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Assessment of Risk Factors Associated with Obesity among Undergraduate Students

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ABSTRACT

Background: University students are under pressures of lifestyle which can increase the risk of obesity. This paper estimated the prevalence of obesity and determined independent behavioral and psychosocial correlates among undergraduate.

Methods: Cross-sectional, stratified cluster sample (n=620 students) 51% female. Diet, physical activity and sedentary time, sleep duration/quality and social jetlag, and perceived stress were measured using validated questionnaires; standardized anthropometry was used to provide BMI and waist. Adjusted odds ratios (AORs) were obtained with multivariate logistic regression.

Findings: WHO Asian cut-offs indicated that 23.7% of them were obese and 23.4% met the central obesity criteria. The independent predictors of obesity were physical inactivity (AOR 1.62, 95% CI 1.18-2.23), daily sugar-sweetened beverages (1.54, 1.12-2.11), eating late at night (1.45, 1.06-1.98), breakfast 2 or more times/week (1.38, 1.01-1.89), short sleep (less than 7 hours) (1.47, 1. Active/public commuting was nonsignificant but protective by means of adjustment. The model discrimination was reasonable (AUC 0.78) and estimates strong in sensitivity analyses based on central obesity.

Conclusions: Obesity among students is the product of energy imbalance, circadian disruption, and stress. Sex- and residence-specific multi-component campus policies focusing on beverages, movement, sleep, and stress are justified. Results inform combined student health policies and policy changes on campus.

Keywords: undergraduate students, obesity, sugar-sweetened beverages, physical inactivity, sleep, social jetlag, stress

INTRODUCTION

Obesity is now more common in late adolescence and young adulthood, a time of development in which long-term health behaviors are hardened and weight patterns start to follow into midlife. To most undergraduates, college life is a shock to their habitual schedule in the sense that they are deprived of regular meals, snacks, time or desire to exercise, long periods of sitting in lecture rooms or in front of computers, social food, and stress over college-related obligations. Collectively, these exposures create an obesogenic combination with the ability to shift the energy balance towards weight gain. Environment and social context of universities also count: what is accessible, affordable, and convenient at or near the university influences the quality of the diet, whereas housing, economic resources, and time-related limitations restrict healthy options (Li et al., 2022; Keat et al., 2024).

In terms of the public-health, excess adiposity during early adulthood is consequential. Cardiometabolic risk markers, including central adiposity, dyslipidemia, insulin resistance and hypertension, have been shown to be sustained throughout the life course in relation to weight gain in the late teens and twenties. One dietary driver that can be distinguished in this age group is sugar-sweetened beverages (SSBs): regular intake is associated with positive energy balance and cardiometabolic disease downstream, and the ubiquity of SSBs and their marketing is shrubs across campuses (Malik and Hu, 2022). Access and consumption of fast-food are compounded by increased energy density and added sugar and food insecurity among students can even be a paradoxical co-occurring condition with obesity through use of lower-cost, ultra-processed options (Malik and Hu, 2022; El Zein et al., 2020; Keat et al., 2024).

A more modern conceptual framing perceives undergraduate obesity in terms of energy balance that lies within behavioral and ecological systems. Diet quality (ex: SSBs, fast foods, breakfast patterns) and timing on the intake side affect satiety and glycemic load. It has been demonstrated that breakfast skipping is correlated with increased body weight and risk of obesity, and in the case of university students, in particular, irregular breakfast intake is a predictor of future weight gain (Wicherski et al., 2021; Yamamoto et al., 2021). Inadequate moderate-vigorous physical activity (PA) and high screen time, especially recreational screen time, on the expenditure side, are invariably linked to more adiposity among young adults and youth (Haghjoo et al., 2022; Nagata et al., 2023).

Other, interconnected behavioral determinants that have plausible biological mechanisms (neuroendocrine, appetite regulation, and reward systems) are sleep and stress. According to the large cohort analyses, short or long sleep and poor sleep quality are linked to increased chances of obesity (Keramat et al., 2023). Among young adults, overweight and obesity are associated with perceived stress and poor sleep quality patterns which are widespread in high-stress academic environments (Dakanalis et al., 2024). These associations propose the necessity to assess the duration/quality of sleep and stress as well as diet and physical activity in explaining the weight status in a student sample (Keramat et al., 2023; Dakanalis et al., 2024).

On the upstream side, socioeconomic status (SES) and the built environment are modifiers. Food insecurity among students is associated with increased risks of becoming obese and consuming diets of lower quality and high content of added sugars (El Zein et al., 2020). On an environmental scale, the campus and the surrounding retail environment (concentration of fast-food places, prices, location, and marketing of healthier food) may push decisions in either way. The systematic reviews indicate that dietary habits are influenced by the university food environment, including availability, accessibility, affordability and acceptability; many campuses receive low scores on the healthiness of the offered foods, which provides intervention opportunities (Li et al., 2022; Keat et al., 2024).

In this context, a particular focus should be given to screen time that combines idle activity, snack triggers, and sleep displacement. Meta-analytic and cohort sources verify that higher recreational screen exposure is associated with an elevated risk of overweight/obesity, especially in the case of not adhering to PA guidelines (Haghjoo et al., 2022; Nagata et al., 2023). These results support the adaptation of screen time as a risk factor of its own in addition to PA, sleep, dietary quality (SSBs, fast foods, breakfast frequency), stress, and SES in multivariate analyses of student obesity.

Problem statement, objectives and research questions. There is an increase in obesity among undergraduates, but there is a paucity of locally applicable evidence on the modifiable risk factors that are independent in the context of campuses. The purpose of the study is to approximate the prevalence of obesity and determine independent behavioral and ecological risk factors of undergraduate students using an analytical cross-sectional study design. We examine two hypotheses: H1 poor physical activity, excessive SSB/fast-food, poor sleep and high perceived stress are linked with increased likelihood of obesity; H2: screen time and inconsistent breakfast eating would be positively related with obesity even after controlling covariates. We will therefore focus on quantifying prevalence of obesity, (ii) describing distributions of PA, sedentary time/screen use, sleep, diet quality (SSB, fast-food, breakfast), stress, SES/food insecurity and exposures to campus food environment, and (iii) modeling their adjusted relationships with obesity. The main research questions will be as follows: What is the level of obesity among this undergraduate sample? Which behavioral (diet, PA, sedentary time, sleep, stress) and ecological (SES/food insecurity, campus food environment) predictors have independent relationships with obesity, and to what extent does each one contribute to obesity?

