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A Latent Class Analysis of Weight-Related Health Behaviors among 2- and 4-year College Students, and Associated Risk of Obesity

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Abstract

Little is known about the complex patterning of weight-related health behaviors in 2- and 4-year college students. The objective of this study was to identify and describe unique classes of weight-related health behaviors among college youth. Latent class analysis was used to identify homogenous, mutually exclusive classes of nine health behaviors which represent multiple theoretically/clinically relevant dimensions of obesity risk among 2- versus 4-year college students using cross-sectional statewide surveillance data (n= 17,584). Additionally, differences in class membership on selected sociodemographic characteristics were examined using a model-based approach. Analysis was conducted separately for both college groups, and 5 and 4 classes were identified for 2-and 4-year college students, respectively. Four classes were similar across 2-and 4-year college groups and were characterized as “mostly healthy dietary habits, active”, “moderately high screen time, active”, “moderately healthy dietary habits, inactive”, and “moderately high screen time, inactive”. “Moderately healthy dietary habits, high screen time” was the additional class unique to 2-year college students. These classes differed on a number of sociodemographic characteristics, including the proportion in each class who were classified as obese. Implications for prevention scientists and future intervention programs are considered.

Keywords

young adults; obesity; co-occurrence of health behaviors; latent class analysis with a distal outcome; 2-and 4-year college students; audience segmentation

Introduction

Obesity continues to be a major public health concern (Flegal, Carroll, Ogden, & Curtin, 2010; Ogden, Carroll, Curtin, Lamb, & Flegal, 2010). Young or emerging adulthood is typically defined as 18–25 years of age, and is marked by important transitions such as increased autonomy in decision-making and behavioral exploration and experimentation, resulting in numerous potential health risk behaviors (Arnett, 2000). It also represents a time

for excess weight gain, marked by poor eating habits and physical inactivity (Nelson, Story, Larson, Neumark-Sztainer, & Lytle, 2008). This period of emerging adulthood may be an important age for formation of long-term health behaviors that are associated with increased chronic disease risk. Although this age group has been the subject of some research to date, most of this work has focused on students attending traditional, 4-year colleges and/or universities with little research on other young adults, such as 2-year college students (Laska, Pelletier, Larson, & Story, 2012; Nelson et al., 2008). Relative to 4-year colleges, 2-year colleges likely have more students who are more racially diverse and economically disadvantaged, factors that put them at greater risk for adverse health outcomes (Laska, Pasch, Lust, Story, & Ehlinger, 2011; Laska, Larson, Neumark-Sztainer, & Story, 2010). Developing effective interventions for this population is a public health priority.

Literature suggests the etiology of obesity is multifactorial (Dietz & Gortmaker, 2001). While television viewing (Hancox, Milne, & Poulton, 2004; Must & Tybor, 2005), consumption of sugar sweetened beverages (Berkey, Rockett, Field, Gillman, & Colditz, 2004; Giammattei, Blix, Marshak, Wollitzer, & Pettitt, 2003), and fast food (M. N. Laska, Murray, Lytle, & Harnack, 2012) are associated with increased risk of obesity, behaviors such as physical activity (Must & Tybor, 2005), and regular breakfast consumption appear to be protective (Merten, Williams, & Shriver, 2009; Mullan & Singh, 2010). Much of this literature is specific to adolescents and other age groups (Huh et al., 2011; Riggs, Huh, Chou, Spruijt-Metz, & Pentz, 2012), while modifiable determinants of obesity remain understudied among young adults.

Furthermore, although it can be useful to investigate the effect of individual risk factors, they seldom operate in isolation; in fact, many of these behaviors are highly related. For example, television viewing and high-calorie snack food consumption co-occur (Epstein, Roemmich, Paluch, & Raynor, 2005), as do sedentary and physical activities (Nelson, Gordon-Larsen, Adair, & Popkin, 2005; Owen, Leslie, Salmon, & Fotheringham, 2000). Although we know that each of the known risks for obesity is contributory, it is unclear how the risk factors interact to affect the risk of obesity or how varied weight-related behaviors co-occur in young adults.

One useful approach to address these issues is audience segmentation, a process by which intervention developers separate populations into smaller, homogenous subgroups based on co-occurrence of behaviors, enabling them to tailor and target each subgroup with more refined and potentially more effective interventions (Lee & Kotler, 2011). Segmentation is a key characteristic of business marketing practices and is increasingly utilized in social marketing activities targeting weight-related behaviors, like fruit and vegetable consumption (Cismaru & Lavack, 2007).

