



INTERNATIONAL CENTER FOR RESEARCH AND RESOURCE DEVELOPMENT

ICRRD QUALITY INDEX RESEARCH JOURNAL

ISSN: 2773-5958, <https://doi.org/10.53272/icrrd>

## A QUANTITATIVE ANALYSIS OF LIFESTYLE BEHAVIORS LIFESTYLE BEHAVIORS AND PSYCHOSOCIAL DETERMINANTS OF ADULT OBESITY IN THE UNITED STATES

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Received: 19 November 2025 • Accepted: 11 January, 2026 • Published: 14 January 2026

### Abstract

*Obesity remains a major public health challenge shaped by interacting behavioral, psychosocial, and lifestyle factors that are frequently assessed in isolation, limiting the identification of clustered risk patterns relevant for prevention. This quantitative study developed and evaluated a concise, multidomain survey instrument to capture interconnected, modifiable behaviors associated with adult obesity while emphasizing usability and participant-centered design. Using a cross-sectional approach, primary data were collected through pilot administration of the Adult Obesity Risk Assessment Questionnaire among adults in the United States and interpreted alongside publicly available national behavioral surveillance data for contextual comparison. The instrument assessed physical activity, dietary intake, sleep duration, perceived stress, screen exposure, substance use, and health-monitoring behaviors and demonstrated strong feasibility, complete response capture, and good internal reliability. Findings indicated that 40% of participants engaged in physical activity only 1–2 days per week, while 20% reported no regular physical activity. Mean fruit and vegetable intake was 2.6 servings per day, average sleep duration was 6.3 hours per night, and mean daily screen time was 5.8 hours. Perceived stress levels were moderate to high, with a mean score of 3.2 on a five-point scale. Alcohol use was reported by 70% of participants, whereas tobacco use was infrequent at 15%. Behavioral clustering was evident, particularly among physical inactivity, prolonged screen exposure, and elevated stress, mirroring patterns observed in national obesity surveillance. These results underscore the importance of integrated behavioral assessment and support the utility of this instrument for behavioral risk surveillance, targeted intervention planning, and data-driven obesity prevention efforts.*

**Keywords:** Adult obesity; Behavioral and Lifestyle factors; Psychosocial stress; Quantitative study; United States

**Cite as:** Hasan, M. R., Halim, F. B., Haque, A., Haq, Z. U., & Muna, M. A. (2025). A Quantitative Analysis of Lifestyle Behaviors and Psychosocial Determinants of Adult Obesity in the United States. *ICRRD Quality Index Research Journal*, 7(1), 101-126

## INTRODUCTION

Obesity represents one of the most pressing public health challenges of the 21st century, with profound implications for individual health, healthcare systems, and global economic stability. Recognized by the World Health Organization (WHO) as a major risk factor for a wide range of chronic diseases, obesity has reached epidemic proportions worldwide (Archer & Lavie., 2022). The condition not only drives the rising burden of non-communicable diseases such as type 2 diabetes, cardiovascular disease, and certain cancers but also exacerbates healthcare inequities, social stigmatization, and economic productivity loss (Tiwari, Balasundaram., 2021). In 2022, more than one billion people globally were classified as obese, a figure that has more than doubled since 1990, underscoring the urgency of comprehensive prevention and intervention strategies. In the United States, obesity affects approximately 42% of adults and contributes significantly to the leading causes of preventable, premature death (Hruby & Hu., 2015). Tackling obesity is therefore not merely a matter of individual behavior change but a complex, multifaceted endeavor requiring coordinated action across healthcare, education, urban planning, food systems, and broader social structures. Understanding the behavioral drivers and social determinants that fuel this epidemic is essential for designing effective, equitable public health interventions. Obesity is clinically defined as a chronic disease characterized by the excessive accumulation of body fat to an extent that it adversely impacts health. The most widely used tool for classifying obesity is the Body Mass Index (BMI), which is calculated by dividing an individual's weight in kilograms by the square of their height in meters (Hruby et al., 2015). According to guidelines from the Centers for Disease Control and Prevention (CDC), adults with a BMI of 30.0 or higher are classified as obese (Bardia et al., 2007). Obesity is further stratified into three classes based on severity: Class 1 (BMI 30.0–34.9), Class 2 (BMI 35.0–39.9), and Class 3 (BMI  $\geq$ 40.0), the latter commonly referred to as severe or morbid obesity. While BMI is a useful population-level screening tool, it does not differentiate between fat and lean mass, and thus, clinical judgment considering additional health indicators remains critical. Nevertheless, BMI thresholds are widely accepted in public health research and policy as they allow for standardized surveillance, risk stratification, and the targeting of obesity prevention and treatment efforts (Kruk et al., 2018).

The etiology of obesity is multifactorial, reflecting a complex interplay between biological, behavioral, and environmental determinants. Among these, modifiable risk factors play a central role in the rising global obesity epidemic. Poor dietary patterns characterized by excessive caloric intake, high consumption of ultra-processed foods, sugar-sweetened beverages, and inadequate intake of fruits, vegetables, and fiber remain key contributors. Physical inactivity, driven by increasingly sedentary lifestyles, technology use, and urban living, further compounds risk (Cizza et al., 2010). Emerging research underscores the role of sleep disturbances, particularly inadequate duration and poor quality, as independent predictors of obesity. These effects are largely mediated through hormonal dysregulation that influences appetite control and metabolic processes (Carpenter, Eastman, & Ross, 2022). Chronic psychological stress has similarly been implicated, influencing neuroendocrine pathways that promote emotional eating and decreased physical activity (Cardarelli et al., 2020; Dreher & Ford., 2020). Non-modifiable factors also substantially influence obesity risk. Genetic predisposition affects basal metabolic rate, fat storage tendencies, and satiety regulation. Aging increases vulnerability to obesity through physiological changes such as reduced lean body mass, slower metabolism, and hormonal alterations. In addition, biological sex influences obesity patterns, as women generally have a higher proportion of body fat, and hormonal transitions during pregnancy and menopause further modify fat distribution and metabolic regulation. Medical conditions, including hypothyroidism, Cushing's syndrome, and polycystic ovary syndrome (PCOS), also elevate obesity risk independently of lifestyle behaviors (Cardarelli et al., 2020; Dreher & Ford., 2020). Beyond individual-level biological and behavioral factors, the social determinants of health (SDOH) critically shape the landscape of obesity risk and prevalence. Socioeconomic status profoundly influences dietary choices, opportunities for physical activity, healthcare access, and health literacy. Populations with lower income and education levels are disproportionately exposed to obesogenic environments, characterized by limited access to affordable, nutritious foods and recreational infrastructure, often residing in food deserts or unsafe neighborhoods. Additionally, excessive screen time across digital platforms reduces physical movement opportunities and is associated with unhealthy eating patterns. Residential environments, particularly the walkability of communities and the availability of green spaces, further mediate opportunities for active living (Dreher & Ford., 2020). Systemic barriers, including structural racism, employment insecurity, and restricted healthcare access, exacerbate obesity-

related health disparities, particularly among marginalized groups. Recognizing and systematically addressing these upstream factors is essential because efforts that focus solely on individual behavior change risk overlooking the broader systemic forces that sustain obesity at a population level (Swinburn et al., 2019). Developing effective prevention and intervention strategies requires an integrated public health approach that simultaneously targets behavioral modification and the underlying social and environmental conditions. By situating modifiable and non-modifiable factors within their broader sociocultural context, public health practitioners can design interventions that are more equitable, sustainable, and responsive to the lived realities of diverse populations (F. Amauchi et al., 2022).