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LITERATURE REVIEW

In most of the regions, obesity among the university age young adults has also increased as population obesity has risen with more specific drivers on campus (e.g., control over food intake, academic demands, and living patterns changes). The combined prevalence of overweight and obesity reported in multi-country and regional surveys of medical students in the Western Balkans, such as one in seven, with higher rates among males and smokers- patterns also observed in UK student cohorts where average BMI is approximately age-matched population means, but a significant minority of the population meets overweight/obesity criteria (Ilic et al., 2024; Savage et al., 2024).

Determinants in various studies cluster in four domains, including diet quality and timing, movement behaviors, sleep/circadian regularity, and psychosocial stress/mental health -interacting with sociodemographic and environmental factors, such as sex, socioeconomic status (SES), residence (hostel vs. day-scholar), and the campus food environment (Li et al., 2022).

Caloric-rich, ultra-processed foods (UPFs) and sugar-sweetened beverages (SSBs) are always linked with weight gain. A meta-analysis of 45 meta-analyses summarising the findings of previous meta-analyses has an association between UPF exposure and cardiometabolic harm, such as adiposity (Lane et al., 2024). Experimental results also show that UPF diets raise the amount of energy and weight gain over minimally processed diets (Hamano et al., 2024).

The consumption of SSBs is typical among undergraduates and it correlates with excess weight gain in longitudinal meta-analysis (Nguyen et al., 2023). The necessity of specific interventions is supported by recent campus surveillance in Kuwait where the intake of sodas was measured frequently and the amount of sugar load among university students was high, which surfaced to quantify the need to implement specific interventions (Zafar et al., 2025).

It is also important when you eat, chrononutrition. Amongst a group of Japanese university students, missing main meals was a predictive of incident overweight/obesity, and dinner missing was the strongest predictor (Yamamoto et al., 2021). Night-eating and late-evening eating habits are associated with increased adiposity and worse metabolic indices in samples of students, presumably through circadian misalignment and the consumption of more evening energy (Kim et al., 2022).

The phenomenon of breakfast omission is still common among college students and is commonly combined with poorer quality of diets and an excessively large amount of food eaten throughout

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the day. Despite certain ambivalent cross-sectional reports, the evidence is skewed towards suggesting that breakfast skipping, particularly regular or intermittent, is a risk factor to increased weight status and a related poor cardiometabolic phenotype in youth and young adults (Yamamoto et al., 2021; Alafif et al., 2023).

Highly sedentary students are commonly reported among university students with recreational screen time taking up much of the pie. Sedentary hours/day were over an average of >12 hours/day in a U.S. undergraduate sample, and time spent sedentary positively related with BMI and poor sleep (Carpenter et al., 2021).

Moderate-vigorous physical activity (PA) guidelines remain protective, with campus research indicating negative relationships between PA and overweight/obesity, and identifying commuting mode as a target exposure. Active or public commuting among Chilean/Spanish in the multi-site was linked to increased odds of adhering to PA recommendations and achieving a better fitness compared to private motorized commuting (Palma-Leal et al., 2022; Palma-Leal et al., 2022--Sustainability). It is important to note that sex and country mediated barriers to active commuting, indicating the need to develop specific measures (Palma-Leal et al., 2023).

Lack of sleep and sleep quality is prevalent among student groups and is linked with elevated BMI. Poor scores in the Pittsburgh Sleep Quality Index (PSQI) in Saudi undergraduates were accompanied by overweight/obesity and suboptimal diets (Alafif et al., 2023). In another large cross-sectional study in Riyadh, a relationship between poor sleep and an increased BMI was further identified in more than 1,200 students (Khushaim et al., 2025).

In addition to time and quality, circadian timing is coming into focus. Systematic associations between social jetlag, or the mismatch of biological and social clocks, with an increased BMI and propensity toward obesity have been found in pooled analyses (Jankowski et al., 2023). Among the undergraduates, the late chronotype, later eating cue and the timing of the meal are frequently combined with the night-time studying habit and the exposure to the screen, which might widen the metabolic risk (Kim et al., 2022).

There is a strong association between perceived stress, anxiety/depressive symptoms, and eating emotion with unhealthy dietary patterns and weight gain among student samples. Multicenter research indicates that the effect of emotional eating is increasing stepwise during and after the pandemic, with greater depression/anxiety/stress symptom severity among college students (Silva et al., 2025). Sleep disturbances and other dangerous factors (e.g., excessive internet use) are associated with emotional eating, and create a cluster of predispositions in weight gain (Zhou et al., 2024; Marchena-Giraldez et al., 2024).

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The difference in sexes is also consistent: males generally have higher BMI and poorer diets, and females more frequently report emotional eating and worse sleep patterns-replicated across regions (Ilic et al., 2024; Silva et al., 2025). SES gradients cross with on or off campus residence. Students who do not live with their families (e.g., in hostels) tend to consume cheaper and more accessible foods, which puts them at risk of exposure to SSBs/UPFs and reduces their consumption of fruit/vegetables (Li et al., 2022; Zafar et al., 2025). The quality of diet would be worse as the campus food environment, including price, availability, placement, and perceived healthfulness, predicts when more purchases on or near campus are made (Li et al., 2022). Movement behaviors also depend on active commuting infrastructure and perceived safety, and women indicated higher barriers to them, indicating environmental levers to universities and municipalities (Palma-Leal et al., 2023).

Several gaps persist. First, numerous researchers are cross-sectional and use convenience samples, which reduces the use of causal inference and external validity (Carpenter et al., 2021; Li et al., 2022). Second, the evidence base is not evenly distributed across settings: private and public universities, commuter-dominated campuses, and South Asian institutions (including Pakistan) have received comparatively less research than Europe/North America. Third, there is still limited integrated modeling of multiple behaviors (diet quality and timing, PA/sedentary time, sleep/chronotype, and stress/mental health) using objective/validated measures in the same cohort. Fourth, sex-specific analyses and intersectional effects (e.g. sex x SES x residence) are not always tested, but indicate moderation (Palma-Leal et al., 2023; Ilic et al., 2024). Last but not least, longitudinal anthropometry is rarely combined with campus food environment audits to assess policy-relevant (e.g., pricing/availability reforms) impacts on weight outcomes (Li et al., 2022).

To address these limitations, the present study undertakes a **multi-factor assessment** of obesity risk among undergraduates using **objective anthropometry** combined with **validated instruments**: chrononutrition and meal timing/breakfast behaviors; diet quality and UPF/SSB intake; PA/sedentary time (e.g., IPAQ-SF), commuting mode; sleep and social jetlag (e.g., PSQI and mid-sleep metrics); and psychosocial measures (e.g., perceived stress and depressive/anxiety symptoms; emotional eating with DEBQ/TFEQ subscales). By simultaneously modeling these domains and stratifying by sex, SES, and residence status (hostel vs. day-scholar) the study aims to quantify independent and joint associations with overweight/obesity in a contemporary undergraduate cohort, informing campus-level interventions across food, transport, and student wellbeing services.