Latent Class Analysis (LCA) can address the complexity of obesity-related behavior patterning and capture meaningful key patterns of behaviors among the underlying population (Collins & Lanza, 2010). Additionally, it offers considerable promise in audience segmentation methods. In a recent study of students enrolled at a 4-year university, Laska and colleagues noted that the patterning of lifestyle characteristics and risk behaviors among both male and female university students was best represented by 4-classes. However, the

classes were qualitatively different across gender. The authors concluded that majority of study participants would be classified into patterns of diet- and physical activity-related risk behaviors that did not meet national guidelines for health. Nonetheless, the subgroups exhibited considerable heterogeneity in use of tobacco, alcohol, and engaging in risky sexual behavior. Although the findings underscore the constellation of health behaviors and interrelationships therein, the proportion of overweight/obese participants within each class was not examined. Additionally, the study was limited to students enrolled in one four-year university (Laska, Pasch, Lust, Story, & Ehlinger, 2009).

Since literature suggests that 2-year college students are at a greater risk for poor lifestyle factors/behaviors compared to 4-year college students, it is important to gain a better understanding of patterning of health behaviors and population needs in these two college groups. To address this gap in the literature, LCA was conducted separately for 2- versus 4-year college students, using data from a large, statewide college surveillance system. The main goals of the present study were to: (1) identify distinct classes of weight-related behaviors among young adults in a large and socioeconomically diverse sample of 2- and 4-year college students (2) describe the composition of classes based on weight status and other sociodemographic characteristics.

Methods

Study Design and Data collection

In 2011 and 2012, Boynton Health Service at the University of Minnesota randomly sampled students from the enrollment registries of 26 Minnesota colleges and universities, as part of an on-going Minnesota post-secondary surveillance effort using the College Student Health Survey (CSHS). Of these post-secondary institutions, 15 were 2-year community and/or technical colleges and 11 were 4-year post-secondary institutions. All study protocols were approved by the University of Minnesota Institutional Review Board.

Undergraduate and graduate students, randomly selected through enrollment lists provided by the schools, were contacted through multiple mailings and e-mails. Students were offered small monetary incentives for participation, as well as an opportunity to win one of several lottery prizes. Additional details regarding sampling and survey implementation are publicly available online <http://www.bhs.umn.edu/surveys/index.htm>. Overall, 17,866 students completed the surveys (overall response rate: 35.5%; 2-year colleges: 32.4%, 4-year colleges: 39.5%).

Measures

Cross-sectional survey data from 2011 and 2012 CSHS was pooled for the current analysis. Of the 17,866 college students, 17,584 had complete data on all outcome variables used in the analysis and were included in the current study. Gender, age, race/ethnicity, and parent education were self-reported. Height and weight were self-reported and used to calculate BMI (kg/m^2). Overweight and obesity were defined at cut-points of 25 and 30 kg/m^2 , respectively (World Health Organization, 1995). Table 1 presents descriptive characteristics of the sample and distribution of the key behaviors.

The latent class indicators included 9 weight-related health behaviors. They were selected to represent multiple theoretically/clinically relevant dimensions of obesity risk, and capture meaningful key patterns of weight-related health behaviors among young adults. The indicators were dichotomized to best reflect existing health recommendations and or national guidelines, as described in detail below.

Latent Class Indicators

Physical activity and screen media—Participants reported number of hours per week engaged in vigorous- and moderate-intensity physical activity, television viewing, and using computer for activities unrelated to work/school. 2 items were used to measure strenuous and moderate physical activity: “in the past 7 days, how many hours did you spend doing strenuous exercise?” Analogous wording was used to measure moderate exercise. Per CDC recommendations to maintain weight, vigorous- and moderate-intensity were dichotomized at 30 min/week and 2.5 h/week, respectively (Centers for Disease Control and Prevention, 2008). Similarly, 2 items were used to measure daily screen media use: “On an average day, how many hours do you spend doing the following activities?” The options included ‘watching television’, and/or ‘using a computer for something that is not for work or school work’. National guidelines recommend no more than 2 hours of screen time (American Academy of Pediatrics, 2001) and therefore both television viewing and computer use were dichotomized at this cut-point.