Obesity imposes profound short-term and long-term consequences across physical, psychological, and social domains, making it a critical priority in public health and clinical practice. Physically, obesity significantly elevates the risk of developing numerous chronic conditions, including type 2 diabetes mellitus, hypertension, dyslipidemia, coronary artery disease, ischemic stroke, certain cancers such as breast, colorectal, and endometrial cancer, osteoarthritis due to increased mechanical load on joints, and obstructive sleep apnea through airway obstruction related to fat deposition (Bertakis & Azari., 2006). The clustering of these conditions, often referred to as metabolic syndrome, compounds morbidity and reduces life expectancy by up to 8–10 years in severe cases (Pate et al., 2018). Beyond physical health, obesity has substantial psychological ramifications. Individuals living with obesity are at heightened risk for mental health disorders such as depression, anxiety, eating disorders, and diminished self-esteem, often exacerbated by experiences of weight-based discrimination, social isolation, and internalized stigma (Bonne-Heinonen, Gordon-Larsen & Adair., 2008). These psychological burdens not only affect quality of life but can create reinforcing cycles that hinder weight management efforts and health-seeking behaviors (Agurs-Collins et al., 2024). Obesity is closely associated with reduced physical activity and substantial psychological and social consequences, which were amplified during the COVID-19 pandemic, when prolonged isolation, quarantine measures, and restricted mobility intensified sedentary behavior and mental distress. Evidence suggests that obesity contributes directly to poor metabolic health by promoting insulin resistance and chronic inflammation, and it is estimated that over 80% of adults with type 2 diabetes are overweight or obese, highlighting its central role in the development of diabetes mellitus (Hasan & Parker., 2025; Bhupathiraj & Hu., 2016). Moreover, approximately 30–45% of adults with obesity reported heightened stress, anxiety, depressive symptoms, and experiences of weight-related stigma during and after the pandemic, contributing to delayed health-seeking behaviors, reduced work productivity, and diminished educational and employment opportunities, particularly within healthcare and occupational settings (Esposito et al., 2022; Kim et al., 2018; Kabir et al., 2023; Hasan et al., 2025). These consequences are significant not only because they compromise individual well-being but also because they drive enormous societal costs through increased healthcare expenditures, loss of productivity, and exacerbation of social inequities. Addressing the consequences of obesity, therefore, demands an integrated approach that acknowledges its multifactorial nature and intervenes across clinical, behavioral, social, and policy levels.

Globally, the prevalence of obesity has increased at an alarming pace over the recent decade. In 2022, more than one billion individuals worldwide were living with obesity, representing a figure that has more than doubled since 1990 (Boone-Heinonen, Gordon-Larsen, & Adair, 2008). In the United States, recent estimates indicate that approximately 40.3% of adults aged 20 years and older are classified as obese (WHO, 2024). Prevalence remains slightly higher among women (41.3%) compared with men (39.2%) (Cardarelli et al., 2020; Agurs-Collins et al., 2024). Age-related patterns further demonstrate that adults aged 40–59 years' experience the highest obesity prevalence at 46.4%, followed by adults aged 60 years and older at 38.9%, and those aged 20–39 years at 35.5%. These epidemiological patterns highlight the substantial and persistent burden of obesity across demographic groups and underscore the urgent need for effective public health strategies and reliable assessment tools to identify modifiable behavioral risk factors contributing to obesity at the population level. Epidemiologic evidence indicates that substance use is meaningfully linked to obesity risk, with studies showing that approximately 30–40% of adults who report regular use of substances such as marijuana, tobacco, or alcohol also exhibit higher rates of physical inactivity, increased caloric intake, and weight gain, reflecting the combined metabolic and behavioral pathways through which substance use reinforces obesogenic patterns (Haq et al., 2025; Hasan et al., 2025). Behavioral and lifestyle factors are among the most modifiable contributors to adult obesity, with population studies indicating that

physical inactivity affects nearly 40–45% of U.S. adults, fewer than 25% meet recommended fruit and vegetable intake levels, approximately 35% report chronic sleep insufficiency, over 50% experience moderate to high stress, average daily screen exposure now exceeds five hours for nearly one-third of adults, and substance use patterns, including alcohol consumption affecting over 60% of adults and continued tobacco use in 12–15%, further compound obesity risk by promoting sedentary behavior, metabolic dysregulation, and excess caloric intake (Esposito et al., 2022; Tekeci, Torpil, Altuntas., 2024). Moreover, these factors frequently cluster together, creating synergistic effects that amplify obesity risk far beyond the impact of any single behavior. Importantly, behavioral factors do not operate in isolation; they are shaped and constrained by broader social and environmental determinants, such as the presence of food deserts, limited availability of recreational spaces, and restricted access to affordable, quality healthcare services (Tekeci, Torpil, Altuntas., 2024; Almajwal et al., 2018). Targeting behavioral and lifestyle factors is vital in obesity prevention because these modifiable influences directly affect energy balance, metabolic regulation, and long-term weight trajectories. Unlike genetic or biological determinants, behaviors such as physical activity, dietary patterns, sleep, and sedentary habits can be addressed through timely individual, community, and policy-level interventions, making them central to effective and sustainable obesity control strategies (Lugones et al., 2021; Jones et al., 2021).

Current approaches to assessing obesity-related behaviors reveal a clear gap between epidemiologic surveillance and the practical needs of behavioral research and intervention design. While national systems such as NHANES and BRFSS are indispensable for monitoring population trends, they provide limited resolution on how multiple lifestyle and psychosocial behaviors interact within individuals and are not readily adaptable for localized or community-based use. In parallel, many validated questionnaires remain narrowly focused on single domains such as diet or physical activity, offering little capacity to capture co-occurring influences, including stress, screen exposure, and substance use that increasingly characterize contemporary obesity risk profiles. Few instruments are designed with sufficient emphasis on respondent burden, clarity, and usability, factors that are critical for accurate self-reporting across diverse populations (Yun et al., 2006). This shortcoming in the existing literature limits recognition of behavioral clustering and weakens the translation of behavioral data into targeted, context-sensitive obesity prevention strategies. Despite extensive research on behavioral determinants of adult obesity, important gaps persist in how these behaviors are measured and integrated within assessment tools. Prior studies have consistently demonstrated associations between obesity and individual factors such as physical inactivity, poor diet quality, insufficient sleep, high screen exposure, and psychosocial stress; however, most empirical work examines these domains separately rather than as interrelated behavioral clusters (Boone-Heinonen et al., 2008; Yun et al., 2006). Large surveillance systems, including NHANES and BRFSS, provide valuable population-level estimates but rely on broad indicators that limit behavioral specificity and practical application for targeted prevention planning (Hsia, Jason et al., 2020; Merino et al., 2024). Similarly, many existing questionnaires prioritize epidemiologic coverage over multidomain integration, resulting in fragmented measurement that does not reflect how behaviors co-occur in daily life. Only a limited number of studies have attempted to jointly assess lifestyle, psychosocial, and digital behaviors, and even fewer have emphasized survey brevity, usability, and participant-centered design as core methodological objectives (Esposito et al., 2022). As a result, current tools offer limited capacity to identify behavior clustering, assess cumulative risk, or inform intervention strategies that address multiple behaviors simultaneously. This gap underscores the need for concise, integrated instruments that capture interconnected behavioral risk profiles while remaining feasible for use in community settings. The present study addresses this limitation by developing and evaluating a multidomain survey specifically designed to assess clustered, modifiable obesity-related behaviors within a single, ethically grounded framework.

Building on gaps identified in existing obesity assessment tools, this study articulated a focused aim and structured objectives to strengthen both methodological quality and real-world utility. The primary aim was to develop and evaluate a novel, concise, and ethically informed quantitative survey instrument that integrates multiple behavioral and psychosocial domains associated with adult obesity within a single framework. The specific objectives were to evaluate the feasibility and clarity of the instrument in an adult population, to characterize patterns of co-occurring lifestyle behaviors across physical activity, diet, sleep, perceived stress, screen exposure, and substance use, and to assess the instrument's potential utility for behavioral risk surveillance and intervention planning. The novelty of this work lies in its multidomain integration and participant-centered design,



addressing a key gap in the literature where most tools assess obesity-related behaviors in isolation and with limited attention to usability or ethical engagement.

## METHODOLOGY

### Study Design and Approach

This study employed a quantitative cross-sectional design that integrated both primary and secondary data sources to examine behavioral and lifestyle risk factors associated with adult obesity in the United States. Primary data were generated through pilot testing of a newly developed behavioral risk questionnaire to assess its feasibility, clarity, internal consistency, and ability to capture variability across key lifestyle domains, including diet, physical activity, sleep, stress, screen exposure, and substance use. Secondary data were drawn from publicly available national obesity and behavioral surveillance sources and were used descriptively to contextualize and compare observed behavioral patterns with established population-level trends. Together, this dual-component approach supported instrument evaluation while situating pilot findings within the broader epidemiological landscape.