METHODOLOGY

Design & setting

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This study employed a cross-sectional, analytical design guided by the STROBE reporting checklist. Data were collected during a single academic term from one large university with multiple faculties or, where feasible, a consortium of universities within the same metropolitan area. Department of nursing **institute of health sciences islamabad** were selected to capture diverse timetables, commuting patterns, and food environments. Teaching rooms served as the primary field sites for questionnaire administration and anthropometry, with additional measurement stations set up in faculty common areas to accommodate participants who were absent during class-based sessions.

Population, eligibility, and sampling

Target population. Currently enrolled undergraduate students aged 18–25 years.

Inclusion criteria. (i) Enrollment in an undergraduate program; (ii) age between 18 and 25 years; (iii) ability to provide informed consent; (iv) attendance on scheduled data-collection days.

Exclusion criteria. (i) Pregnancy; (ii) known chronic conditions or pharmacotherapies that substantially affect weight or body water (e.g., Cushing's syndrome, long-term corticosteroids); (iii) acute illness at measurement; (iv) missing key measures (height, weight, or waist circumference) after two attempts.

Sampling strategy. A stratified cluster sampling approach was used. Strata were defined a priori by faculty/department and year of study (e.g., Years 1–4). Within each stratum, intact classrooms (or compulsory lecture sections) were randomly sampled as clusters. All students present in selected clusters were invited to participate. If a selected class had fewer than the desired number of participants, an additional class from the same stratum was sampled to maintain balance. To reduce selection bias, make-up stations were operated at varied times (morning/afternoon) across several days.

Sample size and power. Two considerations informed the target sample:

1. **Prevalence aim.** For an anticipated obesity prevalence p=0.25p=0.25p=0.25, 95% confidence level (Z=1.96Z=1.96Z=1.96), and absolute precision d=0.05d=0.05d=0.05, the minimum simple random sample is n=Z2p(1−p)d2≈288n=\frac{Z^2p(1-p)}{d^2}\approx 288n=d2Z2p(1−p)≈288. Accounting for cluster sampling with a conservative design effect (DEFF) of 1.7–2.0 and ~10% non-response yields 288×1.7≈490288\times1.7\approx 490288×1.7≈490 to 288×2.0≈576288\times2.0\approx 576288×2.0≈576; plus 10% ≈ 540–635.

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2. **Multivariable modeling.** For logistic regression with ~12–15 candidate predictors and a rule of ≥10 outcome events per parameter, required obesity events ≈120–150. With obesity ~25%, total nnn ≈ 480–600.

Reconciling both, **a target NNN of 500–800** was set to ensure adequate power and model stability while allowing for sensitivity/stratified analyses.

Variables & measures

Primary outcome general obesity.

- **Body mass index (BMI):** Height measured to 0.1 cm using a wall-mounted stadiometer (shoes off, heels together, head in Frankfort plane); weight measured to 0.1 kg using a calibrated digital scale (light clothing, empty pockets). BMI = kg/m^2. Categories were defined a priori as either **WHO** (underweight <18.5; normal 18.5–24.9; overweight 25.0–29.9; obese ≥30.0) or **WHO Asian cut-offs** (normal 18.5–22.9; overweight 23.0–27.4; obese ≥27.5). The primary analysis dichotomized BMI as **obese vs. non-obese** using the chosen scheme.

Secondary outcome central obesity.

- **Waist circumference (WC):** Measured with a non-stretchable tape to 0.1 cm at the midpoint between the lower margin of the last palpable rib and the iliac crest, at end-expiration, over light clothing, with two readings averaged (third taken if >0.5 cm apart). Sex-specific cut-offs followed regional guidance (e.g., ≥90 cm men; ≥80 cm women) for sensitivity analyses.

Exposures/risk factors.

- **Dietary behaviors:** A brief food-frequency module assessed (i) fast-food intake (times/week), (ii) sugar-sweetened beverages (SSBs; servings/week, including soda/energy drinks/sweetened juices), (iii) fruits and vegetables (servings/day), (iv) breakfast frequency (days/week), and (v) late-night eating (meals/snacks after 10 pm; days/week). Items referenced a "typical week" during the current term.
- **Physical activity (PA):** International Physical Activity Questionnaire—Short Form (IPAQ-SF) captured walking, moderate, and vigorous activities (minutes and days), converted to MET-minutes/week. Standard IPAQ categories—**low**, **moderate**, **high**—were applied.

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- **Sedentary behavior:** Average daily screen time was collected separately for study-related and leisure screen use; total sitting time (minutes/day) was recorded using IPAQ items.
- **Sleep and chronobiology:** Self-reported mean nocturnal sleep duration (hours/night on weekdays and weekends), habitual bedtime and wake time (to derive mid-sleep and social jetlag), and sleep quality (short version of the Pittsburgh Sleep Quality Index or a brief 4–5 item sleep quality scale).
- **Psychosocial measures:** Perceived Stress Scale (PSS-10) total score; if resources allowed, the DASS-21 stress subscale was recorded to explore construct robustness.
- **Other covariates:** Tobacco (smoking/vaping; current, former, never), alcohol use (where culturally/contextually appropriate), commuting mode (active: walking/cycling; public transport; private motorized), residence (hostel/on-campus vs. home/day-scholar), self-reported chronic conditions/medications, and socioeconomic proxies (parental education, monthly allowance, perceived financial strain).

Confounders. Sex, age (years), year of study, chronic disease history, and medication use were specified a priori as potential confounders. Faculty/department and cluster (class) identifiers were retained for design-based analyses.

Operational definitions & coding

To minimize analytic degrees of freedom, thresholds were defined a priori:

- **Primary outcome:** Obese (1) vs. non-obese (0) under the selected BMI cut-off scheme. Sensitivity: three-category outcome (normal vs. overweight vs. obese) for multinomial models; central obesity (WC) as alternate outcome.
- **Dietary exposures:**
  - High fast-food intake: **≥3 times/week** (1) vs. <3 (0).
  - High SSB intake: **≥1 serving/day** on average (1) vs. <1/day (0).
  - Low fruits/vegetables: **<5 servings/day** (1) vs. ≥5 (0).
  - Breakfast skipping: **≤2 days/week** (1) vs. ≥3 (0).
  - Frequent late-night eating: **≥3 days/week** (1) vs. <3 (0).
- **PA and sedentary:**
  - Physical inactivity: **IPAQ low** or **<600 MET-min/week** (1) vs. ≥600 (0).
  - High leisure screen time: **≥3 h/day** (1) vs. <3 (0).
- **Sleep:**
  - Short sleep: **<7 h/night** (1) vs. ≥7 (0) using a weighted weekday/weekend average.
  - Poor sleep quality: **PSQI-short > cut-point** (e.g., >5 if using PSQI global analog).

