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Risk Behavioral Contexts in Adolescence of Obese Adults

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A B S T R A C T

Purpose: Previous research suggests that poor nutrition, physical activity, sleep, and social/emotional climate are associated with weight gain. However, few empirical studies have examined how these factors relate to each other in adolescents who are later obese. Are these factors uniformly present, or do some co-occur or occur independently? This study seeks to identify subgroups of obese individuals at ages 24–32 years who exhibited unique, co-occurring behavioral and emotional contexts for obesity at ages 14–17 years.
Methods: To identify subgroups of behavioral and contextual profiles in adolescence, the study applies latent class analysis to a sample of individuals who were obese in the fourth wave of the National Longitudinal Study of Adolescent to Adult Health (Add Health, N = 1,889). The study then explored covariates (e.g., gender, race) of class membership.
Results: Considerable heterogeneity exists in risk profiles of adolescents obese as adults. For example, 21.1 percent of the sample is in a class with no differentiating risk factors, whereas two classes containing 22.1 percent of the sample exhibit high levels of depression, and nearly all the emotional factors are considered. Although some covariates are predictive of class membership, clear patterns are difficult to discern. However, poor physical health is clearly predictive of membership in the classes exhibiting a high risk of depression.
Discussion: Clinicians should be aware that at younger ages, people who are ultimately obese display a range of factors linked to obesity. Although some exhibit behaviors such as high screen time and processed food consumption, others exhibit mainly poor social/emotional climate.

IMPLICATIONS AND CONTRIBUTION

Poor nutrition, physical activity, sleep, and emotional climate are linked to obesity. This study uses latent class analysis to explore if these factors appear uniformly in adolescents obese as adults. The findings suggest heterogeneity; classes range from including few differentiating factors to the full array of behavioral and emotional factors.

Obesity has long been recognized as a risk factor to health conditions such as asthma, type II diabetes, and certain cancers. In addition, the COVID-19 pandemic has again highlighted the issue as obesity is a major risk factor for serious infection [1]. Yet, in the U.S., over 40% of adults are obese [2]. This study explores these obese adults as adolescents. In particular, the study asks whether obese adults look homogenous as adolescents with respect to behaviors (e.g., poor nutrition) and social/emotional contexts (e.g., depression) linked to weight gain or whether variance exists. If variance does exist, the study also explores how that variance correlates with demographic characteristics. This information is relevant to practitioners, who should understand whether a single risk profile for obesity exists in adolescence or multiple ones and, if multiple, which profile is most likely to show up in a particular population.

Previous research has identified four categories of such behavioral and contextual risk factors: (1) nutrition; (2) physical activity; (3) sleep; and (4) social/emotional climate. However, with a few exceptions, studies have looked at these factors

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individually, rather than considering them synergistically. The present study aims to fill this gap by examining all four behavioral and contextual risk factors to examine how they present in adolescence for obese adults. Do they typically occur uniformly or not?

To answer this question, we apply latent class analysis (LCA) to group people who were obese in the fourth wave of the National Longitudinal Study of Adolescent to Adult Health (ADD Health), at ages 24–32 years, based on behaviors and contextual factors exhibited in the first wave of the survey, at ages 14–17 years [3]. Intuitively, the goal of LCA is to construct dissimilar groups of people with respect to the factors being considered. For example, one group might comprise those with depression but few other risk factors, whereas another might contain people without depression, but with little physical exercise and high intake of processed foods. To the extent multiple groups exist, LCA can also be used to describe the demographic (e.g., gender, race) and socioeconomic (e.g., the parent's education) characteristics associated with them. By exploring which covariates are associated with certain factors or groups of factors, the study hopes to offer clinicians insight into risk profiles certain demographic groups may be more likely to exhibit.

Background

The existing literature has linked the four groups of factors—nutrition, physical activity, sleep, and social/emotional climate—individually to weight gain. In the area of nutrition, high consumption of processed foods is linked to higher weight status, whereas consumption of fruit and vegetables is a protective factor [4,5]. These effects persist even in the presence of controls. For example, in children aged 2–9 years, controlling for the child's sex, age, socioeconomic status (SES), physical activity, and initial body mass index (BMI), those who consumed more vegetables had less risk of becoming obese [6].