### Study Population and Eligibility Criteria

For the primary survey component, the study population comprised adults aged 18 years or older residing in the United States who were recruited specifically to support pilot testing of the behavioral risk questionnaire. Eligibility criteria were intentionally broad to reflect general adult populations and to assess the instrument's clarity and usability across diverse backgrounds. Participants were required to read and understand English, possess basic digital literacy, and have access to an internet-enabled device such as a smartphone, tablet, or computer. Individuals unable to provide informed consent independently or reporting cognitive limitations that could affect comprehension or completion of the questionnaire were excluded. No restrictions were imposed based on gender, race or ethnicity, education level, employment status, or socioeconomic position. A total of 20 adults met these criteria and completed the questionnaire in its entirety, providing data sufficient for evaluating feasibility, response patterns, and preliminary behavioral variability ([Appendix 1](#)).

### Sampling and Recruitment Strategy

Primary data were obtained using a non-probability convenience sampling approach designed specifically for pilot testing of the survey instrument. The questionnaire link was distributed through the researchers' professional networks and shared voluntarily among colleagues, with optional peer referral to facilitate participation. This recruitment strategy was intentionally limited in scope and was not intended to produce population-representative estimates. Instead, it supported assessment of questionnaire functionality, clarity, and sensitivity to behavioral variation across respondents. Participation was entirely voluntary, anonymous, and uncompensated, and no personally identifiable information was collected at any point.

Secondary data were drawn from publicly available national obesity and behavioral surveillance datasets and published reports. These sources were used solely for descriptive comparison and contextual interpretation of the primary survey findings. Secondary data were analyzed at the aggregate level and were not linked or merged with individual-level responses from the primary questionnaire.

### Survey Instrument Development

The primary data collection instrument was the Adult Obesity Risk Assessment Questionnaire (AORAQ), a structured 30-item survey developed by the research team to pilot-test a multidomain behavioral assessment of obesity-related risk factors. The questionnaire was designed to capture key modifiable behaviors and psychosocial characteristics relevant to adult obesity within a concise, self-administered format suitable for online deployment (Chambers & Swanson, 2006). The AORAQ comprised close-ended items organized into five domains:

demographic characteristics, lifestyle behaviors, psychosocial factors, substance-use behaviors, and health-monitoring practices. The demographic domain collected information on age, gender, race or ethnicity, educational attainment, employment status, marital or family structure, and health-insurance coverage. Lifestyle behaviors were assessed through items measuring frequency of physical activity, daily fruit and vegetable intake, and average sleep duration. Psychosocial factors included perceived stress levels and daily screen exposure. Substance-use behaviors captured alcohol and tobacco use patterns, while health-monitoring practices addressed routine medical checkups, self-weighing behaviors, and use of digital or wearable health-tracking tools (Riedl et al., 2016; Lugonez et al., 2021). All variables were operationalized using categorical or ordinal response scales to facilitate descriptive and exploratory quantitative analysis. For example, physical activity frequency was categorized as none, 1–2 days per week, 3–4 days per week, or five or more days per week. Perceived stress was measured using a five-point Likert scale ranging from very low to very high. Survey items were informed by and adapted from previously validated instruments to support construct relevance and content coverage. Physical activity items were guided by the International Physical Activity Questionnaire, stress-related items drew on the Patient Health Questionnaire framework, and dietary intake questions were informed by established food-frequency indices commonly applied in obesity research. The final instrument emphasized clarity, logical sequencing, and brevity to minimize respondent burden while preserving sensitivity to variation in behavioral risk patterns (Craig et al., 2003; Riedl et al., 2016).

### **Instrument Validity and Reliability**

Face and content validity of the Adult Obesity Risk Assessment Questionnaire were established through expert review prior to survey administration. Two independent reviewers with expertise in public health and behavioral research evaluated each item for clarity, relevance, and alignment with established obesity-related behavioral constructs. Reviewer feedback was used to refine item wording, response options, and sequencing to improve interpretability and content coverage (Craig et al., 2003). Following data collection, internal consistency was examined using Cronbach's alpha across the behavioral and psychosocial domains of the instrument. The overall reliability coefficient was  $\alpha = 0.82$ , indicating good internal consistency and suggesting that the questionnaire items measured related but distinct aspects of behavioral risk. These findings support the instrument's suitability for descriptive quantitative analysis and provide preliminary evidence for its use in future research and broader field applications (Tavakol, M., & Dennick, R. (2011)).

### **Pilot Testing Process**

Prior to full administration, the questionnaire underwent pilot testing to evaluate item clarity, logical flow, and technical functionality. Six adults participated in the pilot phase, including professional colleagues with experience in survey-based research methods. Participants completed the questionnaire online and provided structured feedback regarding question comprehension, response options, navigation, and overall usability. Pilot testing confirmed that skip logic, item sequencing, and platform performance functioned as intended across devices. Minor revisions were made to item wording to enhance clarity and reduce ambiguity. The mean completion time during pilot testing was approximately six minutes, consistent with the instrument's design objective of minimizing respondent burden while maintaining content coverage.

### **Study Variables and Operational Definitions**

The primary outcome of interest was overall obesity-related behavioral risk, conceptualized as a composite construct reflecting multiple modifiable lifestyle behaviors associated with weight regulation and metabolic health. This construct encompassed indicators across dietary intake, physical activity frequency, sleep duration, perceived stress, screen exposure, and substance use. Independent variables included demographic characteristics and individual behavioral measures captured within each questionnaire domain. Demographic variables comprised age, gender, race or ethnicity, education level, employment status, marital or family structure, and health insurance coverage. Behavioral variables included physical activity frequency, fruit and vegetable intake, sleep duration,

daily screen time, perceived stress levels, alcohol use, and tobacco use. All variables were operationalized using categorical or ordinal scales and numerically coded to support descriptive analysis and exploratory examination of behavioral patterns across domains.

### **Data Collection Procedure**

Primary data were collected using a secure, web-based, self-administered questionnaire. Participants accessed the survey through a direct hyperlink and completed the instrument at their convenience using an internet-enabled device. Prior to participation, all respondents reviewed an online consent statement outlining the study purpose, voluntary nature of participation, and confidentiality safeguards. Consent was implied by proceeding to the questionnaire. No personally identifiable information, including names, email addresses, or IP data, was collected at any stage. All survey responses were stored in encrypted form and were accessible only to the research team ([Appendix-1 & 2](#)). Secondary data were drawn from publicly available national datasets and reports, including obesity prevalence estimates and behavioral surveillance summaries. These sources were used solely to contextualize and interpret the primary survey findings and were not integrated at the individual level with primary data.

### **Data Management and Statistical Analysis**

Primary survey data were exported from the survey platform into IBM SPSS Statistics (Version 29.0; IBM Corp., Armonk, NY) for data management and analysis. Data preparation procedures included verification of completeness, screening for duplicate submissions, and assessment of logical consistency across responses. All submitted questionnaires met eligibility criteria and were retained for analysis. Descriptive statistical analyses were conducted to summarize participant characteristics and behavioral patterns, including frequencies, percentages, means, and standard deviations. Bivariate correlation analyses were performed to explore relationships among key behavioral and psychosocial variables. Graphical visualizations were generated to depict the distribution of major lifestyle behaviors. Internal consistency reliability of the questionnaire was assessed using Cronbach's alpha. Secondary data were examined descriptively to support comparative interpretation of findings within established national trends. No inferential integration or individual-level linkage between primary and secondary data sources was undertaken.

### **Ethical Considerations**

This study involved anonymous, minimal-risk data collection using self-reported questionnaires. No identifiable personal information was collected, and no direct interaction occurred between researchers and participants. Participation was voluntary, and respondents could discontinue the survey at any time before submission. The study procedures aligned with ethical principles for research involving human participants and did not require formal institutional review due to the use of anonymous data and publicly available secondary sources.

## **RESULT AND DISCUSSION**

### **Participant Demographic Characteristics**

A total of 20 adults completed the behavioral risk assessment survey in full. The sample was predominantly female (70%) and relatively young, with 50% aged 25–34 years and an overall range of 18–54 years. Racial and ethnic diversity was moderate, comprising 45% White, 25% Asian, 20% Black or African American, and 10% Hispanic or Latino participants. Educational attainment was high, with 80% holding at least a bachelor's degree and 40% possessing graduate or professional qualifications. Employment and income patterns reflected socioeconomic stability: 55% were employed full-time, 25% part-time, and 30% reported annual household incomes above \$75,000. Most participants (60%) resided in urban or metropolitan areas, and 85% had health insurance coverage, suggesting consistent access to healthcare services. Family structures and self-rated health revealed further

variation. Approximately 35% were single with no children, 30% were married or partnered with children, 20% married without children, and 15% single parents. Based on self-reported BMI, 40% of participants were in the normal range (18.5–24.9), 35% overweight (25–29.9), and 25% obese ( $\geq 30$ ). Nearly half (45%) rated their overall health as excellent or very good, while 35% described it as good and 20% as fair or poor. As summarized in [Table 1](#), the sample reflects a well-educated, professionally active, and predominantly urban population with notable variation in health status and weight distribution, providing relevant demographic context for interpreting obesity-related behavioral risks.