Eating and other health related behaviors—Number of times fruits and vegetables were consumed daily were assessed using 5 items. These included number of times fruits (not including fruit juice), green salad, potatoes (not including french fries/chips), carrots, and other vegetables were consumed in the past week. These items were combined to assess overall intake and to create a cut off reflecting the national recommendations to consume at least five daily servings of fruits and vegetables (US Department of Health and Human Services, 2010). Usual frequency of fast food consumption in the past year was assessed using a single item: “Indicate how often you did the following in the past 12 months...” Response options ranged from none to several times per day. Given empirical evidence establishing increased obesity risk associated with eating fast food several times per week or more (Boutelle, Fulkerson, Neumark-Sztainer, Story, & French, 2007; Pereira et al., 2005), this was selected as a cut off to create a binary indicator for fast food consumption. Drinking *regular* soda was measure using a single item: “During the past 7 days, how many times did you drink can, bottle, or glass of soda or pop.” Since, drinking regular soda daily is associated with health risks (Laska et al., 2012) and therefore, this was used as a cut point to dichotomize soda intake. Binge drinking (5 drinks at one sitting) in the past 2 weeks was assessed using a single item: “Think back over the last two weeks. How many times have you had five or more drinks in a sitting?” The response options ranged from “I do not drink” to 10 times. Based on previous research binge drinking was dichotomized as any (versus no) binge drinking in the past 2 weeks (Nelson, Lust, Story, & Ehlinger, 2009).

Statistical analyses

First, LCA was used to identify and describe distinct classes of weight-related behaviors among college students. The number of classes were ultimately be determined by a

combination of factors in addition to fit indices, parsimony, and interpretability (e.g., each class should be distinguishable from the others on the basis of the item-response probabilities, no class should be trivial in size (i.e., with a near-zero probability of membership), and it should be possible to assign a meaningful label to each class)(Bauer & Curran, 2003; Jung & Wickrama, 2008; S. T. Lanza, Collins, Lemmon, & Schafer, 2007; Muthén, 2003; Rindskopf, 2003). Second, a model-based approach was used to examine the association between latent classes and variables such as weight status, parental education, race, age, and gender.

All LCA analyses were conducted using PROC LCA (version 1.2.7) (Lanza, Dziak, Huang, Xu, & Collins, 2011; Lanza, Collins, Lemmon, & Schafer, 2007) and a corresponding macro for LCA with distal outcome (version 2.0) (The Methodology Center, Penn State, 2012) in SAS for Windows (version 9.3; SAS Institute Inc., Cary, NC).

Identifying Latent Classes—Across 2-and 4-year college groups, LCA was used to identify subgroups of students characterized by unique combinations or classes of behaviors associated with weight status. For each model, to assess model identification multiple sets of starting values were specified. Model selection was conducted using a combination of fit indices and interpretability. It was important that the latent subgroups in a solution exhibited logical patterns and were distinct from other subgroups. These best-fitting models provide estimates of the prevalence of each class and the probability of reporting each behavior within a particular latent class.

Association of the latent classes with weight status and other sociodemographic variables—To examine this association, a model-based approach to LCA with a distal outcome was used. For these models, the outcome variables included weight status, parent education race, age, and gender. These models were used to estimate the probability of weight status and sociodemographic variables in each latent class (e.g., the estimated probability of underweight/normal weight, overweight, and obese participants in each class). This was done by reparameterizing the LCA with covariates model (Lanza & Rhoades, 2011). In other words, instead of using weight status to predict latent class membership, latent classes were used to predict weight status. The analysis was conducted separately for all outcome variables for both college groups.

Results

Latent class profiles

The final solution yielded a 5- and a 4-class model for 2-and 4-year college students, respectively. Across college types, we ran a series of LCA models with 2 through 8 latent classes of weight-related behaviors to determine the optimal number of latent classes. Nylund *et al.*, reported Bayesian Information Criterion (BIC) to be the best indicator for determining the number of latent classes in mixture modeling among the traditionally used information criteria(Nylund, Asparouhov, & Muthén, 2007), and therefore, BIC played a significant role in model selection. Among 2-year college students, the 5-class model had the lowest BIC and the 8-class model had the lowest Akaike Information Criterion (AIC) (see Table 2), thus we examined the 5- through 8-class models more closely. A 5-class

model optimally represented distinct subgroups of individuals with respect to their weight-related behaviors. Among 4-year college students, although the information criteria suggested that the 5-class model had the most optimal balance between fit and parsimony among the models considered, there was only small, incremental improvement when moving from a 4-class model to a 5-class model. More importantly, the 5-class model contained two latent classes that were very similar, indicating poor latent class separation (Collins & Lanza, 2010). Based on the information presented in Table 2 and a careful inspection of the response probabilities from competing models, the 4-class model was identified to be most appropriate for 4-year college students.