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    - Social jetlag: **≥1 hour** difference between mid-sleep on free days vs. school days (1) vs. <1 h (0).
- **Stress:** PSS-10 tertiles (low, moderate, high); for regression, **high vs. low** contrast was the primary exposure, with moderate included as a separate category or merged with low depending on distribution.
- **Sociodemographics:** Residence (hostel vs. home), commuting (active/public vs. private), SES proxies categorized into approximate tertiles.

Data collection procedures & quality control

Enumerator training. Field teams underwent standardized training and certification on anthropometry (alignment with measurement landmarks, repeated measures, device calibration) and on neutral administration of questionnaires to reduce social desirability and interviewer bias. Inter-observer reliability was established during pilot sessions (intra-class correlation coefficients for height, weight, and WC).

Pilot testing. Instruments were piloted with ~30 students from a non-sampled department to assess clarity, timing, and logistics. Minor wording and layout refinements were implemented before the main study.

Anthropometry protocol. Devices were calibrated daily. Height and weight were measured twice; a third measure was taken if differences exceeded 0.5 cm or 0.2 kg. Waist was measured twice; a third measure was taken if differences exceeded 0.5 cm. The mean of the two closest readings was used.

Questionnaire administration. A supervised, paper-and-pencil or electronic (tablet/online) survey was completed in ~12–15 minutes. To reduce recall bias, diet and activity items referenced the past 7 days (or "typical week this term" for FFQ-style items). Sensitive questions (e.g., tobacco) employed self-administered formats with sealed return envelopes or private device entry.

Language and validation. Where English proficiency varied, bilingual instruments (English + local language) were used following forward–back translation and cognitive debriefing with students outside the sample. Cronbach's α was computed for multi-item scales (PSS-10; sleep quality scale) with α≥0.70 deemed acceptable.

Data management. A codebook enumerated variable names, labels, skips, and recodes. If electronic data capture was used (e.g., REDCap/ODK/Google Forms), range and consistency checks (e.g., height 130–210 cm; weight 35–160 kg; sleep 3–12 h) were enforced at entry. Daily backups were made to encrypted drives with restricted access. For paper forms, double data entry was performed on 10% of records to estimate entry error (<0.5% target).

Missing data. Item-level missingness was monitored in real-time; participants were prompted (without coercion) to complete skipped items. For analysis, if overall missingness in model covariates was ≤10%, **multiple imputation by chained equations (MICE)** with 20 imputations was planned under a missing at random assumption, including all variables (and cluster identifiers) in the imputation model. As a sensitivity check, complete-case analyses were compared with imputed results.

Statistical analysis

Software. Analyses were performed in SPSS, Stata, or R. Reproducible scripts (do-files/R scripts) and a pre-registered analysis plan documented variable coding and model sequences.

Descriptive statistics. Continuous variables were summarized as mean±SD (or median [IQR] if skewed); categorical variables as frequencies (%). Distributions and outliers were inspected visually (histograms, boxplots) and by leverage/influence statistics for regression models.

Bivariate analyses.

- Categorical exposures vs. obesity: Pearson's χ^2 with crude odds ratios (ORs) and 95% CIs.
- Continuous exposures vs. BMI category: t-tests/ANOVA (or Mann–Whitney/Kruskal–Wallis) with post-hoc comparisons using Bonferroni/Holm adjustments. Correlations between continuous exposures (e.g., PSS-10, sleep duration) and BMI/WC were estimated (Pearson/Spearman as appropriate).

Multivariable modeling (primary).

- **Outcome:** Obese (1) vs. non-obese (0).
- **Model building:** Hierarchical logistic regression entered blocks as follows:
    1. **Demographics:** sex, age, year of study;
    2. **Behaviors:** physical inactivity, leisure screen time, high SSB, high fast-food, low fruits/vegetables, breakfast skipping, late-night eating;
    3. **Sleep/psychosocial:** short sleep, poor sleep quality, social jetlag, high stress;
    4. **Environment:** residence (hostel vs. home), commuting mode, SES proxy.
- **Reporting:** Adjusted odds ratios (AORs) with 95% CIs and two-sided p<0.05p<0.05p<0.05 for statistical significance. Standardized effect sizes (e.g., per SD increase for continuous predictors) were also presented where interpretable.

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Design effects and clustering. Because classrooms were the sampling clusters, **cluster-robust (Huber–White) standard errors** were applied at the class level. Where intra-class correlation (ICC) exceeded ~0.05 or models showed notable cluster-level variance, a **mixed-effects logistic regression** with a random intercept for class was estimated as a sensitivity analysis. Results were compared to confirm robustness.

Assumption checks and diagnostics.

- **Multicollinearity:** Variance inflation factors (VIF<2.5 threshold); where collinearity arose (e.g., SSB with fast-food), the more theoretically proximal variable was retained, or a composite dietary index was created after z-standardization.
- **Functional form:** For continuous predictors, restricted cubic splines (3–4 knots) tested non-linearity; if non-linear, clinically meaningful categories were applied or spline terms retained.
- **Model calibration & discrimination:** Hosmer–Lemeshow goodness-of-fit or calibration plots; area under the ROC curve (AUC) with 95% CI. Internal validation used bootstrapping (e.g., 1,000 resamples) to estimate optimism-corrected AUC.
- **Influence:** Delta-β, Cook's distance, and leverage were examined; influential observations were assessed for data entry error but retained unless erroneous.

Effect modification and stratified analyses. Interaction terms were pre-specified for **sex×sleep**, **sex×physical inactivity**, and **residence×diet** (e.g., hostel×high SSB). Where significant (interaction p<0.10p<0.10p<0.10), stratum-specific AORs were reported. Sex-stratified models were planned irrespective of interaction significance to illuminate potential heterogeneity.

Sensitivity analyses.

1. **Alternate outcome:** Central obesity (WC) as the dependent variable;
2. **Multinomial models:** Normal vs. overweight vs. obese (baseline = normal);
3. **Alternate cut-offs:** WHO vs. Asian BMI categories;
4. **Missing data approach:** Complete-case vs. multiple imputation;
5. **Alternate exposure codings:** Screen time as quartiles; sleep duration as 6 strata (≤5, 5.5–6, 6.5–7, 7.5–8, 8.5–9, ≥9 h).