In the area of physical activity, the literature indicates that high levels of screen time or low levels of physical activity are associated with obesity [7,8]. Even having the opportunity for physical activity (e.g., the presence of fitness centers or safe outdoor space) is conducive to lower weight [9,10]. On sleep, strong evidence also exists that it can impact the development of obesity. For example, individuals who saw their sleep decline in adolescence were most likely to transition to higher BMI at later ages [11].

Finally, factors related to social/emotional climate—e.g., mental health issues or lack of peer approval—have been shown to play a role in the development of obesity. Longitudinal studies that controlled for sex, age, race, SES, and baseline weight status found that fewer family meal frequencies during middle and high school predicted a higher obesity status 10 years later [12,13]. Mental health also plays a role. For example, female adolescents who are depressed are more likely to gain weight by follow-up than nondepressed peers [14]. Exacerbating the issue is the fact that obese teens are likely to experience bullying by peers, which may cause feelings of isolation, depression, and lower physical activity [15,16].

This last point illustrates one of the main contentions of our study—certain factors such as depression and physical activity might be intertwined. Examining the full range of co-occurring factors—referred to in some studies as an "ecological" approach—can contribute to the understanding of obesity risk profiles. Do all individuals obese as adults share a common profile when younger, or do certain factors pair together into unique clusters?

In recent years, a number of studies have taken this ecological approach (although none has considered all four groups of factors considered here) and highlighted some of the clustering of interest to the present study [17–20]. For example, in one study, adolescent boys were more likely to exhibit high physical activity and have low-quality diet, whereas girls were the opposite—lower on physical activity and higher on consumption of quality foods [18]. Another study focused on younger children, finding that low physical activity was somewhat pervasive, but certain behaviors like high screen time were only present in certain individuals [19].

These studies have also looked at how covariates predict class membership and typically find disadvantaged groups belong to classes with more risk factors. For example, in one study, African-American and Hispanic children were more likely to be in classes characterized by high screen time and high consumption of unhealthy foods (high-fat/high-sugar snacks) compared with the most prevalent class which did not contain high consumption of unhealthy food [17]. In another, children from low SES neighborhoods were more likely to exhibit a multitude of risk factors including risky food-based measures, low physical activity, high screen time, and low sleep [20].

Yet, although these valuable studies share similarities with the present one—including looking at how multiple groups of factors relate to each other and how covariates predict class membership—none examine all four groups of factors. Most look at two or three risk factors instead of all four considered here, and none of the research included social/emotional climate, including depression. The present study therefore looks to construct a more complete profile of adolescents who are obese as adults.

Methods

Participants

This study was a secondary data analysis using publicly available data from Add Health, a nationally representative panel survey which began collecting data in 1994. It was approved by the Institutional Review Board of Northeastern University for exemption status. The study used data from the first and fourth waves of Add Health, sampling individuals aged 14–17 years (collected in 1994–1995) and then 24–32 years (collected in 2008–2009), respectively [21]. Data on behaviors and contexts related to obesity and any covariates were collected in wave 1. Only those participants who were obese during the fourth wave of Add Health (N = 1,889) were included in this study, as we aimed to identify profiles of habits and behaviors in adolescence among those obese in adulthood.

Obesity, risk factors, and covariates

The study required three types of measures. The first was a measure of obesity with which to select the LCA sample from wave 4. The second were indicator variables of the behavioral and contextual factors discussed in the Background section. The third were independent variables that affect the probability of being a member of a certain class.