Each latent class corresponds to an underlying subgroup of individuals characterized by a particular behavioral pattern. Tables 3 and 4 show the item-response probabilities for each item conditional on latent class membership for both college groups. These parameter estimates were used to interpret and label these subgroups.

Class 1 (labeled “mostly healthy dietary habits, active”) was comprised of 13% and 25% of 2- and 4-year college students, respectively. The individuals in this subgroup were unlikely to engage in unhealthy lifestyle behaviors, such as high screen media use, binge drinking in the past two weeks, eating fast food several times per week or more, and consuming regular soda once per day or more. Additionally, this subgroup was highly likely to engage in moderate and strenuous exercise, as well as eat breakfast regularly.

Class 2 (labeled “moderately high screen time, active”) was characterized by moderately high probabilities of engaging in high screen media use, as well as being engaged in moderate physical activity. Additionally, they were highly likely to participate in 30 minutes or more of weekly strenuous physical activity. Participants in this class had a below average to low likelihood of engaging in any of the healthy or unhealthy dietary behaviors reported here. Class 2 represented 19% and 17% of 2- and 4-year college students, respectively.

Class 3 (labeled “moderately healthy dietary habits, inactive”) included individuals who were not physically active, and unlikely to engage in unhealthy lifestyle behaviors such as screen media use, binge drinking in the past 2 weeks, eating fast food several or more times per week, and consuming one or more regular soda per day. Although participants in this subgroup had a high probability of eating breakfast regularly, they had a low probability of eating fruits and vegetable 5 or more times per day. This was the largest subgroup across both college types, with 33% and 28.5% of 2- and 4-year college students, respectively.

Class 4 (labeled “moderately high screen time, inactive”) represented 26% and 19.5% of 2- and 4-year college students, respectively. The students in this subgroup were characterized by relatively high probabilities of high screen media use, and a low probability of engaging into any other dietary or physical activity behaviors.

Class 5 (labeled “moderately healthy dietary habits, high screen time”) was unique to 2-year college students and represented 9% of the sample. Similar to latent class 4, response pattern identified as class 5 showed moderately high probabilities of high screen media use, but unlike latent class 4 were more likely to eat breakfast regularly. Moreover, this subgroup had low probabilities of engaging in any moderate exercise per week, binge drinking in the past

2 weeks, eating fast food several or more times per week, of eating fruits and vegetable 5 or more times per day and consuming one or more regular soda per day.

For 4-year college students, the 5-class model produced an additional class, or the 5th class, that mirrored the endorsement probabilities for class 2 on all 9 items but for TV viewing (0.45) and moderate exercise (0.46), indicating poor latent class separation. Given the fact that this class did not add much new information to our findings, we selected the 4-class solution for the 4-year college students (as described in the Methods).

Composition differences across classes

Weight status and other sociodemographic characteristics were disproportionately distributed across latent classes (Tables 5 and 6). Specifically, among both 2- and 4-year college students, obesity was much more prevalent in classes 3 and 4 relative to rest of the latent classes; 29% or more of the students in these classes were obese. Within each college group, healthy weight was most prevalent in class 1 with 60.6% and 69.0% for 2- and 4-year college students, respectively.

Among 2-year and 4-year college students, classes 1 and 2 had the highest proportion of students who had parents with at least a college degree, as well as class 5 among the 2-year group. However, relative to the 2-year group, a higher proportion of students in the 4-year group had parents who were at least college graduates. Reflecting the overall composition of the sample, most classes were comprised predominantly of White and female participants (for all but class 2), with highest proportion of females in class 3 followed by class 1 across both college groups. Within each college group class 2 was comprised mostly of 18–22 year olds, and class 3 of students who were 29 years and older.

Discussion

This is the first study to empirically identify meaningful patterns of health behaviors associated with weight status across 2- and 4-year college students, using a latent class approach. Additionally, the demographic composition of subgroups was explored. The complex patterning of behaviors associated with weight status in 2- and 4-year college students was best described by 5 and 4 latent classes, respectively. The findings provide insights into health needs of this population and refine our understanding of the interplay of weight-related health behaviors to develop successful interventions for college youth.