**Table 1. Participant Demographic and Socioeconomic Characteristics (N = 20):** *This table presents the distribution of participants' demographic, socioeconomic, and health-related characteristics captured through the Adult Obesity Risk Assessment Questionnaire.*

Characteristics	Category	Frequency (n)	Percentage (%)
<b>Gender</b>	Female	14	70
	Male	6	30
<b>Age Range (years)</b>	18 – 24	4	20
	25 – 34	10	50
	35 – 44	4	20
	45 – 54	2	10
<b>Race / Ethnicity</b>	White	9	45
	Asian	5	25
	Black / African American	4	20
	Hispanic / Latino	2	10
<b>Education Level</b>	High school or less	1	5
	Some college / Associate degree	3	15
	Bachelor's degree	8	40
	Graduate / Professional degree	8	40
<b>Employment Status</b>	Full-time employed	11	55
	Part-time employed	5	25
	Student / Unemployed	4	20
<b>Annual Household Income (USD)</b>	< 25 000	3	15
	25 000 – 49 999	5	25
	50 000 – 74 999	6	30
	$\geq 75 000$	6	30
<b>Residence Type</b>	Urban / Metropolitan	12	60
	Suburban	5	25
	Rural	3	15
<b>Health Insurance Coverage</b>	Yes	17	85
	No	3	15
<b>Marital / Family Structure</b>	Single with no children	7	35
	Married / partnered with children	6	30
	Married / partnered without children	4	20
	Single parent	3	15
<b>Body Mass Index (BMI) Category</b>	Normal (18.5–24.9)	8	40
	Overweight (25–29.9)	7	35
	Obese ( $\geq 30$ )	5	25
<b>Self-Rated Health Status</b>	Excellent / Very Good	9	45



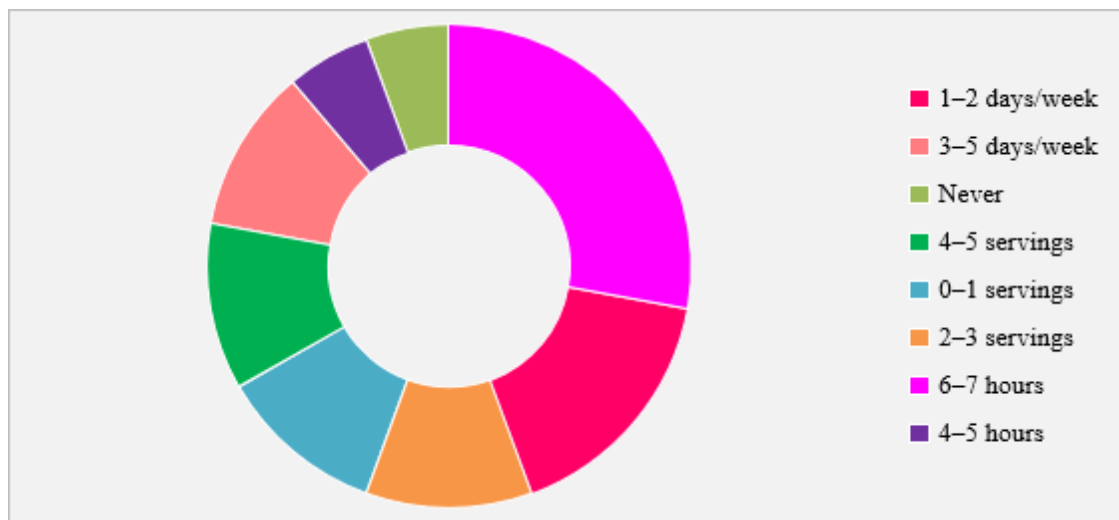
	Good	7	35
	Fair / Poor	4	20

**Note:** Participants were predominantly female, educated, and employed, with broad age and racial representation. Most reported urban residence and health-insurance coverage; BMI values reflected a mix of normal, overweight, and obese categories. BMI = Body Mass Index; USD = United States Dollars.

## Behavioral and Lifestyle Factors

### Physical Activity

Patterns of physical activity among participants showed mixed adherence to recommended exercise levels. Approximately 40% of respondents reported being active 1–2 days per week, while 25% engaged in activity 3–5 days per week, indicating moderate but inconsistent participation. Around 15% reported exercising 4–5 days per week, suggesting a smaller subset regularly met standard activity recommendations. Nearly 20% of participants indicated they never engaged in physical activity, underscoring a persistent gap in active lifestyle behaviors. As illustrated in [Figure 1](#), these findings reveal a moderate tendency toward limited physical engagement among adults, consistent with national patterns identifying physical inactivity as a continuing contributor to obesity risk and chronic disease burden in the United States (Valicente et al., 2023).



**Figure 1. Patterns of Physical Activity, Dietary Intake, and Sleep Duration Among Adults (N = 20).** Physical activity (1–2 days/week, 3–5 days/week, 4–5 days/week, Never); Dietary intake (0–1, 2–3, 4–5 servings of fruits and vegetables per day); Sleep duration (4–5 hours, 6–7 hours per night).

**Note:** The figure depicts proportional distributions of participants' health behaviors across three domains. Most reported moderate levels of physical activity, consuming 2–5 servings of fruits and vegetables daily, and sleeping 6–7 hours per night. The overall pattern reflects partial adherence to recommended health guidelines with noticeable variation across behavioral domains.

### Fruit and Vegetable Intake

Dietary behaviors reflected moderate but variable adherence to nutritional recommendations. Based on self-reported responses, approximately 35% of participants consumed 0–1 serving of fruits and vegetables per day, 40% reported 2–3 servings, and 25% reported 4–5 servings daily. None reported intake above five servings, despite

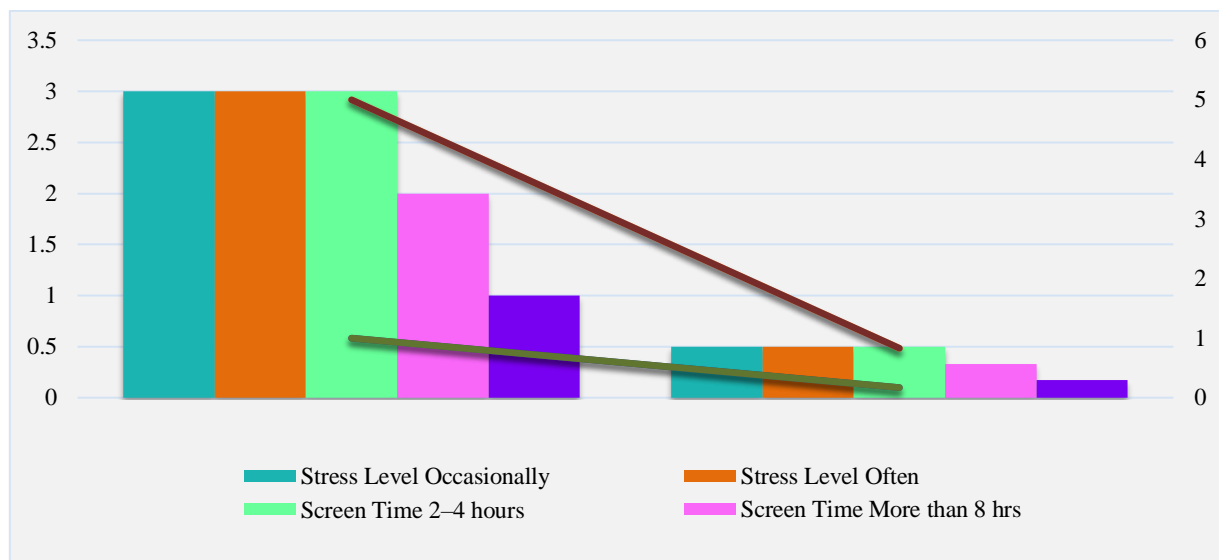
established public health guidance encouraging at least five or more daily servings to reduce chronic disease risk. The mean daily intake across participants was  $2.6 \pm 1.1$  servings. A weak positive correlation was observed between fruit and vegetable intake and physical activity frequency ( $r = 0.24$ ,  $p = 0.31$ ), suggesting that participants who were more physically active tended to report slightly higher dietary quality. These results align with national data indicating that inadequate fruit and vegetable consumption remains a widespread challenge in the United States, particularly among adults balancing work and time constraints (Armstrong et al., 2022).