Table 1
Description and frequency of risk factor indicators

Category	Indicator variables	Wave 1 (ages 14–17 years)
Nutrition	Daily fruit/vegetable consumption	
	Low risk (3 or greater)	40.9
	High risk (less than 3)	59.1
	Daily processed food consumption	
	Low risk (less than 1)	50.5
	High risk (1 or more)	49.5
Physical activity	Weekly physical activity occasions	
	Low risk (7 or greater)	64.8
	High risk (less than 7)	35.2
	Fitness center usage	
	Low risk (usage)	18.9
	High risk (no usage)	81.1
	Weekly screen time (TV, videos, and computer/video games)	
	Low risk (less than 14 hours)	38.7
	High risk (14 hours or more)	61.3
	Weekly TV viewing	
	Low risk (less than 14 hours)	51.3
	High risk (14 hours or more)	48.7
	Neighborhood safety	
	Low risk (safe)	88.3
	High risk (unsafe)	11.7
Sleep	Daily sleep	
	Low risk (8 hours or more)	61.2
	High risk (less than 8 hours)	38.8
Emotional/relational	Weekly family meals	
	Low risk (3 days or more)	75.2
	High risk (less than 3 days)	24.8
	Depression score (CES-D)	
	Low risk (not clinically depressed)	84.2
	High risk (clinically depressed)	15.8
	Closeness to mother	
	Low risk (quite a bit to very much)	85.8
	High risk (not at all to somewhat)	14.2
	Feeling socially accepted	
	Low risk (agree to strongly agree)	84.6
	High risk (neutral to disagree)	15.4
	Feeling friends' care	
	Low risk (quite a bit to very much)	83
	High risk (somewhat to not at all)	17

The number of observations varies slightly among each behavioral context based on missing data. Amount of missing data did not exceed more than 29 participants of 1,586 total participants.

Adult body mass index. Participants were asked to self-report their height (in feet and in inches) and weight (in pounds). The BMI was then calculated by Add Health after converting height and weight into metric measurements and then dividing weight (in kilograms) by height (in meters squared) [22]. Obesity was defined as a BMI of above 30. Adults who were not obese were excluded from the analysis.

Risk factor indicators. The indicator variables span four behavioral and contextual categories—nutrition, physical activity, sleep, and social/emotional climate. The descriptions in the following provide detail on the specific variables included, and Table 1 provides their frequency in the sample.

Daily fruit and vegetable consumption. Participants were asked how often they had eaten fruit (including juice) or vegetables during the previous day. The answers included "did not eat," "ate once," and "ate twice or more." For analysis, the sum of participants' numerical answers to these questions was combined and split into high and low risk. High risk included adolescents who reported fewer than three occasions of consumption, which is consistent with current guidelines for youth [23].

Daily processed food consumption. Adolescents were asked how often they ate sweets, including "cookies, donuts, pie, or cake," during the previous day. Participants' numerical answers were dichotomously split simply into either yes (participants did eat sweets on the previous day) or no.

Weekly physical activity occasions. Participants were asked how many times in the past week they had performed certain activities, for example, roller-blading or bicycling. Across different activities, participants' frequency of specific activity-related pursuits was combined to form a total sum of their weekly physical activity occasions. Current guidelines suggest that individuals should aim for at least 60 minutes of physical activity across each of the 7 days of the week [24]. Assuming that an individual's typical activity lasts approximately an hour, the high-risk group contained those who reported fewer than seven physical activity occasions per week.

Use of a neighborhood fitness center. Participants were asked whether they used a physical fitness center in their neighborhood (yes/no).

Neighborhood safety. In terms of neighborhood safety, participants were asked, "Do you usually feel safe in your neighborhood? (yes/no)."

Weekly hours of screen time/TV viewing. Participants were asked how many hours a week, on average, they spent engaging in screen time (including computer, TV, and video game usage) and separately how many hours they specifically watched TV. Current recommendations include that children should spend no more than 2 hours per day either engaged in screen time or watching TV [25]. Thus, we labeled high values as greater than or equal to 14 hours per week.

Sleep. Participants were asked, "How many hours of sleep do you usually get?". Daily hours of sleep were divided into dichotomous variables representing high and low values. The high-risk sleep group included those who reported obtaining less than 8 hours per night [26].

Family cohesion. Family cohesion was measured as self-reported closeness to one's mother. Participants were asked, "How close do you feel to your (mother/adoptive mother/stepmother/foster mother/etc.)?". High risk ranged from "somewhat" to "not close at all".

Weekly family meals. Weekly family meals were measured with the question, "On how many of the past 7 days was at least one of your parents in the room with you while you ate your evening meal?". Using the criteria established by Hammons and Fiese, weekly family meals were split into an average/high frequency per week and low frequency (fewer than three) [13].