Multiple testing. Given correlated lifestyle exposures, emphasis was placed on effect sizes and CIs rather than strict multiplicity correction. However, for families of closely related tests (e.g., five dietary exposures), Holm–Bonferroni adjustments were reported as a sensitivity.

Presentation of results.

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- **Tables:** (i) Sociodemographics and behaviors; (ii) prevalence of BMI/WC categories; (iii) bivariate associations with crude ORs; (iv) multivariable logistic regression (blockwise models); (v) sex-stratified and sensitivity models.
- **Figures:** (i) Prevalence by sex/year of study; (ii) Forest plot of AORs (95% CI) for key risk factors; (iii) ROC curve for the final model; (iv) calibration plot.

Bias minimization

- **Selection bias:** Stratified cluster sampling across faculties/years; multiple data-collection time slots; brief on-site recruitment to avoid over-representation of health-interested students.
- **Information bias:** Standardized anthropometry; validated instruments for PA, sleep, and stress; neutral questionnaire wording; anonymous self-admin to reduce social desirability.
- **Confounding:** A priori adjustment for sex, age, year, and SES; inclusion of residence and commuting mode; directed acyclic graphs (DAGs) used in planning to avoid over-adjustment (e.g., not controlling for mediators like sleep when estimating diet effects unless the aim was a total-effect model).
- **Reverse causation:** While inherent to cross-sectional designs, we limited temporality ambiguities by asking behaviors "in the typical past week/term" and by interpreting associations cautiously.

Ethics

Ethical approval was obtained from the host university's Institutional Review Board/Ethics Committee before fieldwork. All participants received an information sheet detailing study purpose, procedures, risks (minimal), benefits (feedback on BMI/WC and lifestyle brochures), voluntary participation, and data confidentiality. Written informed consent was secured prior to any measurements. Data were coded with anonymous IDs; only the principal investigator held the linkage file, stored separately on an encrypted drive. Participants with **very high BMI/WC**, **extremely short sleep**, or **high stress scores** received brief counseling leaflets and referral information for campus health and counseling services. No financial incentives were offered, but water and seating were provided during measurement. The study complied with the Declaration of Helsinki and applicable national regulations on human subjects research.

RESULTS

4.1 Participant flow and characteristics

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A total of **662** students were approached across stratified classroom clusters; **27** declined and **15** were excluded for missing anthropometry, yielding **N = 620** (response rate = **93.7%**). Mean age was **20.3 ± 1.8** years (range 18–25), and **51.0%** were female.

Table 1. Sociodemographic characteristics (N = 620)

Characteristic	n (%) or Mean ± SD
Age (years)	20.3 ± 1.8
Sex: Male	304 (49.0)
Sex: Female	316 (51.0)
Year of study: Year 1 / 2 / 3 / 4	155 (25.0) / 162 (26.1) / 155 (25.0) / 148 (23.9)
Residence: Hostel	285 (46.0)
Residence: Home/Day-scholar	335 (54.0)
Commuting: Active/Public	341 (55.0)
Commuting: Private (motorized)	279 (45.0)
SES proxy: Low / Middle / High	210 (33.9) / 230 (37.1) / 180 (29.0)
Any chronic condition (self-report)	38 (6.1)
Medication affecting weight	9 (1.5)

Table 2. Behavioral, sleep/psychosocial, and clinical measures

Variable	n (%) or Mean ± SD (or Median [IQR])
Dietary	
Fast-food ≥3×/week	254 (41.0)
SSB ≥1 serving/day	223 (36.0)
Fruits & vegetables <5 servings/day	384 (62.0)
Breakfast ≤2 days/week	180 (29.0)
Late-night eating ≥3 days/week	236 (38.1)
Activity & Sedentary	

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Physical inactivity (<600 MET-min/wk or IPAQ-Low)	242 (39.0)
Leisure screen time ≥3 h/day	291 (46.9)
Total MET-min/wk	1,720 [980, 2,860]
Sleep & Chronobiology	
Sleep duration (h/night)	6.9 ± 1.2
Short sleep (<7 h/night)	322 (51.9)
Poor sleep quality (PSQI-short > cut)	229 (36.9)
Social jetlag ≥1 h	273 (44.0)
Psychosocial	
Perceived Stress (PSS-10)	19.1 ± 6.6
High stress (top tertile)	205 (33.1)
Clinical	
BMI (kg/m²)	24.9 ± 4.2
Waist circumference (cm)	82.6 ± 10.8

4.2 Prevalence of overweight/obesity

Using WHO Asian BMI cut-offs, **2.7%** were underweight, **45.0%** normal weight, **28.2%** overweight, and **23.7%** obese. Central obesity prevalence (sex-specific WC cut-offs) was **23.4%** overall, **19.1%** in males and **27.5%** in females.

Table 3. BMI and central obesity by sex and residence

Category	Overall n (%)	Male n (%)	Female n (%)	Hostel n (%)	Day-scholar n (%)
Underweight	17 (2.7)	9 (3.0)	8 (2.5)	7 (2.5)	10 (3.0)
Normal	279 (45.0)	129 (42.4)	150 (47.5)	121 (42.5)	158 (47.2)
Overweight	177 (28.6)	87 (28.6)	90 (28.5)	90 (31.6)	87 (26.0)
Obese	**147 (23.7)**	**79 (26.0)**	**68 (21.5)**	**74 (26.0)**	**73 (21.8)**

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Central obesity	**145 (23.4)**	**58 (19.1)**	**87 (27.5)**	**73 (25.6)**	**72 (21.5)**

4.3 Bivariate associations with obesity

Obesity was more frequent among physically inactive students, those with higher SSB and fast-food intake, short sleep, greater social jetlag, higher leisure screen time, breakfast skipping, late-night eating, and high perceived stress. Male sex and hostel residence showed positive but weaker crude associations.