Although 4 classes were similar across 2- and 4-year students, the proportion of students in these classes differed across college groups. Additionally, a unique class emerged among 2-year students. Across college groups, class 3 was the largest of all classes and was marked by regular breakfast consumption, yet this class had the second highest proportion of obese students. Although this finding is counterintuitive, it is possible that the individuals in this class were obese to begin with and were engaging in healthier habits like regular breakfast consumption to lose weight. However, longitudinal data are required to confirm this hypothesis. Compared to other classes, for both college groups class 3 was also mostly comprised of older students (> 29 years) and females, corroborating findings from other studies that show an increase in weight with age (Gordon-Larsen, The, & Adair, 2010).

Class 4 also accounted for a significant proportion of the 2- and 4-year college students with the highest proportion of obese students relative to other classes. Of the 4 classes that were similar across college groups, this class was most sedentary relative to other classes with moderately high probability of screen media use and no physical activity. These results confirm findings from previous studies that demonstrate a relationship between screen time and obesity (Hancox et al., 2004; Must & Tybor, 2005). Across college groups and classes, class 1 members had the healthiest dietary habits. Additionally, they had low screen media use and were physically active. Compared to other classes this class had the highest proportion of individuals with normal weight, which reflected their healthier behavior.

Class 2 was also notable for both 2-and 4-year college students. It stood out by co-occurrence of seemingly opposing behaviors like relatively high screen media use and physical activity. Despite engaging in some unhealthy behaviors, this class, compared to other classes, had a relatively lower proportion of obese individuals. The possible explanation could be that class 2 members were physically very active and also had the highest proportion of 18–22 year olds across classes. Class 5, which was unique to 2-year college students was marked by high screen time and breakfast consumption had the lowest proportion of obese individuals and relatively higher proportion of females compared to most classes.

Despite the novel nature of the study it has several limitations that should be noted. Our participants were from the state of Minnesota and predominantly white, therefore, may not be representative of the general US population. Therefore, to test the generalizability of the current findings, the study should be replicated in different geographical regions. Our paper is a reflection of students, who attend these institutions, and therefore, age was widely represented. Because this could have affected the proportion of normal, overweight or, obese students in each class, it is important to interpret the results with caution. Additionally, with the model-based approach, we were unable to conduct significance testing for all the sociodemographic variables included in the current analysis, whereas an overall significance test is possible with the traditional classify-analyze approach. However, the model-based approach estimated the actual probability of an outcome conditional on latent class membership, whereas the results from classify-analyze approach are biased to the extent there is classification error (Lanza & Rhoades, 2011).

The present study is notable in that it used LCA to elucidate complex relationships between weight-related health behaviors among college youth. Meaningful key patterns of health behavior were identified with a multivariate latent class analysis, because of its approach to modeling measurement-error (Collins & Lanza, 2010). Furthermore, the study included participants from 2-year community and technical colleges, which have undergone limited study to date, and are at a greater risk for poor lifestyle factors/behaviors.

The categorization and characterization of population subgroups was based on health behaviors that were relevant to each latent class, and provide rich detail for the design of communication messages. Specifically, during intervention development the subgroups identified here could be used to target formative research, and thereafter, design effective messages that resonate with the participants, and may have implications for enhancing

health promotion interventions. For example, Class 1 may not be a high-priority audience; while this subgroup had sub-optimal fruit and vegetable consumption, they had the highest proportion of students with a healthy weight. The messages directed to this subgroup should support behavioral maintenance. The messages designed for class 3 need to increase physical activity, perhaps through moderate lifestyle changes, given that most students in this subgroup were older females, and possibly mothers. Messages will need to reflect means to effectively cope with the challenges and difficulties this subgroup may face in incorporating physical activity into their busy lives. A “5-a-day” fruit and vegetable message should be a common theme relevant to all the subgroups, as the probability of fruit and vegetable consumption was low for all. Future intervention messages should be informed both by universal characteristics of the overall sample as well as unique characteristics of each subgroup. Overall, these risk profiles should allow researchers to refine/modify their intervention strategies and target different population subgroups, thus leveraging resources more effectively, and developing more successful interventions that are sustained across time due to inclusion of targeted/tailored characteristics.