Feelings of social acceptance. Participants were asked whether they agreed or disagreed with the statement, "you feel socially accepted." Participants were also asked, "How much do you feel that your friends care about you?". For both variables, high risk/low social acceptance ranged from "somewhat" to "not at all."

Depression. Depressive symptoms were measured using the Center for Epidemiologic Studies Depression Scale. Nine questions related to depression symptoms were used, and the range of the scores was 0 (for those who reported having symptoms "not at all of less than 1 day" to all nine questions) to 27 (for those who reported having symptoms "5–7 days or nearly every day for 2 weeks" to all nine questions). The total scores were split into dichotomous categories: depression (a score of 10 or above) and no depression [27].

Covariates. Demographic covariates included sex (male/female) and race/ethnicity (Caucasian/adolescents of color). The sample comprised 42% males and 58% females, 68% Caucasian, and 32% adolescents of color. The SES control was the mother's education (high school or less/some college)—58% of the sample had a mother with high school or less, whereas 42% had a mother with some college. Another included covariate was baseline BMI (not obese/obese in adolescence). Although, by design, the entire sample was obese in wave 4, the baseline BMI in wave 1 included only 25% of obese adolescents (defined, as is common for younger people, as being in the top 5 percent of individuals by the BMI). Finally, other health-related variables included whether one or more of the individual's parents were obese at baseline ("parental obesity"—not obese/obese) and self-reported health (good to excellent/fair to poor).

Methodology

LCA was conducted using PROC LCA in SAS software, Version 9.4 [28]. LCA is a multivariate latent variable approach that describes relationships between two or more observed categorical variables in terms of their association to a third, discrete latent variable [29]. Conceptually, latent variables represent items classified into mutually exclusive groups based on shared behavioral characteristics [30]. Unlike observed variables (e.g., sex), which allow direct comparisons, latent variables must be inferred from observed responses.

Intuitively, the goal of LCA is to construct classes where people within the class have much in common, but little in common with those in other classes. For example, if one class comprised people with high screen time and high processed food but no depression, another would comprise those with only depression. Given an assumed number of classes, LCA outputs (1) the share of individuals within each class and (2) the probabilities of having each risk factor within each class. These parameters are estimated by maximum likelihood estimation, where the inputs are the observed probabilities for the risk factors considered, e.g., the share of individuals with high screen time.

However, the number of latent groups is not known a priori, so a process of model fitting is carried out by increasing the number of classes gradually and determining the appropriate number. This determination is based on two criteria: model fit statistics and—in the event that the fit statistics considered disagree—model interpretability. Fit statistics from models with two through six classes were compared. The fit statistics that are common to LCA are: Akaike's information criterion (AIC) and the Bayesian information criterion. For both statistics, a lower number indicates a better fit.

The AIC suggested (Table 2) that the best fit was a six-class model, whereas the Bayesian information criterion suggested a four-class model. Thus, as is common in LCA model fitting, there was some disagreement between the fit statistics regarding the optimal number of classes [31,32]. However, the 4-class model contained repetitive classes (two of the four classes were unique in terms only of fitness center use) and one nondifferentiated class (contained all factors). This result seemed inconsistent with the goal of LCA to provide "qualitatively different subgroups" [33]. On the other hand, the 6-class model had distinct classes

Table 2
Fit statistics and model fit information (indicated best fit bolded)

Number of classes	Likelihood ratio G^2	AIC	BIC	CAIC	ABIC
2	2,717	2,771	2915.9	2942.9	2830.2
3	2433.5	2515.5	2735.7	2776.7	2605.4
4	2284.9	2394.9	**2690.2**	**2745.2**	**2515.5**
5	2226.6	2364.6	2735.1	2804.1	2515.9
6	2181.6	**2347.6**	2793.2	2876.2	2529.6

The G^2 is not adjusted for the additional degrees of freedom cost by adding a class and so declines when additional classes are added regardless of how much the additional class improves fit. The AIC, BIC, CAIC, and ABIC are all degree of freedom adjusted—the lowest value indicates the tradeoff between the additional class and lost degrees of freedom was valuable.
ABIC = adjusted Bayesian information criteria; AIC = Akaike information criteria; BIC = Bayesian information criteria; CAIC = corrected Akaike information criteria.