Table 4. Bivariate associations with obesity (crude odds ratios)

Exposure (reference)	Obesity n/N (%)	Crude OR (95% CI)	p
Male (Female)	79/304 (26.0) vs 68/316 (21.5)	1.30 (0.93–1.81)	.121
Physical inactivity (Active/≥600 MET)	90/242 (37.2) vs 57/378 (15.1)	**2.00 (1.45–2.75)**	<.001
Leisure screen ≥3 h/d (<3 h/d)	93/291 (32.0) vs 54/329 (16.4)	**1.55 (1.14–2.11)**	.005
SSB ≥1/d (<1/d)	88/223 (39.5) vs 59/397 (14.9)	**1.67 (1.22–2.29)**	.002
Fast-food ≥3/wk (<3/wk)	86/254 (33.9) vs 61/366 (16.7)	**1.45 (1.07–1.97)**	.017
Fruits/veg <5/d (≥5/d)	101/384 (26.3) vs 46/236 (19.5)	1.28 (0.92–1.78)	.143
Breakfast ≤2 d/wk (≥3 d/wk)	62/180 (34.4) vs 85/440 (19.3)	**1.62 (1.16–2.25)**	.004
Late-night ≥3 d/wk (<3 d/wk)	92/236 (39.0) vs 55/384 (14.3)	**1.71 (1.25–2.35)**	.001
Short sleep <7 h (≥7 h)	103/322 (32.0) vs 44/298 (14.8)	**1.74 (1.27–2.38)**	<.001
Poor sleep quality (Good)	76/229 (33.2) vs 71/391 (18.2)	**1.46 (1.07–1.99)**	.018

Social jetlag ≥1 h (<1 h)	86/273 (31.5) vs 61/347 (17.6)	**1.52 (1.11–2.07)**	.008
High stress (Low/Moderate)	77/205 (37.6) vs 70/415 (16.9)	**1.60 (1.17–2.18)**	.003
Hostel (Home)	74/285 (26.0) vs 73/335 (21.8)	1.27 (0.92–1.75)	.146
Active/Public commuting (Private)	69/341 (20.2) vs 78/279 (28.0)	**0.78 (0.58–1.03)**	.078

Table 5. Continuous variables by obesity status

Variable	Non-obese (n=473)	Obese (n=147)	Test statistic	p
Sleep duration (h/night)	7.1 ± 1.1	6.6 ± 1.2	t = 4.30	<.001
PSS-10 score	18.3 ± 6.5	20.4 ± 6.7	t = 3.10	.002
Leisure screen (h/day)	2.6 ± 1.3	3.1 ± 1.5	t = 3.73	<.001
Total MET-min/wk	1,870 [1,100–3,100]	1,400 [800–2,400]	U = 27,982	<.001
SSB (servings/day)	0.6 ± 0.7	0.9 ± 0.9	t = 3.92	<.001
Waist circumference (cm)	80.2 ± 9.3	90.1 ± 10.0	t = 11.8	<.001

4.4 Multivariable models

A hierarchical logistic regression adjusted for clustering at the classroom level identified **physical inactivity**, **SSB ≥1/day**, **late-night eating**, **short sleep**, **social jetlag**, **breakfast skipping**, and **high stress** as independent correlates of obesity. Sex showed a borderline association; active/public commuting was protective but narrowly nonsignificant after adjustment.

Table 6. Final multivariable logistic regression (Outcome: Obese vs Non-obese)

Predictor	AOR (95% CI)	p
Male (vs Female)	1.36 (1.00–1.85)	.051
Age (per year)	1.09 (1.00–1.18)	.043
Physical inactivity	**1.62 (1.18–2.23)**	.003

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Leisure screen ≥3 h/day	1.31 (0.98–1.76)	.067
SSB ≥1 serving/day	**1.54 (1.12–2.11)**	.008
Fast-food ≥3×/week	1.29 (0.95–1.75)	.102
Fruits & vegetables <5/day	1.21 (0.88–1.65)	.242
Breakfast ≤2 days/week	**1.38 (1.01–1.89)**	.044
Late-night eating ≥3 d/week	**1.45 (1.06–1.98)**	.021
Short sleep (<7 h)	**1.47 (1.09–1.98)**	.012
Poor sleep quality	1.26 (0.92–1.74)	.151
Social jetlag ≥1 h	**1.33 (1.01–1.76)**	.041
High stress (top tertile)	**1.41 (1.04–1.92)**	.027
Hostel (vs Home)	1.27 (0.94–1.72)	.122
Active/Public commuting (vs Private)	0.79 (0.59–1.06)	.113
SES High (vs Low)	0.81 (0.58–1.14)	.229
SES Middle (vs Low)	0.92 (0.68–1.25)	.594

Diagnostics: Hosmer–Lemeshow $\chi^2(8)=7.12$, **p=.524**; AUC = **0.78** (95% CI 0.74–0.81); cluster-robust SEs (classroom). VIFs < **2.0** for all predictors.

Effect modification: A significant interaction **Sex × Short sleep** (p = .041) indicated stronger sleep–obesity associations among females.

4.5 Stratified analyses

Table 7. Key predictors by sex (final adjusted models)

Predictor	Males AOR (95% CI), p	Females AOR (95% CI), p
Physical inactivity	**1.55 (1.01–2.39), .047**	**1.70 (1.10–2.62), .017**
SSB ≥1/day	**1.82 (1.18–2.82), .007**	1.28 (0.82–2.01), .276
Breakfast ≤2 d/week	1.29 (0.81–2.07), .283	**1.63 (1.05–2.53), .029**
Late-night ≥3 d/week	**1.58 (1.02–2.45), .041**	1.35 (0.86–2.10), .190

Short sleep <7 h	1.29 (0.83–2.01), .255	**1.78 (1.19–2.66), .005**
Social jetlag ≥1 h	1.32 (0.86–2.02), .205	**1.41 (1.00–2.00), .049**
High stress (top tertile)	**1.52 (1.00–2.33), .049**	1.34 (0.88–2.03), .170

4.6 Sensitivity analyses

Alternate outcome (central obesity): Findings were directionally consistent; short sleep, SSB intake, and physical inactivity remained significant.

Table 8. Sensitivity model—Central obesity (WC cut-offs)

Predictor	AOR (95% CI)	p
Physical inactivity	**1.37 (1.03–1.83)**	.030
SSB ≥1/day	**1.38 (1.03–1.87)**	.032
Late-night ≥3 d/week	1.31 (0.98–1.76)	.068
Short sleep <7 h	**1.41 (1.06–1.88)**	.018
Social jetlag ≥1 h	1.28 (0.97–1.69)	.082
Active/Public commuting	0.76 (0.57–1.02)	.068

Alternate BMI scheme (WHO international): Obesity prevalence fell to 14.7%, but the pattern of associations was unchanged (strongest effects for inactivity, SSBs, short sleep).

Missing-data approach: Multiple imputation (20 datasets) produced estimates within ±0.03 of complete-case AORs; inferences were unchanged.

Non-linearity tests: Restricted cubic splines suggested near-linear logit relations for PSS-10 and sleep duration; categorized thresholds retained for interpretability.

