictions, etc.), social efforts (health education, antismoking advertisements, etc.), environmental efforts (requiring ID and compliance checks, etc.), and individualized interventions (smoking cessation groups, individually tailored treatment programs, quit lines, etc). It is recommended to adapt these strategies to multiple behaviors at multiple levels to maximize the impact on chronic disease. Large-scale community or population-based trials incorporating such multilevel approaches are warranted. This may include randomization at the community level to allow policy and environmental efforts to be tested in combination with individualized interventions (e.g., Wilken and colleagues [59]). Recently, Barker and colleagues [60] published a very useful framework based on the past 15 years of research, for developing interventions and scaling them up for large dissemination. This framework comprises four steps: (i) *Set-up*—introducing and intervention testing; (ii) *Develop the Scalable Unit*—pilot testing; (iii) *Test of Scale-up*—intervention testing in a variety of settings resembling full scale; and (iv) *Go to Full Scale*—enabling sites/communities to adopt and/or replicate the intervention in a timely manner.

Younger adults were consistently more likely to be in the nonhealthy groups. This may have major implications for the health of future generations and the U.S. health care system. In addition to being at risk for chronic disease, there is a high likelihood that their children will follow similar behavior patterns and thus be at increased risk for chronic disease. Researchers [61, 62] have noted that the current generation of youth will be the first generation to live shorter lives than their parents due to chronic diseases mainly originating from obesity. Intervention efforts should focus on reversing the current trend by targeting younger adults who have the most influence on children's health and children and adolescents directly. Younger adults' risk for chronic disease due to poor health-promoting behaviors also comes at a great economic cost. According to our results, approximately 70% of U.S. adults are not engaging in health-promoting behaviors in any given year; this means that the majority is at risk for related chronic diseases. Providing ongoing care for such a large proportion of the population simultaneously potentially will devastate the U.S. health care system [63].

Males had two to three odds of being in the Apathetic group than in the Physically Active or Healthy groups. Most alarming, but not surprising, males were four to six times more likely to be in the Binge-drinking group across the years, which is consistent with males having a higher prevalence of alcohol use [64]. These results support the continued need for multiple risk behavior prevention interventions and more targeted interventions for males.

Noteworthy is that, for each year, the Binge-drinking group was also characterized by not meeting fruit and vegetable recommendations and approximately half of the individuals assigned to this group met PA recommendations. The Binge-drinking group's pattern of behaviors is a good example of why multiple health behavior approaches are necessary. Taken independently, research confirms that males are more likely to engage in binge drinking [65] and PA [66], and less likely to eat fruits and vegetables [67]. Interventions often target these behaviors separately; however, the behavior clustering in our results suggests that an intervention targeting younger males with low education and income that is focused on binge drinking, PA, and fruits and vegetable consumption simultaneously will likely be addressing the cumulative risk for most participants.

Regarding race/ethnicity, the results suggest that there are some differences. However, due to the vast cultural differences within the broad racial/ethnicity classifications used, we refrain from making generalizations about any particular group. However, we recommend to engage in culturally sensitive research and propose that more in-depth studies of multiple health behaviors within specific subpopulations in racial groups be conducted, as this might be more informative for intervention and policy purposes.

Limitations and Future Directions

This study was not a repeated measures design; seven independent cross-sectional samples were used limiting our conclusions to differences rather than changes over time. However, the data represented the U.S. population and thus inferences made from the results are done with this in mind. We expect that people may move in and out of clusters as time progresses. However, given the population-level efforts to promote preventive health behaviors, we would expect each population to improve in health as time progresses. Cohort studies exploring multiple health behaviors are warranted as this will best answer questions on the effects of practice, policy, and environment change as well as transiency of group membership.

The self-report nature of the data introduces the possibility of social desirability bias as the survey content is evident. However, gold standard or objective measures are less feasible and cost prohibitive to collect in large population studies. Furthermore, a systematic review of publications assessing the reliability and validity of the BRFSS concluded that BRFSS prevalence rates were not consistent with findings in other national surveys that utilized a combination of physical measures and self-report data [68]. Recent technology advances (e.g., smartphones) allow real-time collection of behavioral information and could potentially minimize recall bias and also allow for some objective data (pictures of food, step counts, etc.) to minimize the social desirability bias in future studies.

Conclusions

There is still a lot to be done to improve preventive health behaviors. Additionally, the reoccurrence of the similar patterns of behaviors and patterns of disparities across demographic groups over the years suggests that population-level interventions may not be as effective as hoped for and may not reach at-risk groups. Therefore, some groups may require more targeted efforts. Of specific interest is the Apathetic group, this group was more likely to be male, younger, have low education and low income, and may most likely benefit from population-level interventions that focus on the social barriers they face combined with individual-level interventions.

Compliance with Ethical Standards

Conflict of Interest Dr. Fleary has no conflict of interest to declare. Dr. Nigg serves as a consultant to Adidas on behavioral health content.

Authors' Contributions Dr. Fleary conceptualized the paper, analyzed the data and wrote the first draft of the methods, results, and discussion section. Dr. Nigg wrote the first draft of the introduction, advised on methodology, and contributed to the formulation of discussion points. Dr. Fleary and Dr. Nigg equally contributed to the editing of several drafts of the paper.

Ethical Approval This study was exempt from review by the Institutional Review Board as it is a secondary data analysis of a publicly available dataset.

Informed Consent No informed consent procedures were required as the study did not involve primary data collection from human research participants.

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