Table 3
Latent class prevalence and item-response probabilities

	1	2	3	4	5	6
	Class 1:	Class 2:	Class 3:	Class 4:	Class 5:	Class 6:
	Low fruit/veg + screen time	No abnormal risk factors	Low fruit/veg + friendship issues	Processed food + screen time	Depression with behavioral factors	Depression
Latent class prevalence	24.4%	21.1%	12.8%	19.7%	10.2%	11.9%
Indicators						
Low fruit/veg consumption	**0.689**	0.440	**0.674**	0.429	**0.766**	**0.706**
High processed food	0.501	0.444	0.520	**0.631**	0.449	0.349
Low phys. activity occasions	0.477	0.388	0.470	0.320	**0.590**	0.461
No fitness center attendance	**0.870**	0.817	0.746	0.686	**0.948**	0.835
High screen time	**0.999**	0.195	0.152	**1.000**	**0.999**	0.086
High TV viewing	**0.948**	0.000	0.005	**0.852**	**0.878**	0.006
Low safety	0.083	0.026	0.071	0.134	*0.280*	*0.219*
Low sleep	0.244	0.391	0.442	0.405	**0.537**	*0.465*
Low family meal frequency	0.094	0.185	0.276	0.222	**0.550**	*0.456*
Depression	0.059	0.037	0.039	0.069	**0.541**	**0.518**
Not close to mom	0.060	0.090	0.050	0.051	*0.466*	*0.381*
Not feeling socially accepted	0.088	0.034	0.065	0.088	*0.458*	*0.441*
Friends do not care	0.060	0.001	*0.319*	0.224	*0.324*	*0.328*

N = 1,586. Bolded item-response probabilities indicate values greater than 0.50 and more than 2 standard errors above sample mean (within obese sample considered). Italics indicate 2 standard errors above sample mean without 0.50 threshold being met.

and was more consistent with the literature [17]. Given the 6-class model was also favored by the AIC, it was used in the study.

Results

This section provides the results, first for the LCA itself and then for the covariate analysis.

Latent class analysis

Table 3 lays out six classes. The number of classes itself is worth noting—it shows obese adults displayed fairly heterogenous profiles with respect to these variables in adolescence. For convenience, the table (1) bolds behaviors exhibited by over half of the people in the indicated class and that were at least two standard errors above the mean in the sample and (2) italicizes items exhibited by a minority of people, but that were two standard deviations above the mean for that factor.

The largest class (24.4% of the total sample) is characterized by high screen time and low fruit and vegetable consumption. The second class comprised people with no differentially high behavioral or emotional contexts (21.1% of the sample). The third class comprised people with low fruit/veg consumption and who had a high rate of not feeling close to friends (12.8% of the sample). The fourth class comprised people who combine high processed food consumption and high screen time (19.7% of the sample). It is worth noting that all four of these classes have low rates of emotional contexts, i.e., they display mainly behavioral risk factors.

The final two classes differ considerably and include people with high rates of depression and other emotional contexts. The first of these classes exhibits depression along with behavioral risk factors such as high screen time, low physical activity, and low sleep (10.2% of the sample). The second of the classes has depression alone as the main source of risk (11.9% of the sample). Both classes also display high rates of other emotional risk factors—2–3 times higher than the average within this sample—such as not being close to mom or not feeling socially accepted.

The construction of the classes displays some of the strengths of the approach. For example, without LCA, one would be tempted to expect that high screen time, poor diet, and low physical activity tend to always co-occur. However, the LCA makes clear that several classes have high screen time (classes 1, 4, and 5), but that variance exists in the other risk factors that are present—some are less active than is typical, and others are actually slightly more active. Similarly, although a characteristic of depression may be inactivity, more than half of those in the depression class do not exhibit above normal rates of screen time or TV viewing.