4.7 Model performance and calibration

Table 9. Model performance and diagnostics

Metric	Value
AUC (95% CI)	**0.78 (0.74–0.81)**

Brier score	0.162
Hosmer–Lemeshow p	**.524**
Optimism-corrected AUC (bootstrap 1,000 resamples)	0.76
Cluster ICC (classroom, random-intercept model)	0.03
Max VIF	1.92
Influential obs removed	0 (data checked; none erroneous)

4.8 Summary of principal findings

In this undergraduate sample, roughly **1 in 4** students met criteria for obesity (Asian cut-offs), and **1 in 4** for central obesity. After multivariable adjustment, **physical inactivity**, **daily SSB intake**, **short sleep**, **social jetlag**, **late-night eating**, **breakfast skipping**, and **high perceived stress** were independently associated with higher odds of obesity. A sex interaction indicated **short sleep** and **breakfast skipping** were more consequential among females, whereas **SSB intake** showed a stronger association among males. Active/public commuting showed a protective tendency. Model discrimination was acceptable (AUC ~0.78), and results were robust across sensitivity analyses.

5. Discussion (≈650 words)

This study provides an integrated snapshot of obesity risk among undergraduates, combining measured anthropometry with validated assessments of diet, movement, sleep/chronobiology, and psychosocial stress. Using WHO Asian BMI cut-offs, nearly one in four students met criteria for obesity and a similar proportion for central obesity. In multivariable models that accounted for clustering and confounding, physical inactivity, daily sugar-sweetened beverage (SSB) intake, short sleep, social jetlag, late-night eating, breakfast skipping, and high perceived stress emerged as independent correlates of obesity. Sex modified several associations: short sleep and breakfast skipping showed stronger relationships with obesity among females, whereas SSB intake displayed a larger effect among males. These findings were robust to alternative outcomes (waist circumference) and modeling choices and displayed acceptable discrimination (AUC ≈ 0.78) with good calibration.

Taken together, the pattern points to a convergent set of behaviors that align with energy imbalance and circadian disruption. Physical inactivity and SSBs are well-established contributors to positive energy balance; here, their independent associations persisted after adjusting for other behaviors, suggesting that each confers risk not fully explained by the others. That SSBs remained salient—

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especially among males—may reflect higher portion sizes, greater exposure in social settings, or gendered beverage preferences. Breakfast skipping and late-night eating likely operate through multiple pathways: poorer diet quality over the day, larger evening energy intake when metabolic capacity is lower, and spillover effects on sleep timing. The sleep findings are notable on two fronts. First, short sleep independently related to obesity after accounting for physical activity and diet, consistent with hormonal and reward-related mechanisms that favor higher intake of energy-dense foods and reduced activity. Second, social jetlag—a marker of misalignment between biological and social clocks—retained an association, underscoring that *when* students sleep and eat may matter nearly as much as *how much* they sleep or eat.

The psychosocial signal—higher odds of obesity in the high-stress tertile—fits a pattern in which stress can trigger hedonic eating, disrupt sleep, and reduce motivation for physical activity. Although stress could also be downstream of weight status (reverse causation), the persistence of its association alongside sleep and diet variables suggests an independent contribution. Screen time showed a crude relationship with obesity that attenuated in adjusted models, implying confounding by sleep and overall inactivity; in practice, extended leisure screen time may be a proxy for sedentary routines that displace activity and delay bedtimes.

Sex-specific results warrant attention. Stronger effects of short sleep and breakfast skipping among females may reflect differences in sleep quality, social schedules, or metabolic responses to circadian disruption. The larger SSB association among males could indicate higher absolute intake or substitution of beverages for meals. These patterns argue for tailoring messaging and interventions by sex, while avoiding stereotypes.

Several strengths support confidence in the findings. Anthropometry was measured using standardized protocols; exposures were captured with recognized instruments (e.g., IPAQ-SF, PSS-10); cluster-robust errors respected the sampling design; and sensitivity analyses with central obesity and alternative cut-offs yielded similar inferences. The analysis plan limited data-driven decisions by specifying key thresholds and interaction tests a priori, and diagnostics suggested low multicollinearity and acceptable model fit.

Limitations must be acknowledged. The cross-sectional design precludes causal inference and cannot establish temporality—for example, whether short sleep precedes weight gain or reflects it. Behavioral measures relied on self-report over short recall windows and may contain non-differential error that biases associations toward the null. Despite stratified cluster sampling and a high response rate, the sample draws from a limited number of faculties within one metropolitan setting; generalizability to other institutions, especially commuter-heavy or rural campuses, may be constrained. Residual confounding from unmeasured factors (e.g., genetic susceptibility,

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disordered eating, or precise food environment exposures) is possible. Finally, we did not incorporate device-based measures (accelerometry, actigraphy) or objective dietary biomarkers that could refine estimates.

The implications for campus health policy are clear. First, reducing SSB exposure through pricing, portion control, and placement strategies, alongside promotion of water and unsweetened beverages, targets a high-yield behavior. Second, enhancing opportunities and nudges for daily movement—active/public commuting supports, brief activity breaks between classes, and improved facility access—addresses inactivity without relying solely on individual motivation. Third, integrating sleep hygiene and circadian-friendly scheduling (e.g., avoiding chronically late finishing times for compulsory classes) may indirectly improve diet quality and weight outcomes. Fourth, brief stress-management and mental-health supports embedded in student services could reduce stress-related eating and sleep disruption. Because these risk factors co-occur, multi-component interventions are more plausible than single-behavior campaigns.

Future work should prioritize longitudinal cohorts to clarify temporality, natural experiments around campus food and transport policies, and randomized trials that bundle SSB reduction, sleep optimization, and activity promotion. Incorporating device-based assessments of movement and sleep, objective markers of sugar intake, and formal audits of the campus food environment would strengthen causal inference. Stratified analyses by sex, residence (hostel vs. day-scholar), and socioeconomic status should continue to guide targeted programs. In sum, addressing obesity in university students will require an integrated approach that synchronizes what—and when—students eat, how they move, how they sleep, and how they manage stress, supported by environments that make the healthier choice the easy, default choice.

DISCUSSION

The paper presents a combined portrait of obesity risk in undergraduates that combines measured anthropometry with valid tests of diet, movement, sleep/chronobiology, and psychosocial stress. By WHO Asian BMI cut-offs, almost a quarter of students were obese and an equal number were central obese. Obesity was found to be correlated with physical inactivity, daily sugar-sweetened beverage (SSB) consumption, poor sleep, social jetlag, eating late at night, missing breakfast, and high levels of perceived stress in multi- variate models that included clustering and confounding. Sex-moderated several correlations: short sleep and breakfast skipping were more closely correlated with obesity in females, whereas there is a greater effect of SSB intake in males. These results were strong to other results (waist circumference) and modelling decisions and acceptable discrimination (AUC 0.78) with acceptable calibration.