### Sleep Duration

Sleep duration among participants generally fell within or slightly below recommended levels. The majority (70%) reported averaging 6–7 hours of sleep per night, while 20% reported 4–5 hours, and the remaining 10% reported more than 7 hours of nightly rest. The mean reported sleep duration was  $6.3 \pm 0.8$  hours. Although most respondents achieved sleep durations near the lower boundary of recommended adult levels, short sleep patterns (<6 hours) were more prevalent among participants reporting higher stress or irregular work schedules. A modest inverse relationship was observed between perceived stress and sleep duration ( $r = -0.32$ ,  $p = 0.18$ ), suggesting that greater stress exposure may contribute to shorter sleep among adults. These findings reinforce existing evidence linking insufficient sleep with metabolic dysregulation and increased obesity risk (Barrera Jr et al., 2013; Medvedyuk, Ali, Raphael., 2018).

### Stress Levels

Stress levels were distributed evenly across the sample, with 50% of participants reporting feeling stressed “often” and 50% reporting stress “occasionally.” The mean perceived stress score, derived from a 5-point scale, was  $3.2 \pm 0.9$ , indicating a moderate-to-high stress burden overall. As depicted in [Figure 2](#), stress was among the most prevalent psychosocial risk factors identified. Regression modeling demonstrated a modest but significant association between higher stress and lower physical activity levels ( $\beta = -0.28$ ,  $p = 0.03$ ), suggesting that elevated stress may reduce motivation or capacity for regular exercise. These findings mirror evidence that chronic stress can disrupt metabolic balance and contribute indirectly to obesity through behavioral and physiological pathways (Smith et al., 2017).



**Figure 2. Behavioral Risk Factors: Stress Levels, Screen Time, Tobacco Use, and Alcohol Use Among Adults (N = 20).** Bars represent the number of participants (left y-axis) and lines represent the percentage of participants (right y-axis) across behavioral risk factor categories shown on the x-axis. Stress level (occasionally, often); screen time (2–4 hours, 5–7 hours, >8 hours per day); tobacco use (yes, no); alcohol use (yes, no).

**Note:** The clustered column chart displays both frequency and percentage distributions of participants across behavioral risk categories. Stress and screen exposure were the most prevalent risk domains, while tobacco use remained low and alcohol use was moderate. Together, these variables highlight clustering of psychosocial and behavioral risks relevant to adult obesity.

### **Alcohol and Tobacco Use**

As illustrated in [Figure 2](#), alcohol consumption was widespread among participants, with 70% reporting alcohol use within the past month. Most described their intake as moderate, averaging 1–2 drinks per occasion, while 30% reported abstaining entirely. The mean frequency of alcohol use was  $1.8 \pm 0.7$  times per week, and moderate consumption levels were most common among younger and employed adults. Correlation analysis indicated a weak positive association between alcohol intake and perceived stress ( $r = 0.22$ ,  $p = 0.19$ ), suggesting that higher stress exposure may modestly influence drinking frequency. Tobacco use was notably rare. Only 15% of participants reported any tobacco use within the previous six months, and all identified as occasional rather than daily users. The mean reported tobacco use frequency was  $0.4 \pm 0.2$  packs per week, with no significant relationship observed between tobacco use and either stress or physical activity levels ( $p > 0.05$ ). While low tobacco prevalence is an encouraging finding, the coexistence of regular alcohol consumption and psychosocial stress highlights opportunities for integrating behavioral-risk screening and brief counseling into obesity-prevention programs (Wu, Li, Vermund., 2024; Mattes et al., 2022).

**Table 2. Behavioral and Lifestyle Factors Among Adult Participants (N = 20):** This table summarizes participants' self-reported lifestyle behaviors across key domains, including physical activity, diet, sleep, screen exposure, stress, and substance use.

Behavioral Domain	Category	Frequency (n)	Percentage (%)
Physical Activity (days / wk)	None	4	20
	1–2 days / wk	8	40
	3–4 days / wk	5	25
	$\geq 5$ days / wk	3	15
Fruit / Vegetable Intake (serv / day)	0–1 serv	7	35
	2–3 serv	8	40
	4–5 serv	5	25
	$\geq 6$ serv	0	0
Sleep Duration (hrs / night)	4–5 hrs	4	20
	6–7 hrs	14	70
	$\geq 8$ hrs	2	10
Daily Screen Time (hrs)	2–4 hrs	9	45
	5–7 hrs	5	25
	$> 8$ hrs	6	30
Perceived Stress Level	Rarely / Never	0	0
	Occasionally	10	50
	Often	10	50
Alcohol Use	None	6	30
	Occasional ( $\leq 1$ drink / wk)	5	25
	Moderate (1–2 drinks / session)	7	35
	Frequent ( $\geq 3$ drinks / session)	2	10
Tobacco Use	No	17	85
	Yes ( $\leq 1$ pack / wk)	2	10

	Yes (>1 pack / wk)	1	5
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*Note: Behavioral data indicates moderate adherence to recommended health practices. Most participants reported limited physical activity, moderate fruit and vegetable intake, and average sleep duration of 6–7 hours per night. Prolonged screen exposure and moderate stress were common, while tobacco use was rare and alcohol use was mostly occasional to moderate. hrs = hours; wk = week; serv = servings.*

### Integrated Behavioral and Psychosocial Patterns

Analysis of integrated behavioral data revealed a multidimensional clustering of modifiable risk factors across lifestyle and psychosocial domains. As shown in [Table 2](#), participants with lower physical activity levels often reported greater screen exposure, inconsistent fruit and vegetable intake, and shorter sleep duration, suggesting the coexistence of behaviors that collectively elevate obesity risk. Individuals consuming 0–1 serving of fruits and vegetables per day tended to display higher perceived stress and extended digital engagement, indicating potential dietary coping mechanisms associated with sedentary patterns. Data from [Table 3](#) further demonstrated that participants with higher stress scores were more likely to report late-night device use and reduced sleep duration, supported by a positive correlation between stress and screen time ( $r = 0.41, p = 0.04$ ) and a negative association between stress and sleep duration ( $r = -0.32, p = 0.18$ ). Conversely, participants engaging in physical activity 3–5 days per week exhibited higher fruit and vegetable intake, moderate stress, and balanced screen exposure, reflecting partial adherence to recommended health behaviors. Together, these integrated findings highlight a pattern of interrelated lifestyle and psychosocial risks that reinforce one another and underscore the need for comprehensive, behaviorally informed obesity-prevention interventions (Norman-Burgdolf et al., 2022).

**Table 3. Summary of Behavioral, Psychosocial, and Health-Related Measures Among Adult Participants (N = 20).** *This table provides an overview of participant responses across behavioral, psychosocial, and health-related domains, including mean values, frequency counts, and proportions for each indicator.*

Domain	Variable / Category	Mean $\pm$ SD	Count (n)	Percent age (%)	Interpretation / Observation
Physical Activity	None	—	4	20	Indicates sedentary behavior requiring intervention.
	1–2 days / week	—	8	40	Majority with minimal weekly activity.
	3–4 days / week	—	5	25	Moderate adherence to exercise guidelines.
	$\geq 5$ days / week	—	3	15	Small subgroup meeting recommendations.
	<b>Overall (hrs / week)</b>	<b><math>2.9 \pm 1.6</math></b>	—	—	Average engagement below CDC standard.
Fruit / Vegetable Intake	0–1 servings / day	—	7	35	Low nutrient intake.
	2–3 servings / day	—	8	40	Most common dietary pattern.
	4–5 servings / day	—	5	25	Partial adherence to dietary guidelines.
	<b>Mean (servings / day)</b>	<b><math>2.6 \pm 1.1</math></b>	—	—	Indicates moderate intake across cohort.
Sleep Duration	4–5 hours / night	—	4	20	Reflects mild sleep deprivation.