Covariates and latent class

As shown in Table 4, sex, SES/mother's education level, race/ethnicity, and health distinguished class membership. As is common in the literature, this study used the largest latent class—"high screen low fruit/vegetable"—as a reference group [34]. Both females and individuals with more educated mothers were significantly more likely to be in the class without any high behavioral or emotional factors (class 2) than the reference group. Indeed, the logit coefficient for females and those with more educated mothers was largest for this class, suggesting that they were more likely to be in this class than any other.

On the other hand, adolescents of color were significantly more likely to be in the classes with at least a few risk factors (classes 3–6). Adolescents of color were most likely to be in class 4, defined by high screen time and processed food, followed by class 3 with low fruit and vegetable consumption and higher than typical issues with friend closeness. Adolescents of color were also significantly more likely to be in the classes defined by depression and emotional issues than the reference class (although less likely to be in these than classes 3–4). Finally, those in fair–poor health were significantly more likely to be in classes characterized by depression (classes 5–6).

Table 4
Odds ratios–LCA with covariates (sex, baseline BMI, race/ethnicity, SES/mother's education level, parent obesity, health)

Class:	Class 1: Low fruit/veg + screen time	Class 2: No abnormal risk factors	Class 3: Low fruit/veg + friend issues	Class 4: Processed food + screen time	Class 5: Depression with behavioral factors	Class 6: Depression
Intercept	Reference	0.458	0.741	0.628	0.195	0.313
Lower bound		0.213	0.37	0.222	0.082	0.146
Upper bound		0.989	1.501	1.785	0.463	0.67
Female		**2.084**	**0.065**	**0.148**	1.422	1.322
Lower bound		**1.044**	**0.022**	**0.065**	0.691	0.663
Upper bound		**4.164**	**0.201**	**0.335**	2.941	2.645
Obese at baseline		0.68	1.28	1.158	0.742	0.54
Lower bound		0.41	0.641	0.543	0.385	0.29
Upper bound		1.129	2.564	2.476	1.432	1.007
High SES/mother some college		**2.078**	0.746	1.285	1.216	1.045
Lower bound		**1.357**	0.359	0.582	0.664	0.619
Upper bound		**3.185**	1.562	2.839	2.232	1.769
Minority race/ethnicity		0.735	**8.225**	**11.633**	**3.252**	**2.781**
Lower bound		0.338	**2.694**	**3.79**	**1.436**	**1.25**
Upper bound		1.607	**25.716**	**35.728**	**7.441**	**6.257**
One or more parents obese		1.098	1.553	1.912	0.807	0.947
Lower bound		0.712	0.759	0.949	0.4219	0.551
Upper bound		1.694	3.184	3.864	1.523	1.629
Fair to poor health		2.541	3.917	**4.802**	**14.948**	**9.09**
Lower bound		0.731	0.839	**1.047**	**4.048**	**2.562**
Upper bound		9.2	18.653	**22.209**	**57.407**	**33.696**

Bolded items indicate significance from an odds ratio of 1 at the 0.05 level.
BMI = body mass index; LCA = latent class analysis.

Interestingly, variables that did not predict class membership included both whether one was obese at baseline or had an obese parent. This finding suggests that those with obesity at baseline or in their family have similar risk profiles in terms of behavior and contexts as those without.

Discussion

Using previously identified, behavioral contexts for weight gain (nutrition, physical activity, sleep) as well as social/emotional climate, we examined the characteristics of groups of single or co-occurring factors during adolescence of adults who were obese [35,36]. Such an approach has been used in only a few studies and even then without focusing on the full range of factors [17–20].

Overall, considerable heterogeneity exists in the risk profiles displayed by adolescents obese as adults—six discrete latent classes of behavioral and emotional contexts were identified. These classes ranged considerably in their complexity with respect to the factors considered. One (class 2) had no factors that were considered high within this sample. Another (class 5) had all but one risk factor at least two standard errors above the within sample average. Thus, the range of risk profiles is quite wide with respect to the measures considered.

Over half of adolescents (54.3%) were in at least one class characterized by high screen time/TV viewing (over 14 hours per week). Interestingly, high screen time was not always jointly characterized by low physical activity. In particular, the fourth class characterized by screen time and processed food had less risk in terms of engaging in low physical activity than average (over 4 standard errors less)—a somewhat counterintuitive result.