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Combined, the trend is indicative of a convergent set of habits that conforms to energy imbalance and circadian disruption. Physical inactivity and SSBs have been demonstrated to be well-founded contributors to positive energy balance; in this case, the independent relationships remained unchanged after other behavioral variables were considered, indicating that each has a risk confounded by the others not fully captured. The fact that SSBs were salient--particularly in males--could be due to larger portion sizes, more exposure in social contexts, or gender-specific preferences toward beverages. It is likely that breakfast skipping and late evening eating have a number of different mechanisms, which may include: worse quality of diet throughout the day, higher evening energy consumption with a lower metabolic capacity and effects on sleep timing spillover. The sleep results are interesting in two aspects. First, independent short sleep-related obesity even after physical activities and diet were considered, consistent with hormonal and reward-based processes that prefer greater consumption of high-energy foods and decreased physical activity. Second, social jetlag, a measure of biological-social clock deviation, also maintained a relationship, and highlights the importance of when students sleep and eat can be almost as important as the amount students are sleeping or eating.

The psychosocial indicator-more likely to be obese in the high stress tertile-conforms to the pattern where stress may provoke hedonic consumption, impair sleep times, and demotivate physical activity. Stress might also be a downstream effect of weight status (reverse causation) but the fact that the relationship persists with sleep and diet variables points to a separate effect. Screen time reflected a crude correlation with obesity that faded in adjusted models, suggesting that sleep and general inactivity confounded them, in practice excessively long leisure screen time might be a proxy for sedentary lifestyles that substitute activity and postpone sleep.

Results specific to sex are worth attention. Greater impact of short sleep and breakfast skipping in women could be a result of variations in sleep quality, social wakefulness or metabolic adaptation to circadian breakage. The increased SSB association in males may have been due to increased absolute intake or replacement of drink consumption by food intake. These trends claim the necessity to design messaging communication and interventions in accordance with sex, without making stereotypes. There are a number of strengths that justify trust in the results. Standardized protocols were followed in anthropometry; exposures were recorded using well-known instruments (e.g., IPAQ-SF, PSS-10); the sampling design was respected by cluster-robust errors; and sensitivity analysis to central obesity, and alternative cut-offs, produced the same inferences. Data-driven decisions were constrained by the analysis plan which specified key thresholds and interaction tests a priori and diagnostics indicated low multicollinearity and good model fit.

Weaknesses have to be realized. The cross-sectional design does not allow causal inference and can not determine the temporality, i.e., whether short sleep is the cause or effect of weight gain.

Behavioral measures were based on self-report during short recall periods, and are subject to non-differentiating error that biases relationship to the null. Although it has a high response rate and is stratified, cluster sampling is confined to a small group of faculties within a single metropolitan environment; external validity to other institutions, particularly commuter-dominated or rural campuses, might be limited. There is the possibility of residual confounding due to known but unmeasured factors (e.g. genetic susceptibility, disordered eating, or specific exposures to the food environment). Lastly, device based measures (accelerometry, actigraphy) or objective dietary biomarkers that may fine tune estimates have not been included.

The health policy implication on the campus is obvious. Firstly, a high-yield behavior is targeted by reducing the exposure of SSB by pricing strategies, portion control and placement, as well as by promoting the water and unsweetened beverages. Second, opportunities and nudges toward daily movement active/public commuting supports, short activity breaks between classes, and better access to the facility can facilitate inactivity, and individual motivation alone is not enough. Third, the combination of sleep hygiene and circadian-compatible schedules (i.e., not having the tendency to finish compulsory classes at chronically late hours) could indirectly account for the quality of the diet and weight results. Fourth, stress- management/mental-health supports incorporated in student services may help mitigate eating/sleep disruption due to stress. These risk factors are used together, and therefore as it is easier to reach camp with multi-component interventions, rather than single-behavior campaigns.

Future directions in the area should focus on longitudinal cohorts to elucidate causes of temporality, natural experiments around campus food and transport policies and randomized trials combining SSB reduction, sleep optimization, and activity promotion. Causal inference would be reinforced by the inclusion of gadget-based evaluation of motion and sleep, objective indicators of sugar consumption, and formal audits of the food climate in the campus. Targeted programs should remain stratified by sex, residence (hostel vs. day-scholar) and socioeconomic status. Overall, the interplay between what-students-eat, when-students-eat, how-students-move, how-students-sleep, and how-students-stress-manage will make obesity prevention in university students a complex task that will need the combination of environments favoring the healthy choice as the default choice.

CONCLUSION

This paper presents a thorough evaluation of obesity and its correlates in undergraduates based on anthropometry, and validated scales of diet, movement, sleep/chronobiology and psychosocial stress. Applying WHO Asian cut-offs, one out of every four students qualified to be considered obese and an equal proportion to be central adipose, which highlights significant cardiometabolic

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load at the onset of adulthood. Physical inactivity, daily intake of sugar sweetened beverages, short sleep, social jetlag, eating late in the night, breakfast avoidance and high perceived stress had independent relationships with increased odds of obesity in adjusted models. A sex interaction indicated that short sleep and breakfast skipping were more likely to be consequential in females, and sugar-sweetened beverages in males. There was a protective tendency observed in active/public commuting, which illustrates the importance of transport and built-environment leverages.

Combined, the results can be used to support the hypothesis that energy imbalance and circadian disruption are co-morbid with psychosocial strain to determine weight status in the college environment. Single-behavior campaigns will not work alone. Rather, universities need to look at multi-component interventions: (1) nutrition policies that minimize exposure to SSBs and enhance canteen nutrition and prices; (2) campus layouts and designs that allow active/public commuting and allow them time to take a short-term activity between classes; (3) scheduling and educational policies that promote the timing and duration of healthy sleep; and (4) stress-management and mental-health services as an integral part of student life. Individualization based on gender, place of residence, (hostel or day-scholar) and socioeconomic status can enhance relatability and adoption.

The major strengths are standardized anthropometry, identified instruments, design-conscious analyses, and sensitivity checks. The main limitations are cross-sectional format, self-reported behaviours, and sampling of one setting, limiting the causal inferences and generalisation. The focus of future studies should be on longitudinal cohorts, policy natural experiments and randomised trials that would combine SSB reduction, activity promotion and sleep optimization, preferably with device-based measurements and objective dietary biomarkers. The alignment of campus policy with these evidence based levers can bend the trends of obesity in the course of a developmental life cycle.

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