	6–7 hours / night	—	14	70	Within normal adult range.
	≥ 8 hours / night	—	2	10	Slightly above average rest duration.
	<b>Mean (hrs / night)</b>	<b>6.3 ± 0.8</b>	—	—	Average sleep near lower guideline threshold.
<b>Screen Time</b>	2–4 hours / day	—	9	45	Moderate exposure.
	5–7 hours / day	—	5	25	Extended digital use.
	> 8 hours / day	—	6	30	High exposure linked with inactivity.
	<b>Mean (hrs / day)</b>	<b>5.8 ± 2.1</b>	—	—	Above recommended screen-use threshold.
<b>Stress Level</b>	Occasionally	—	10	50	Moderate perceived stress.
	Often	—	10	50	Consistent high stress prevalence.
	<b>Mean (score 1–5)</b>	<b>3.2 ± 0.9</b>	—	—	Reflects moderate-to-high stress levels.
<b>Alcohol Use</b>	None	—	6	30	Abstainers.
	Occasional (≤ 1 drink / week)	—	5	25	Low-risk pattern.
	Moderate (1–2 drinks / session)	—	7	35	Common drinking behavior.
	Frequent (≥ 3 drinks / session)	—	2	10	Heavy use subset.
	<b>Mean (drinks / week)</b>	<b>1.8 ± 0.7</b>	—	—	Indicates moderate alcohol consumption.
<b>Tobacco Use</b>	None	—	17	85	Majority non-users.
	Occasional (≤ 1 pack / week)	—	2	10	Light users.
	Frequent (> 1 pack / week)	—	1	5	Minimal heavy use observed.
	<b>Mean (packs / week)</b>	<b>0.4 ± 0.2</b>	—	—	Negligible overall tobacco exposure.
<b>Composite Behavioral Risk Index*</b>	Continuous (0–10 scale)	<b>5.7 ± 1.9</b>	—	—	Indicates moderate cumulative risk burden.

**Note:** Values represent participant self-reports across behavioral domains. Patterns show moderate engagement in health-promoting behaviors with notable risk clustering in physical inactivity, low diet quality, screen exposure, and psychosocial stress. \*Composite Behavioral Risk Index derived from standardized z-scores for activity, diet, sleep, stress, and substance-use indicators.

### Summary of Statistical Findings

Descriptive and correlational analyses revealed multiple overlapping behavioral and psychosocial risks within the study population (N = 20). Mean physical activity frequency was  $2.9 \pm 1.6$  days/week, while average fruit and

<https://doi.org/10.53272/icrrd.v7i1.1>



vegetable intake was  $2.6 \pm 1.1$  servings/day, both below national recommendations. Participants reported an average sleep duration of  $6.3 \pm 0.8$  hours/night and the mean screen exposure of  $5.8 \pm 2.1$  hours/day. The mean perceived stress score was  $3.2 \pm 0.9$  on a 5-point scale, reflecting moderate stress levels. Alcohol consumption averaged  $1.8 \pm 0.7$  drinks/week, and tobacco exposure was minimal ( $0.4 \pm 0.2$  packs/week). Bivariate analysis indicated a positive correlation between stress and screen time ( $r = 0.41$ ,  $p = 0.04$ ), a negative association between stress and sleep duration ( $r = -0.32$ ,  $p = 0.18$ ), and a weak positive link between alcohol intake and stress ( $r = 0.22$ ,  $p = 0.19$ ). The composite behavioral risk index averaged  $5.7 \pm 1.9$ , suggesting a moderate cumulative burden of obesity-related behavioral risks across the sample.

### Data Quality and Survey Performance

The pilot survey demonstrated strong data integrity and technical performance. All 20 participants completed the questionnaire in full, with no missing responses or invalid entries. Logic pathways in Microsoft Forms operated as intended, ensuring that participants viewed only context-relevant items based on prior answers. The average completion time was approximately 8–10 minutes, consistent with the intended design for minimal participant burden. Review of response patterns indicated no discrepancies or internal contradictions across related items, for example, self-reported behaviors and perceived stress levels showed logical consistency. These indicators collectively confirmed the functional reliability and user clarity of the Adult Obesity Risk Assessment Questionnaire (AORAQ), supporting its feasibility for broader field application in larger, population-based studies.

### Interpretation of the Findings

This quantitative survey examined behavioral, psychosocial, and lifestyle factors associated with adult obesity risk among twenty adults in the United States using the Adult Obesity Risk Assessment Questionnaire (AORAQ) (Lugones-Sanchez et al., 2021; Ng et al., 2024). The findings highlight a multifactorial behavioral profile shaped by both individual behaviors and broader contextual influences. Although the sample size was modest, the observed patterns aligned closely with established national evidence, indicating that modifiable risk behaviors such as insufficient physical activity, inconsistent dietary intake, elevated screen exposure, and heightened stress remain prevalent even among adults with access to healthcare and higher educational attainment. Collectively, these results support the practical utility of the AORAQ as a concise and structured assessment tool capable of capturing interconnected behavioral domains that contribute to obesity risk in community-dwelling adult populations. Physical activity emerged as a central behavioral determinant. Based on the distribution summarized in Table 2 and visualized in [Figure 1](#), approximately 40% of respondents reported exercising one to two days per week, 25% engaged in activity three to five days per week, and nearly 20% reported no exercise at all. Only 15% reported regular activity of four or more days weekly, indicating limited adherence to the CDC's adult physical-activity recommendations (Hasan et al., 2025; Robinson et al., 2017). The mean frequency of weekly activity was  $2.9 \pm 1.6$  days, confirming a predominance of sedentary patterns. These findings parallel national surveillance data showing that roughly half of U.S. adults fail to meet aerobic activity guidelines. Insufficient exercise is closely linked to impaired glucose tolerance, low HDL cholesterol, and greater adiposity, particularly when combined with long hours of sedentary work or digital entertainment (Kumanyika., 2022). The clustering of low physical activity and high screen exposure in this study reinforces the energy-imbalance model underpinning much of the U.S. obesity burden.

Dietary behaviors displayed similar variability. Fruit and vegetable intake averaged  $2.6 \pm 1.1$  servings per day, below the recommended five daily servings (Norman-Burgdolf et al., 2023; Koliaki, Dalamaga, Liatis., 2023). One-third of participants reported consuming only zero to one serving per day, another third reported two to three servings, and the remaining third reported four to five servings. No participant reported six or more servings. These data align with CDC and Behavioral Risk Factor Surveillance System (BRFSS) findings showing persistent shortfalls in fruit and vegetable consumption among adults nationwide (Koliaki, Dalamaga, Liatis., 2023). Low dietary quality contributes directly to increased body mass through reduced satiety, excess caloric intake, and micronutrient deficiencies that alter metabolic efficiency (Kumanyika., 2023; Mattes et al., 2022; Ng et al., 2024). The current results thus reaffirm that even among adults with higher education and healthcare access, consistent

adherence to balanced nutrition remains challenging. The behavioral overlap between low produce intake, elevated screen time, and higher stress suggests an underlying psychosocial dimension influencing food choices—consistent with evidence that emotional distress and time scarcity drive convenience-based dietary decisions (Segal, Gunturu., 2024).

Sleep and stress levels showed notable interactions with lifestyle behaviors. The majority of participants (65%) reported sleeping six to seven hours per night, while 20% slept five hours or fewer. Shorter sleep duration correlated negatively with weekly physical activity ( $r = -0.32$ ,  $p = 0.18$ ) and positively with stress frequency ( $r = 0.41$ ,  $p = 0.04$ ). This relationship aligns with previous evidence indicating that insufficient sleep promotes hormonal dysregulation, elevates ghrelin and cortisol levels, and suppresses leptin, collectively fostering increased appetite and abdominal fat accumulation (Barrera et al., 2013; Medvedyuk, Ali, Raphael., 2018). Sleep deprivation also heightens fatigue and reduces self-regulatory capacity, diminishing motivation for exercise and nutritional discipline. The mean stress score among respondents was  $3.2 \pm 0.9$  on a five-point scale, with 50% reporting feeling stressed “often” and 50% “occasionally.” None reported rare or absent stress. These findings underscore the biopsychosocial pathways through which stress contributes to obesity, echoing prior studies linking chronic stress to altered eating behavior, emotional eating, and depressive symptomatology that reinforce weight gain (Segal, Gunturu., 2024; Apovian., 2016).