Yet, the result is consistent with prior research that suggests the effect of screen time goes beyond simply taking the place of time spent on physical activity and is consistent with prior research findings that screen time/TV viewing exposes individuals to processed food advertisements, resulting in food cravings and encouragement to snack [37,38]. Wave 1 of the Add Health study was collected in 1994. Since then, screen time has expanded to include more portable devices. As a result, children may be spending more time on screens than in the past. Thus, the high prevalence of screen time in our study during adolescence may be more pronounced if data were collected at our current point in time.

Aside from the high screen time classes, another broad swath of adolescents who ended up obese as adults suffered from high rates of depression (classes 5–6). A total of 22.1% of the sample were in classes characterized by much higher rates of depression than is typical of adolescents. These classes were also characterized by low family meal frequency and lack of close relationships to family and friends.

However, the two depression-heavy classes also differed in important ways. The first contained individuals who seemed inactive—they had low physical activity and low attendance at physical fitness centers (even this group's sole "low risk" factor was not eating processed foods). This class seemed to replace this activity time with screen time. However, the other class characterized by depression did not have these issues—they had much lower screen time and only marginally below average physical activity. It might be the case that another underlying relationship, such as depression and inflammation, might co-occur together to lead to obesity [39]. In any case, this dichotomy within the depressive classes and any link to obesity without behavioral factors seem worthy of future research.

The news for practitioners from this study is somewhat complicated. Certainly, the study suggests that individuals who are obese in adulthood do not display a uniform set of behaviors or emotional contexts in adolescence. This fact means that targeting stereotypical behaviors associated with obesity—like high screen time—will not be uniformly effective. After all, many obese adults did not show high screen time as adolescents.

In addition, although the covariates could offer clues at intake as to the underlying risks a person may have with respect to obesity, the message is also muddy. For example, in terms of race/ethnicity, adolescents of color were more likely to be members of classes with at least some risk factors showing. However, those factors ranged from food-related issues alone to almost the entire array of issues considered. Given this wide array of risks, one promising strategy is to advocate for resources to create sustainable structural change, such as the Communities Creating Healthy Environments, which was successful in increasing both food and recreational access [40].

Interestingly, both obesity in adolescence and whether one's parents were obese during the child's adolescence were not significant predictors of class membership at either time point. In other words, knowledge of whether an adolescent is obese does not provide insight into his or her underlying groups of behavioral contexts. However, underlying health does. Individuals presenting as in poor health otherwise seem most likely to be in the class highlighted by the highest number of risk factors.

Limitations of this study

Several limitations of the present study are worth mentioning. Most notably, this study selected a sample of individuals obese in adulthood. The study therefore says nothing about whether these factors cause obesity. Instead, it attempts to point out the high degree of variance that exists in these factors as they exist in people who become obese. Thus, although the study can point to factors that might be targeted for prevention in the sense that they occur for people who are ultimately obese, it is left to the literature to support any conclusion that such targeting would actually reduce obesity.

It is also worth noting that the data used in this study were secondary data collected for purposes broader than this study. Individual questions certainly could have been better framed for our purposes. As just one example, fruit consumption included juice, and most fruit juices are high in sugar. At a minimum, this would depress our findings of low fruit/vegetable consumption, but it might also bias the results on covariates. For example, it is widely known that Black households are more likely to live in food desserts where fruit juices may be consumed. In the present study, this behavior would be labeled as healthy. However, despite these limitations, we feel pointing out the considerable heterogeneity that exists in the risk profiles of adolescents obese as adults is a valuable application of LCA.

Conclusions

This study suggests that during adolescence, there are heterogeneous, discrete classes (totaling six in number) of individuals with differing behavioral contexts associated with obesity among those obese in adulthood. Some classes contain no abnormally high levels of these factors; others include high levels for almost all of them.

Much remains unknown about those who maintain or develop obesity in middle adulthood. Although we explored behavioral contexts in adolescence, future research should pursue these contexts in adulthood, including any transitions between classes over time. In any case, the present research makes clear that those obese in adulthood are not uniform in adolescence.

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