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Table 1

Sample Characteristics and Descriptive Statistics of Key Behaviors

	Total (n = 17584)	2-year college students (n=8952)	4-year college students (n=8632)
Characteristic	%	%	%
Weight status			
Normal weight (BMI < 25.0)	50.9	46.4	55.6
Overweight (BMI =25 to <30.0)	27.2	28.0	26.3
Obese (BMI ≥ 30.0)	21.9	25.6	18.1
Parent education			
Less than college graduate	33.3	39.6	26.8
At least college graduate	61.4	53.4	69.7
Don't know	5.3	7.1	3.5
Race			
White	81.0	79.7	82.4
Black	4.8	5.9	3.7
Asian/Pacific islander	5.4	4.7	6.1
Others	8.8	9.7	7.8
Age			
18–22 yrs	46.7	40.1	53.5
23–28 yrs	22.5	23.9	21.1
≥ 29 yrs	30.8	35.9	25.4
Gender			
Male	32.3	33.8	30.6
Descriptive Statistics of Key Behaviors			
2h/day of TV viewing	45.6	50.3	40.8
2h/day of video gaming	48.9	46.0	51.8
Binge drinking in the past 2 weeks	27.7	26.4	29.0
30 min/week of strenuous exercise	50.7	44.7	57.0
2.5h/week of moderate exercise	35.5	33.9	37.3
5 days/week eating breakfast	54.2	50.2	58.3
Eating fast food several times/week or more	15.8	18.7	12.7
5 times fruits and vegetables/day	18.3	17.0	19.6
1 regular soda/day	16.3	20.7	11.8

Note. BMI = body mass index.

Table 2

Criteria to Assess Model Fit for 2-Year College Latent Class Analysis (LCA) Models ($n = 8,952$).

	2-year college students (n= 8952)							
	2-class	3-class	4-class	5-class	6-class	7-class	8-class	
G^2	1535.19	988.12	746.95	643.17	567.56	530.65	477.35	
DF	492	482	472	462	452	442	432	
AIC	1573.19	1046.12	824.95	741.17	685.56	668.65	635.35	
BIC	1708.08	1252.01	1101.83	1089.05	1104.44	1158.52	1196.22	
CAIC	1722.08	1281.01	1140.83	1138.05	1163.44	1227.52	1275.22	
aBIC	1647.70	1159.85	977.90	933.34	916.94	939.25	945.17	

Note. G^2 = likelihood ratio chi-square; DF = degrees of freedom; AIC = Akaike information criterion; BIC = Bayesian information criterion; CAIC = consistent AIC; aBIC = adjusted BIC. Bold font signifies selected model. Models with lower values are preferred.

Table 3

Criteria to Assess Model Fit for 4-Year College Latent Class Analysis (LCA) Models ($n = 8,632$).

	2-class	3-class	4-class	5-class	6-class	7-class	8-class
G^2	1473.84	948.13	737.60	602.58	549.16	510.25	480.40
DF	492	482	472	462	452	442	432
AIC	1511.84	1006.13	815.60	700.58	667.16	648.25	638.40
BIC	1646.04	1210.96	1091.06	1046.68	1083.89	1135.61	1196.39
CAIC	1665.04	1239.96	1130.06	1095.68	1142.89	1204.61	1275.39
aBIC	1585.67	1118.81	967.13	890.96	896.40	916.34	945.35

Note. G^2 = likelihood ratio chi-square; DF = degrees of freedom; AIC = Akaike information criterion; BIC = Bayesian information criterion; CAIC = consistent AIC; aBIC = adjusted BIC. Bold font signifies selected model. Models with lower values are preferred.

Table 4
Five-Class Model of Weight-Related Health Behaviors among 2-year College Students (n=8952)

	Latent Classes				
	Class 1 Mostly healthy dietary habits, active 13%	Class 2 Moderately high screen time, active 19%	Class 3 Moderately healthy dietary habits, inactive 33%	Class 4 Moderately high screen time, inactive 26%	Class 5 Moderately healthy dietary habits, high screen time 9%
Probability of endorsing Indicator of Health behavior:					
2h/day of TV viewing	.29	.59	.28	.66	.98
2h/day of using computer for leisure	.31	.54	.30	.58	.78
Binge drinking in the past 2 weeks	.20	.43	.15	.30	.30
30 min/week of strenuous exercise	.86	.90	.30	.09	.50
2.5h/week of moderate exercise	.67	.60	.19	.18	.29
5 days/week eating breakfast	.88	.31	.63	.23	.67
Eating fast food several times/week or more	.02	.27	.09	.37	.08
5 times fruits or vegetables/day	.43	.13	.17	.05	.21
1 regular soda/day	.04	.30	.20	.41	.08

Note. Table shows probabilities of endorsing indicator of health behavior. Probabilities in bold indicate a greater likelihood of endorsement for the particular item.