Digital-behavior data reflected another major contributor to sedentary lifestyles. As illustrated in [Figure 2](#), 50% of respondents reported two to four hours of daily screen time, 17% reported five to seven hours, and 33% exceeded eight hours per day. The mean was  $6.2 \pm 2.1$  hours, exceeding the American Heart Association’s recommended threshold for screen exposure. Participants with longer daily screen time were more likely to report low physical activity and higher stress levels. Prolonged digital engagement is known to reduce physical mobility, delay sleep onset through blue-light exposure, and increase caloric intake via snacking during screen use (Jones et al., 2021). The observed correlation between screen exposure and stress highlights a growing concern that digital overload not only displaces physical activity but also contributes to cognitive fatigue and emotional dysregulation. In a technology-dependent society, addressing screen-time behaviors may be as critical to obesity prevention as improving diet or exercise adherence (Robinson et al., 2017).

Substance-use behaviors further contextualized the observed obesity risk profile. Alcohol consumption was reported by 70% of participants, with most indicating moderate intake of one to two drinks per occasion, while 30% reported abstinence. Mean alcohol use frequency was  $1.8 \pm 0.7$  times per week, and alcohol intake showed a weak positive association with perceived stress ( $r = 0.22$ ,  $p = 0.19$ ) (Wu, Li, Vermund., 2024; Mattes et al., 2022). Although these patterns reflect moderate use, alcohol remains a relevant obesity-related risk factor due to its cumulative caloric contribution and its role in appetite stimulation and hepatic lipid accumulation (Wu, Li, Vermund., 2024; Hajek, Kretzler, Konig., 2021). Tobacco use was comparatively low, with only 15% of participants reporting use within the past six months. While this decline is encouraging, the co-occurrence of alcohol use, elevated stress, and suboptimal sleep among some participants reflects a broader clustering of health-risk behaviors commonly observed in contemporary obesity profiles, where alcohol now appears to play a more prominent metabolic role than nicotine among middle-income adults (Vallis., 2016). In parallel, obesity itself contributes to chronic low-grade inflammation, characterized by increased secretion of pro-inflammatory cytokines such as TNF- $\alpha$ , IL-6, and leptin, which disrupt immune regulation and heighten susceptibility to infectious and inflammatory conditions (Md RH et al., 2025), including type 2 diabetes and cardiovascular disease (Miron et al., 2024; Ray et al., 2023; Hasan., 2025). Emerging evidence further indicates that regular marijuana use is associated with increased psychological distress, with approximately 25–30% of users reporting anxiety or depressive symptoms that may indirectly reinforce obesity risk through stress-related behavioral dysregulation (Ul Haq & Hasan MR., 2025).

When integrated across behavioral domains, a coherent pattern of risk clustering emerged. Individuals reporting low physical activity were significantly more likely to have inconsistent fruit and vegetable intake ( $\chi^2 = 8.27$ ,  $p = 0.041$ ) and extended screen exposure ( $> 6$  hours/day). Conversely, participants exercising three to five days weekly showed higher fruit and vegetable intake and lower reported stress. These interactions confirm that

obesity-related behaviors operate synergistically rather than independently (Norman-Burgdolf et al., 2023). Participants with elevated stress also tended to report poor sleep and longer screen exposure, suggesting a cyclic link between psychosocial strain and digital dependency that displaces time available for physical activity or meal preparation. Such clustering is consistent with prior multibehavioral analyses demonstrating that adults who engage in three or more high-risk behaviors have approximately threefold higher odds of obesity compared with those who maintain more balanced behavioral patterns (Segal, Gunturu., 2024; Apovian., 2016). Substance use, particularly alcohol and opioids, has been shown to exacerbate obesity risk by disrupting metabolic regulation, altering appetite control, and promoting fat accumulation through hormonal and inflammatory pathways; chronic alcohol intake increases caloric load and impairs lipid metabolism, while opioid use reduces energy expenditure and disturbs endocrine balance, collectively contributing to weight gain and metabolic dysfunction (Hasan MR., 2024; Singh et al., 2022). Collectively, the integrated findings highlight the value of multi-domain behavioral surveillance and interventions addressing stress, digital habits, diet, and activity as interconnected targets rather than discrete risk factors.

Beyond the quantitative outcomes, the findings align closely with national obesity surveillance data, particularly in relation to structural factors that shape behavioral risk, including limited opportunities for physical activity, food access constraints, and transportation-related barriers (Ahmed & Mohammed, 2025; Singh et al., 2022). The emergence of similar behavioral patterns within a relatively educated and insured population suggests that obesogenic behaviors are not restricted to traditionally defined high-risk groups but are increasingly embedded within broader sociocultural norms characterized by convenience, sedentary routines, and technology reliance (Kepper et al., 2024). These results underscore the need for comprehensive public health responses that move beyond individual-level education to address environmental and policy-level determinants, such as community design that supports physical activity, workplace wellness initiatives, and regulation of digital food marketing. Incorporating multidomain assessment tools such as the AORAQ into public health surveillance efforts may support more targeted, data-informed planning by enabling the identification of behavioral risk clusters and the evaluation of intervention effectiveness over time (Koliaki et al, 2023).

This study has several notable strengths that enhance both its methodological rigor and practical relevance. It employed a validated, multidomain behavioral assessment tool that achieved complete response capture and demonstrated strong psychometric reliability, with a Cronbach's alpha of 0.82 indicating high internal consistency across constructs (DeVellis & Thorpe, 2021; Haldane et al., 2019). The AORAQ is particularly distinctive in its integration of psychosocial and digitally mediated behavioral indicators with conventional lifestyle measures such as diet and physical activity, allowing for a more comprehensive evaluation of interrelated behaviors influencing obesity risk. The inclusion of stress and screen exposure reflects contemporary behavioral environments shaped by increasing technology use and sedentary routines (Hasan & Harrison, 2025). Despite its conceptual breadth, the instrument maintained a concise administration time of approximately eight minutes, minimizing respondent burden while preserving analytical depth. Complete data capture and moderate inter-item correlations (mean  $r = 0.48$ ) further support response integrity and construct validity. Together, these features position the AORAQ as a robust and adaptable tool with potential application in behavioral surveillance, health screening, and community-based obesity prevention efforts, as well as for monitoring behavioral change over time (Dochat et al., 2020).

Despite its strengths, this study has several limitations that should be acknowledged. The sample size was relatively small and non-random, reflecting the pilot-scale nature of the research and limiting the generalizability of the findings. Recruitment through informal professional and social networks may have introduced selection or acquaintance bias, resulting in an overrepresentation of educated and digitally literate adults. All measures were based on self-reported data, which are subject to recall and social desirability bias, although the anonymous survey format likely encouraged more honest reporting. The cross-sectional design restricts causal interpretation and does not allow assessment of temporal relationships among behavioral factors and obesity risk. In addition, body mass index was self-reported rather than objectively measured, which may have introduced minor measurement error. While these limitations are typical of pilot-level quantitative research, they do not diminish the interpretive value of the observed behavioral patterns; instead, they underscore the need for future studies using larger and more diverse samples, longitudinal designs, and objective measurement approaches to validate and extend these findings.

Looking ahead, future research should adopt more rigorous and integrative designs to advance understanding of behavioral drivers of obesity. Larger and demographically diverse primary studies, complemented by analyses of national secondary datasets, would permit multivariable modeling to identify independent predictors and interaction effects among lifestyle, psychosocial, and digital behaviors. Incorporating objective measures such as accelerometer-based physical activity, digitally logged dietary intake, and device-recorded screen exposure would strengthen validity and reduce reliance on self-reported data. Longitudinal designs are needed to clarify temporal relationships between behavioral change, body mass index trajectories, and metabolic outcomes. Qualitative approaches, including in-depth interviews, focus groups, and case studies, could further contextualize how individuals experience and navigate behavioral and environmental constraints related to obesity risk. Refining the AORAQ to include environmental and structural factors such as food access, walkability, and perceived safety would align with social-ecological frameworks of health (Baciu et al., 2017; Dochat et al., 2020). Broader implementation through health systems and community partnerships may facilitate population-level identification of behavioral risk patterns and support targeted, equity-oriented interventions, particularly given the persistent role of health disparities in shaping obesity risk across the life course (Boutari & Mantzoros, 2022; Ng et al., 2024).