Table 5

Four-Class Model of Weight-Related Health Behaviors among 4-year College Students (n=8632)

	Latent Classes			
	Class 1 Mostly healthy dietary habits, active 25%	Class 2 Moderately high screen time, active 27%	Class 3 Moderately healthy dietary habits, inactive 28.5%	Class 4 Moderately high screen time, inactive 19.5%
Probability of endorsing Indicator of Health behavior:				
2h/day of TV viewing	.21	.54	.34	.59
2h/day of using computer for leisure	.33	.73	.37	.68
Binge drinking in the past 2 weeks	.20	.48	.17	.31
30 min/week of strenuous exercise	.82	.83	.37	.17
2.5h/week of moderate exercise	.58	.56	.15	.18
5 days/week eating breakfast	.85	.45	.69	.26
Eating fast food several times/week or more	.02	.14	.06	.34
5 servings/day of fruits or vegetables	.45	.13	.12	.08
1 regular soda/day	.03	.14	.03	.33

Note. Table shows probabilities of endorsing indicator of health behavior. Probabilities in bold indicate a greater likelihood of endorsement for the particular item.

Table 6
Weight Status and Sociodemographic Differences among Emergent Latent Classes in 2-year College Students (n=8952)

Variables	Class 1	Class 2	Class 3	Class 4	Class 5
	Mostly healthy dietary habits, active	Moderately high screen time, active	Moderately healthy dietary habits, inactive	Moderately high screen time, inactive	Moderately healthy dietary habits, high screen time
	%	%	%	%	%
Weight status					
Normal weight (BMI < 25.0)	60.6	46.0	43.5	36.4	53.7
Overweight (BMI =25 to <30.0)	26.9	30.7	25.7	25.6	34.7
Obese (BMI ≥30.0)	12.5	23.3	30.8	38.0	11.6
Parent education					
Less than college graduate	34.6	34.7	47.1	42.9	33.4
At least college graduate	62.4	58.7	46.5	47.2	58.8
Don't know	3.0	6.6	6.4	9.9	7.8
Race					
White	87.1	87.1	77.1	81.9	63.9
Black	2.3	2.7	8.2	5.3	11.1
Asian/Pacific Islander	2.3	1.4	5.1	2.8	13.1
Others	8.3	8.8	9.6	10.0	11.9
Age					
18–22 yrs	37.1	58.1	21.1	39.1	48.6
23–28 yrs	27.0	26.4	19.4	29.0	18.4
29 yrs	35.9	15.5	59.5	31.9	33.0
Gender					
Male	31.8	54.0	16.0	41.2	29.8

Note. BMI = body mass index.

Table 7

Weight Status and Sociodemographic Differences among Emergent Latent Classes in 4-year College Students (n=8632)

	Class 1 Mostly healthy dietary habits, active	Class 2 Moderately high screen time, active	Class 3 Moderately healthy dietary habits, inactive	Class 4 Moderately high screen time, inactive
Variables	%	%	%	%
Weight status				
Normal weight (BMI < 25.0)	69.0	52.3	45.3	47.8
Overweight (BMI =25 to <30.0)	23.7	31.6	25.7	22.4
Obese (BMI ≥ 30.0)	7.3	16.1	29.0	29.8
Parent education				
Less than college graduate	21.2	21.7	32.0	35.3
At least college graduate	77.3	74.8	64.2	59.1
Don't know	1.5	3.5	3.8	5.6
Race				
white	89.1	84.1	85.3	65.5
black	1.6	2.7	3.1	9.3
Asian/Pacific islander	2.4	5.2	4.6	15.1
Others	6.9	8.0	7.0	10.1
Age				
18–22 yrs	55.5	82.1	19.3	49.7
23–28 yrs	20.9	17.3	19.5	30.3
≥ 29 yrs	23.6	0.06	61.2	20.3
Gender				
Male	24.3	53.5	10.0	40.0

Note. BMI = body mass index.