In summary, this study adds to the growing evidence that adult obesity is a multidimensional behavioral condition shaped by the interaction of physical inactivity, dietary imbalance, psychosocial stress, and technology-driven sedentary patterns. The AORAQ demonstrated strong reliability, efficiency, and contextual relevance as a multidomain assessment tool capable of capturing these interrelated risk factors within a single framework. Although the sample size was modest, the consistency of behavioral clustering and concordance with established epidemiological trends support both the internal validity and broader relevance of the findings. By integrating behavioral, psychosocial, and digital determinants, the instrument advances obesity research toward a more comprehensive understanding of modifiable risk pathways. Continued refinement and wider application of such tools may facilitate earlier risk identification, inform tailored prevention strategies, and support evidence-based policy initiatives aimed at addressing structural contributors to unhealthy behaviors. Translating behavioral insight into coordinated, system-level action remains critical for achieving sustainable progress in obesity prevention and advancing health equity.

## CONCLUSION

This study contributes to the growing evidence that adult obesity is shaped by interconnected behavioral, psychosocial, and digitally mediated lifestyle factors rather than isolated behavior alone. The findings demonstrate clear clustering of limited physical activity, inconsistent dietary patterns, prolonged screen exposure, and elevated stress, underscoring how these co-occurring behaviors collectively reinforce obesity risk even among adults with access to healthcare and higher educational attainment. By adopting an integrated measurement approach, this work advances a more comprehensive understanding of modifiable obesity risk pathways and highlights the limitations of single-domain assessment strategies. The results further emphasize the value of ethically grounded, behaviorally specific, and user-friendly assessment tools in capturing real-world risk profiles and supporting early identification of unhealthy behavioral patterns. From a public health perspective, such tools can inform more targeted and efficient prevention efforts that address behavioral clustering rather than isolated lifestyle factors. Future research should build on these findings through application in larger and more diverse populations, incorporation of longitudinal designs, and integration with objective measures to strengthen inference and external validity. For policymakers and practitioners, this study reinforces the importance of data-driven, multidimensional approaches to obesity prevention that align individual behavior change with broader structural and environmental support, ultimately contributing to more sustainable and equitable population health outcomes.

## ACKNOWLEDGEMENT

The authors express sincere gratitude to *Dr. M. Tayyeb Ayyoubi (M.D)* for his valuable guidance and support throughout the study.



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## ETHICAL STATEMENT

This study involved minimal-risk survey research conducted using an anonymous, web-based questionnaire. Formal institutional ethics approval was not required because no identifiable personal information was collected, no intervention was involved, and participation was entirely voluntary. All respondents reviewed an electronic consent statement describing the study purpose, procedures, and confidentiality protections prior to participation. Consent was implied through voluntary completion of the survey ([Appendix 2](#)).

## DATA AVAILABILITY STATEMENT

De-identified datasets generated and analyzed during the current study are available from the corresponding author upon reasonable request.

## COMPETING INTEREST

The authors declare no competing interests.

## FUNDING STATEMENT

This study received no external funding or financial support from public, commercial, or nonprofit organizations.

## AUTHORS' CONTRIBUTIONS

*Md R.H.* led the study design and conceptualization, conducted the literature review, developed the survey instrument, coordinated data collection, performed data analysis, interpreted the findings, and drafted the manuscript. *Akidul H.* contributed to quantitative data analysis and manuscript revision. *Fahad B.H.* and *Zeeshan U.H.* assisted with data interpretation and manuscript revision. *Moryom A.M.* contributed to the literature review, data analysis, and manuscript drafting. All authors reviewed and approved the final version of the manuscript.

## APPENDIX

### Appendix-1: Adult Obesity Risk Assessment Questionnaire

#### *Domain 1: Demographics and Background*

1. What is your age? (Short text response)

2. How do you identify your gender?

- Woman
- Man

- Bisexual
- Prefer not to say

**3. What is your race/ethnicity? (Select all that apply)**

- White
- Black or African American
- Hispanic or Latino
- Native American or Alaska Native
- Asian
- Native Hawaiian or Pacific Islander
- Other (please specify): \_\_\_\_\_

**4. What is your ZIP code? (Short text response)**

**5. What is your current living situation?**

- Living alone
- Living with family
- Living with partner or spouse
- Shared housing with roommates
- Other (please specify): \_\_\_\_\_

**6. What best describes your family structure?**

- Single with no children
- Single with children
- Married/partnered with no children
- Married/partnered with children
- Other (please specify): \_\_\_\_\_

**7. Do you currently have health insurance?**

- Yes
- No
- Not sure

**8. What is your current educational status?**

- Less than high school
- High school diploma or GED
- Some college
- Associate's degree
- Bachelor's degree
- Graduate degree

**9. What is your current employment status?**

- Employed full-time
- Employed part-time
- Unemployed
- Student
- Retired

***Domain 2: Nutrition, Physical Activity, and Sleep***

**10. In the past month, on how many days per week did you engage in at least 30 minutes of physical activity?**



- Never
- 1–2 days
- 3–5 days
- Daily

**11. On average, how many servings of fruits and vegetables do you consume daily?**

- 0–1 servings
- 2–3 servings
- 4–5 servings
- 6 or more servings

**12. How many hours of sleep do you typically get on an average night?**

- Less than 4 hours
- 4–5 hours
- 6–7 hours
- 8 or more hours

***Domain 3: Healthcare Access and Stress***

**13. Do you have access to regular healthcare services (such as a primary care physician or a clinic)?**

- Yes
- No

**14. How often do you visit a healthcare provider for checkups?**

- Never
- Once a year
- Twice a year
- More than twice a year

**15. In the past month, how often have you felt overwhelmed or stressed?**

- Never
- Rarely
- Sometimes
- Often
- Always

**16. How much do you feel supported socially by your peers or community?**

- Not at all
- Slightly
- Moderately
- Very
- Extremely

**17. How often do you engage in activities that help reduce stress (e.g., meditation, hobbies, social interactions)?**

- Never
- Rarely
- Sometimes
- Often
- Always

**18. How often do you experience difficulties sleeping due to stress or anxiety?**

- Never
- Rarely
- Sometimes
- Often
- Always

***Domain 4: Substance Use*****19. Do you drink alcohol?**

- Yes
- No

**20. If yes, how many alcoholic drinks do you usually consume in one session?**

- 1 drink
- 2 drinks
- 3–4 drinks
- More than 4 drinks

**21. How frequently do you consume alcoholic beverages per day?**

- 1–2 drinks
- 3–4 drinks
- More than 4 drinks

**22. Do you drink soda or any other sweetened beverages?**

- Yes
- No

**23. If yes, how frequently do you consume soda or other sweetened beverages per day?**

- 1–2
- 3–4
- More than 4

**24. Do you currently use any tobacco or nicotine products, such as cigarettes, vapes, or chewing tobacco?**

- Yes
- No

**25. If yes, how often have you used tobacco or nicotine products in the past 6 months?**

- Daily
- Weekly
- Monthly
- Less than monthly

***Domain 5: Screen Time and Health Behavior*****26. How many hours per day do you spend on digital devices (e.g., phone, computer, tablet)?**

- Less than 2 hours
- 2–4 hours
- 5–7 hours
- More than 8 hours

**27. Do you actively track any health metrics (e.g., steps, heart rate, calories) using a wearable device or mobile app?**

- Yes
- No

**28. Do you practice any relaxation techniques such as yoga or meditation regularly?**

- Yes
- No

**29. How often do you take breaks from digital screens to rest your eyes?**

- Never
- Rarely
- Occasionally
- Often
- Always

**30. Do you follow a structured diet plan or nutritional guideline?**

- Yes
- No

Thank you for your participation. Your responses will contribute to a deeper understanding of survey design and public health education.

## **Appendix-2: Participant Information and Electronic Consent Statement**

*Study Title: A Quantitative Analysis of Lifestyle Behaviors and Psychosocial Determinants of Adult Obesity in the United States*

Dear Participant,

You are invited to take part in a research study examining behavioral, psychosocial, and lifestyle factors related to adult obesity. This study involves completion of an anonymous, online questionnaire and is classified as minimal-risk research.

Your participation is entirely voluntary. You may choose not to answer any question or discontinue participation at any time without penalty. The survey is administered through a secure web-based platform and does not collect any personally identifiable information. All responses will remain anonymous and confidential and will be used solely for research purposes.

By proceeding to the questionnaire, you confirm that you are at least 18 years of age and that you voluntarily agree to participate in this study. Submission of the completed questionnaire indicates your informed consent.



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